University of Alberta

River Ice Breakup Forecasting with Fuzzy and Neuro-fuzzy Models

by

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Abstract

Spring river ice breakup on northern rivers can quickly result in ice jams which present severe flood risk to which have little or no advanced warning. Despite the serious threat posed, there are no reliable means to predict the severity of breakup with a significant lead time. Many of the previous studies regarding ice jam flood forecasting methods cite the lack of a comprehensive database as an obstacle to modeling. The ability to transfer a model between river basins is highly desirable but has not previously been achieved due to site specific nature of most river breakup models.

As a foundation, this thesis documents the development of an extensive database containing 106 variables, and covering the period from 1972 to 2004, that was created for ice jam forecasting on the Athabasca River for the community of Fort McMurray, Alberta. The number of historical years of data, rather than the scope of variables was found to be the major limitation for ice modeling at this site.

The potential for short and long time predictive models was evaluated. A short lead time model was achieved though multiple linear regression analysis, equations were developed to model the maximum water level. The optimal model contained a combination of hydrological and meteorological data collected from early fall until the day before river ice breakup. Soft computing including fuzzy logic and artificial neural networks was used to model the

maximum water level. It was found that a simple fuzzy expert system based exclusively on expert experience could qualitatively distinguish years when flooding occurred but produced poor quantitative results. A neuro-fuzzy model with fewer variables was able to simulate water levels equally as well as a multiple linear regression model with fewer input variables which provided a longer lead time.

Basin transferability was evaluated at Hay River in northern Canada. Qualitative results showed that the fuzzy model was transferred between basins because extreme events could be distinguished from years when flooding did not occur. The high quantitative accuracy of the neuro-fuzzy model was not reproduced. Climate change scenarios for the Athabasca River indicated a continuously decreasing risk of severe ice jams while the frequency in the Hay River Basin increased for a period before waning.

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a,b	coefficients;
a_t	transmittance of the atmosphere;
$DDay_{10}$	intensity of cold weather immediately before breakup: number of degree days of freeze-up 10 days prior to river breakup, °C-days;
$DDay_{total}$	measure of the intensity of the winter cold: number of degree days of freeze-up from November 1 until spring breakup, °C-days;
H_B	maximum water level attained on the Athabasca River at the Clearwater River confluence during spring river ice breakup, m;
H_{BO}	water level as measured below the town of Athabasca prior to spring runoff, m;
h_{is}	linear heat transfer coefficient between the air and the ice (or snow) interface, W/m^2/°C;
H_o	initial water level prior to spring melt increase in flow, m;
h_{sn}	snow depth on the ice cover prior to ice melt, m;
H_{sun}	local hour-angle of the sun;
I	characteristics of the ice cover on the expected ice jamming stretch;
$I_{Difference}$	difference between ice thickness measurements at Moberly Rapids at the WSC gauging site;
I_o	solar constant, 1367 W/m^2;
I_{Ratio}	ratio of ice thickness measurements for Moberly Rapids to WSC gauging site;
JD	Julian Day (ie: Jan 1 =1, Jan 2=2....Dec 31=365);
Lat	latitude;
n_{sun}	recorded hours of bright sunshine, hours;
m	optical air mass;
N	day length or maximum possible hours of bright sunshine, hours;
n	number of years of data;
P_{YMM}	soil moisture index: precipitation recorded from May 15 until October 31 at Fort McMurray, mm;
Q_S	incoming short wave radiation, kJ/m^2;
Q_A	solar radiation at the top of the atmosphere, kJ/ m^2;
R^2	coefficient of determination;
R^2_{adj}	adjusted coefficient of determination which accounts for the number of independent variables and reflects the degrees of freedom;
SWE	average SWE in the basin, as determined from satellite data for the entire basin, mm;
S_{avg}	intensity of the daily average solar radiation from March 1 until river breakup, W/ m^2;
S_n	net average hourly solar radiation flux, kJ/m^2;
T_a	mean daily air temperature, °C;
t_i	original thickness of the ice cover, m;

t_{avgi}	mean ice thickness, m;
v	flow velocity at breakup, m/s;
WSC_{March}	ice thickness measured at WSC gauging site in March, m;
WSC_{April}	ice thickness measured at WSC gauging site in April, m;
$WSC_{Average}$	average of ice thickness measurements for March and April,m ;
$WSC_{Difference}$	ice thickness difference between the April and March ice thickness estimates at the WSC gauge, m;
α	acceptable risk of a false positive, directly related to the confidence level;
δ	declination of the sun;
Δgw	change in groundwater levels from January 1 until March 1, m;
ΔH	change in water levels from before snow melt occurs to prior to ice jam formation, m;
ΔH_{bo}	increase in stage at breakup, m;
Δt	difference in time of breakup between on the main river and its large tributaries, which flow into the given river stretch, h;
$\Delta h/t$	rate of water level increase as measured below Fort McMurray prior to major ice movement, m/d;
Φ	parameter describing the morphology of the stream;
Φ_{So}	intensity of radiation incident on a horizontal plane above the earth's atmosphere, W/m^2;
$\sum E_b$	heat input at the bottom of the ice cover;
Θ	onset of negative air temperature in the ice-breakup period;
$\sum q_{in}$	total heat input per unit surface of the snow-ice cover in the region of the ice jamming;
$\sum q_w$	total heat input per unit surface of the snow cover in the region of flood formation during ice jamming;
ϕ	index of daily cumulative heat input, W/m^2;
ϕ_s	incoming solar radiation measured over a single day, W/m^2.

List of Abbreviations

Alberta (AB)
Alberta Environment (AENV)
Alberta Transportation (AT)
Alberta Research Council (ARC)
Artificial Neural Network (ANN)
Canadian Society for Civil Engineering (CSCE)
Meteorological Services of Canada (MSC)
Pacific Decadal Oscillation (PDO)
Regional Municipality of Wood Buffalo (RMWB)
Snow Water Equivalent (SWE)
United States of America (USA)
University of Alberta (UA)
Water Survey of Canada (WSC)

Chapter 1: Introduction

Throughout history and continuing to this day, river ice breakup posses a severe flood threat to both property and lives for many northern communities. In the United States alone, ice jam damages are more than $100 million annually (U.S. Army Corps of Engineers, 2004) and in Canada, the annual estimated economic loss due to ice jams is estimated as $60 million dollars (Beltaos, 1995). As development pressure continues in northern areas, the potential impact of ice jams continues to increase. With ice jam events, there is little time for mitigation if advanced warning is not available because ice jams develop very quickly. The ability to assess the risk of annual risk of ice jam flooding prior to river breakup is an essential tool in reducing the threat of this natural disaster.

Spring river ice jams are a serious and unique threat for several reasons. To begin, river ice jams account for some of the highest water levels recorded at several sites across Canada, exceeding open water flood levels by several metres. Figure 1-1 illustrates the significantly higher water levels associated with a 1:100 river breakup event compared to a similar frequency summer flood event for the Athabasca River at Fort McMurray, AB. The danger associated with river ice jams extends beyond the risk of high water levels. River ice jams can produce rapid changes in water levels as water flow is impeded by a jam or as water is sudden released from storage behind an ice jam. Ice jam formation and release events are among the most dangerous types of flood risk situations, primarily because the sudden congestion of a river channel with ice can result in dramatically rapid water level increases. Water can rise several metres in a matter of minutes, inundating flood prone areas with little or no warning, and providing very little time to perform even the most basic mitigation measures. Large ice floes mixed with the floodwaters increase the potential danger of the situation. Unlike open water flood events that are preceded by heavy rains or snowmelt, spring ice jams events have no identified quantitatively predictable precursor, although numerous hydrometeological variables have been identified as influential in the river ice jam process (eg. see Zhukova, 1979 and Beltaos, 1997).

Because of the risk to lives and property from ice jam related flooding, many rivers in Canada are monitored closely by local, provincial and/or federal governments. Located in north-eastern Alberta, Fort McMurray is one example of a community where the river is actively monitored each spring and the river ice breakup progress is part of every day life. The community has a history of river ice jams resulting in flooding. The earliest documented river breakup flood event on the Athabasca River at Fort McMurray is described in a letter from Henry J. Moberly dated April 25th, 1875, which captures both the emotional distress and economic loss associated with a large ice jam (Blench and Associates Ltd. 1964).

> *"On the 20 Instant about 2 hours after daylight, the river suddenly gave signs of breaking up and in half an hour from that time the water had risen about 60 feet, and the whole place was flooded – the water and ice passing with fearful rapidity and carrying off everything before them. We had just*

time to escape to the hill, in our immediate vicinity, with the families, bedding and a little Provisions and Ammunition, and to throw up stairs the Furs and most of the valuable property, when the water was already rushing through the Fort. From the time the river first gave signs of starting hardly half an hour elapsed before there was 5 feet of water in the highest building in the Fort, and the Interpreter's house was carried bodily away and dashed to pieces in the Woods; the Workshop and Men's houses have been almost destroyed."

This accounts shows that there was no indication that an extreme river breakup event was imminent. Over a century later, the ability to forecast such extreme events has changed little. In 1977, an ice jam caused flooding to the lower town site of Fort McMurray, resulting in damage claims totaling an estimated $2.6 million (Alberta Environment 1985). In 1997, an ice jam again caused millions of dollars in damage and, again, there was little warning of the potential severity of river breakup. Minor flooding has also occurred several times in the last decade, and although these smaller events have only resulted in minimal damage to residential and commercial properties, expenses are still incurred by those government agencies responsible for monitoring the river and for preparing for the potential of a much more severe event. Clearly there is a significant need, both from safety and economic perspectives, to have the ability to forecast the occurrence of high water levels at Fort McMurray before the breakup period.

For river ice jam related research, the Athabasca River has a large advantage over other rivers in Canada as it has been monitored since the early 1970s by government agencies and research groups. Because river breakup is an annual event, it is necessary to have decades of information to produce even a small data set since each year represents only one potential ice jam occurrence. Although contained in fragmented data sets, information is available for the river basin and the progression of river ice breakup. Ice jams occur relatively frequently in the reach of the river surrounding Fort McMurray which has resulted in several documented occurrences and may be responsible for the continuous interest in ice observation at this location.

Unfortunately, many ice jam prone locations in northern Canada do not have regular river basin monitoring programs with decades of information or documentation of ice jam events. Communities such as Hay River, NWT, have developed local river ice breakup monitoring programs which have resulted in small databases. Although these communities have the same need for a river breakup forecast model as Fort McMurray, the potential for model development is more limited.

A basin transferable forecast model would be beneficial for locations like Hay River. Even if the data were not currently available to apply the model, communities could be encouraged to collect appropriate data to support a future model. Since a forecast model does not presently exist, basic guidance is unavailable for a practical community based monitoring program. There are many factors that influence river ice breakup and there are no clear indications which are the most aspects are the most vital to monitor. The expense of an extensive monitoring network is prohibitive, particularly in remote locations where communications and maintenance contribute substantially to the network costs. While river ice breakup continues to be documented through journal articles (Jasek, 2003) and government reports (Robichaud, 2005), much of the data needed to develop a deterministic process based model is not being collected due to the logistics and safety aspects involved in measuring these dynamic events.

In addition to the current issues caused by river ice breakup, there is increasing concern in northern communities about the impacts of climate variability. Changes in the Artic climate have been documented by researchers such as Hinzman et al. (2005). Huntington et al. (2003) correlated trends in ice characteristics in Maine, U.S.A. with meteorological variables. Beltaos and Burrell (2003) suggest that mid-winter jams in Atlantic Canada may become more severe for the current proposed climate change scenarios. Without modeling capabilities, water resource management is limited to responding to changes after a trend has been observed rather than anticipating a potential change such as an increase or decrease in frequency of breakup related flood events.

A river ice breakup forecasting model is needed in Canada for the immediate benefit of flood risk identification leading to flood mitigation. Additional benefits would also be realized from the identification of the important variables contributing to flooding. Once identified, appropriate monitoring programs could be established in communities to collect information that would lead to the development of future river breakup forecast models. The long term benefits in having a forecasting model include the ability to anticipate increases or decreases in river ice breakup risks to communities due to climate variability.

The research goal of this thesis is to identify potential methods for river ice forecasting. To achieve this goal the following aspects have been investigated:

1) Develop a comprehensive database containing relevant and sufficient data for river ice breakup modeling at an ice jam prone location.
2) Research current river ice breakup forecasting methods and evaluate information in the database with any promising methods.
3) Develop fuzzy logic models for river ice breakup forecasting and document the advantages and disadvantages of this method.
4) Develop and implement methods used in conjunction with fuzzy logic modeling, such as artificial neural networks, and possible application to river ice breakup forecasting.
5) Investigate the transferability of fuzzy logic river ice breakup models.
6) Demonstrate the potential for fuzzy logic river ice breakup modeling in water resource management by determining the possible impacts of climate change scenarios on river ice breakup severity.

As this is a paper format thesis, the remainder of this chapter provides a review of the development of river ice breakup theory, discusses relevant forecast models and provides the foundation for the research in this thesis. Chapter 2 describes the creation of an extensive database and the development of a site specific multiple linear regression model. Recognizing the non-linear nature of river breakup, fuzzy logic and neuro-fuzzy models were developed and evaluated in Chapter 3. In Chapter 4, the fuzzy logic and neuro-fuzzy models are evaluated and compared for basin transferability. In addition, the impacts of future climate change scenarios on river ice breakup are evaluated with the fuzzy logic model for both the model prototype river basin and the river basin to which the model was transferred. Chapter 5 summarizes the development and implementation of the models described in previous chapters and outlines areas for future research. Appendix A contains an extensive database for the Athabasca River Basin and a brief explanation of each variable.

1.1 Review of River Ice Breakup Forecast Models

Research into forecasting river breakup forecasting began over 50 years ago with simple single variable models and quickly lead to multivariate models. Early work in this field was led by Shulyakovskii (1963) who viewed river breakup to be the result of deteriorating ice thickness and increases in river flows. Although Shulyakovskii's theory of river breakup is simplistic, he recognized the importance of the energy cycle in river ice processes. Shulyakovskii reported that the amount of heat input, $\sum E$, necessary to cause river break was a function of:

$$\sum E = f(t_{avgi}, h_{sn}, \phi, v, H_o, \Delta H_{bo}, \Delta Y, \sum E_b) \qquad \text{Equation 1.1}$$

where:

t_{avgi}	=	mean ice thickness,
h_{sn}	=	snow depth on the ice cover prior to ice melt,
Φ	=	a parameter describing the morphology of the stream,
v	=	flow velocity at breakup,
H_o	=	the initial water level prior to spring melt increase in flow,
ΔH_{bo}	=	increase in stage at breakup, and
$\sum E_b$	=	heat input at the bottom of the ice cover.

Shulyakovskii acknowledged the importance of atmospheric circulation but also states that the lack of quantitative data and lack of knowledge of atmospheric processes was a limiting factor.

A number of researchers have developed predictive methods for breakup ice jam forecasting but, due the complex interactions between hydrometeorological influences and ice mechanical properties, only limited progress has been achieved to date using purely deterministic approaches for modeling dynamic river breakup. Because of the lack of fundamental data, the development of predictive deterministic process modeling for complex river ice breakup conditions is limited. Fully deterministic models are very complex as natural processes involve nonlinear interactions of several variables and many processes. For example, the "simple" process of water freezing to ice is so complex that it took Japanese researchers six years to make the first realistic computer simulation of it which was completed in the spring of 2002 (Couture, 2004).

River ice breakup on a natural river system is a combination of complex thermal and dynamic processes. A thermal river breakup is more likely if sufficient energy is available to deteriorate the ice prior to any substantial water level increases due to snowmelt runoff. A dynamic or mechanical river breakup occurs when river ice is set in motion before the ice cover has sufficiently decayed. Beltaos (2003) provided criteria to classify river breakups as thermal (less dangerous) or mechanical (associated with ice jams). Each process is influenced by numerous meteorological, hydrological and hydraulic factors both at the site of interest and throughout the river basin. Many of these parameters, such as ice strength and thickness, cannot be safely measured immediately prior to river breakup. From a deterministic point of view, river breakup is an extremely complex problem for which data is not often readily available.

The basic foundation for statistical river ice jam modeling was also presented by Shulyakovskii (1963). Shulyakovskii quantified the concept of forecasting maximum stage rise during river breakup, Δh_m, as a function of several variables as shown in Equation 1.2.

$$\Delta h_m = f(t_i, h_{sn}, \Delta H, \frac{\sum q_{in}}{\sum q_w}, \theta, I, \Delta t) \qquad \text{Equation 1.2}$$

where:

t_i	=	the original thickness of the ice cover on the stretch of river that contributes to the ice cover,
h_{sn}	=	snow depth on the ice cover prior to ice melt,
ΔH	=	change in water levels from before snow melt occurs to prior to ice jam formation,
Θ	=	the onset of negative air temperature in the ice-breakup period,
I	=	the characteristics of the ice cover on the expected ice jamming stretch,
$\sum q_{in}$	=	total heat input per unit surface of the snow-ice cover in the region of the ice jamming,
$\sum q_w$	=	the total heat input per unit surface of the snow cover in the region of flood formation during ice jamming, and
Δt	=	the difference in time of breakup on the main river and its large tributaries, which flow into the given river stretch.

Both threshold models and regression models have evolved from this basic functional relationship.

1.1.1 Threshold Models

Threshold methods attempt to establish lower or upper limits for a particular event, such as an ice jam. Figure 1-2 shows a reasonably successful single variable threshold method model that was provided by Shulyakovskii (1963) for the Yenisel River, Russia. For this site, ice jams were observed in years when the freeze-up water level exceeded 325 cm but ice jams did not form when the freeze-up water level was less than 150 cm. For the freeze-up water level range between 150 and 325 cm, it is not possible to determine if an ice jam will or will not form. However, there is no evidence in the literature of any other successful single variable threshold models for breakup. Robichaud (2003) examined 16 parameters for the Athabasca River and was unable to establish a single reasonable single variable threshold model.

Multivariate threshold models have been applied with modest success, for example, Galbraith (1981) and Webben et al. (1995). However, specific additional variables and weighting factors required made these models highly site specific. Galbraith (1981) used a complex multivariate threshold model to predict ice jam formation for the St. John River in New Brunswick. This model required the estimation of three indices as indicators of the strength of the ice cover and an estimate of another 9 variables to determine the rate of heat transfer. To model 23 years of data (23 data points), Wuebben et al. (1995) used 11 arbitrarily weighted variables to produce a multivariate threshold model for the Missouri River, North Dakota, USA, as shown in Table 1-1. In addition some of the required input parameters, such as date of breakup and rate of heat transfer, are difficult to predict in advance, thus reducing the practicality of these models for operational forecasting purposes. While threshold models provide a forecast of the potential for an ice jam event, they give no indication of the potential flood event that may accompany an ice jam. White (2003) described the main problem with threshold models as the tendency to produce a high frequency of false positive forecasts as the threshold levels are adjusted to decrease false-negative errors.

1.1.2 Regression Models

Single and multiple regression analyses have been applied to the problem of breakup water level prediction with moderate success. The initial work of Shulyakovskii (1963) indicated that single variable regression models had potential for river breakup forecasting. Shulyakovakii (1963) used the freeze-up water level to forecast the water stage at the first ice movement as shown in Figure 1-3. However, no other successful single variable regression river ice breakup models have been reported in literature. Beltaos (1984) used accumulated incoming heat to the ice cover to forecast the stage at breakup initiation, where the stage was a function of freeze-up levels and ice thickness. As illustrated in Figure 1-4, Beltaos (1984) had limited success and large uncertainties in many variables. Both of these models forecast the water level when the first ice movement occurs, but do not indicate the maximum water level during the river breakup.

Significant research with regression models has been done on the Athabasca River at Fort McMurray. Doyle (1987) determined that regression equations based on hydrological and meteorological variables held potential for modeling the severity of river ice breakup. Doyle (1987) was unable to develop an equation for the maximum water level during river break up and concluded that only with the development of a more extensive database could the greater statistical confidence be gained.

After investigating hydrometeorological 16 variables, Robichaud (2003) established that an indicator of the severity of river ice breakup could be established for the Athabasca River at Fort McMurray, with multiple linear regression based on six hydrometeorological variables. These key variables for the model included: (1) accumulated basin average SWE in late spring, (2) ice thickness, (3) soil moisture in late fall, (4) solar radiation accumulated prior to river breakup, (5) accumulated degree days of thaw, and (6) rate of water level rise. The three latter variables are determined at the time of river ice breakup. It was determined that the model, shown in Figure 1-5, had an $R^2_{adj} = 0.74$ and was accurate to ± 1.5 m but no model validation or verification was reported. Robichaud (2003) concluded that although "significant errors" were occurred, the model could be used as an indicator of river ice breakup severity.

1.1.3 Discriminant Function Analysis and Artificial Neural Network Models

Few discriminant function analysis reports have been published for river ice breakup modeling but the results of White and Daly (2002) study has implications for modeling. Discriminant analysis is a multivariate statistical method used to separate data on the basis of predictor variables. White and Daly (2002) used stepwise selection of meteorological and hydrologic parameters to identify statistically significant input variables and then applied discriminant function analysis to predict ice jam occurrence for Oil Creek in Oil City, Pennsylvania, USA. Predicting either a jam or no jam, the model was reported to have a false negative error rate of 12% and a false positive error rate of 40%.

Using the same data as White and Daly, Massie (2000) developed an artificial neural network to produce a daily forecast of jam/no jam for Oil Crrek. This model was data intensive, requiring 22 parameters for daily predictions. In the 67 years of data available, 17 ice jams occurred out of over 7,700 days that were monitored. After logically eliminating selected days from the data set (such as days when there was no flow in Oil Creek) and applying data clustering techniques, the neural network was able to identify 93% of all no-jam events correctly and five of six jam events.

The most significant limitation of the applications of discriminant function analysis artificial neural network model that have been reported in literature is that, while they do provide an assessment of the potential for ice jam occurrence, they cannot provide a prediction of the anticipated flood levels. For Oil City, it was sufficient to forecast the occurrence of a jam but for many rivers, like the Athabasca River at Fort McMurray, ice jams are common and do not always result in flooding. In addition, these models have limited lead time for potential forecasting applications due to the requirement for data that is available only days before river breakup.

1.14 Fuzzy Logic Models

Belonging to the same family of soft computing methods as artificial neural networks but not based exclusively on recorded data, fuzzy logic is another non-linear method that has potential for application in river ice breakup forecasting. Mahabir et al. (2002) described a promising preliminary model based on fuzzy logic for the Athabasca River, Canada, which produced a qualitative prediction of breakup water levels, showing few false positives for moderate events and no false positives for major events. Shouyu and Honglan (2005) used fuzzy logic to optimize an ANN in an attempt to predict the timing of breakup on the Yellow River, China forecasting the breakup date within seven days of actual for the five validation years (but also reporting that over 90% of the time river breakup is within 7 days of the median breakup date.)

Fuzzy logic is a form of artificial intelligence that is ideal for incorporating generalized knowledge. With fuzzy logic, linguistic descriptions are used to represent inputs, to evaluate input sets based on defined rules, and provide a linguistic assessment of the resulting set. Pioneered by Zadeh (1965), fuzzy logic has been effectively used in combination with other soft computing methods for predictive water resource related sciences. One of the primary advantages of fuzzy logic over traditional mathematics is that it is enables the modeler to incorporate a conceptual understanding of cause and effect relationships describing the process to be modeled. This is ideally suited to the river ice breakup flood forecasting application; while it is not yet possible to deterministically model the complex hydrometeorological interactions leading to the occurrence of ice jams, many heuristic "rules of thumb" do exist. For example, Beltaos (1995) states that a high spring runoff would be expected to increase the likeliness of an ice jam occurrence but a quantitative relationship is not developed. A qualitative assessment means that the model is able to distinguish between different outcomes, not in numerical terms, but by linguistic groups. For example water levels could be described as "Low" resulting in no flooding or "High" when flooding occurs. While numerical forecasts are preferable, an indicator of the severity of river breakup would be better than no warning at all.

1.1.5 Hybrid Models

Fuzzy logic has also been combined successfully with other forms modeling to produce hybrid models that incorporate the advantages of both parent models. For example, Nayak *et al.* (2005) found that a neuro-fuzzy model had superior performance to both fuzzy models and ANNs for long lead forecasts in rain-fall runoff process models. For river ice breakup modeling, combining fuzzy logic with the learning ability of ANNs in a neuro-fuzzy model provides the potential to combine available heuristic knowledge with limited recorded data in model development. A hybrid neuro-fuzzy model combines the modeling advantages gained with fuzzy logic with the ability to learn from the limited historical data that is available. Artificial-neural networks are essentially blackbox models which should not be applied at sites other than those for which they are calibrated. However, fuzzy and neuro-fuzzy model are based on logic which the modeler can evaluate for applicability to another site.

1.1 Soft Computing and Climate Change

In addition to model transfer between basins, soft computing has also been identified as a potential tool for climate change analysis, providing an alternative to historical trend analysis. Changes in the climate and the current impacts in the north have been documented by Hinzman et al. (2005). Prowse and Beltaos (2002) stated that changes in meteorological conditions could result in significant changes in breakup severity. Often climate change is evaluated only by observation of a current trend compared with historical data. Wolf et al. (2005) examined potential change in the flooding patterns in the Peace-Athabasca Delta by comparing with historical occurrences and found that a dry spell has been occurring for decades but is within the climate variability that had previously occurred in the last three centuries. Many river ice evaluation methods are limited to establishing trends or relating the statistical analysis of past occurrences. Hodgkins et al. (2005) reporting on the changes to the timing and duration of the ice cover on eastern US rivers based on observational trends and correlation analysis. Statistical analysis assumes that over the time period of investigation, the climate is stationary. Logic models are not built on this assumption. Soft computing has been used previously for evaluating the uncertainties in climate change scenarios. For example, Huang et al (1996) used fuzzy analysis to evaluate the impact of climate change on land use activities in the Mackenzie Basin, Canada. Scherm (2000) evaluated the uncertainty of climate change predictions using fuzzy numbers in a model that used plant pests as an indicator.

1.2 Summary

Considerable advances have been made in the last decade towards river ice breakup models and are documented by Beltaos (2000) and Morse et al. (2005). White (2003) provides a review of the developing science of river breakup forecasting. To date, river ice breakup models are site specific such as those developed for the McKenzie River (Hicks et al, 1997), Hay River (Gerard et al, 1992) and Athabasca River (Robichaud, 2003).

This thesis details the development of fuzzy logic and neuro-fuzzy models for river ice breakup forecasting. It provides insight into the application of fuzzy logic to predicting the severity of river ice breakup and the ability to use ANNs to make optimal use of the limited data. The potential for both

linguistic assessments and quantitative predictions are explored. A prototype model is developed and alternate selections in model design are compared.

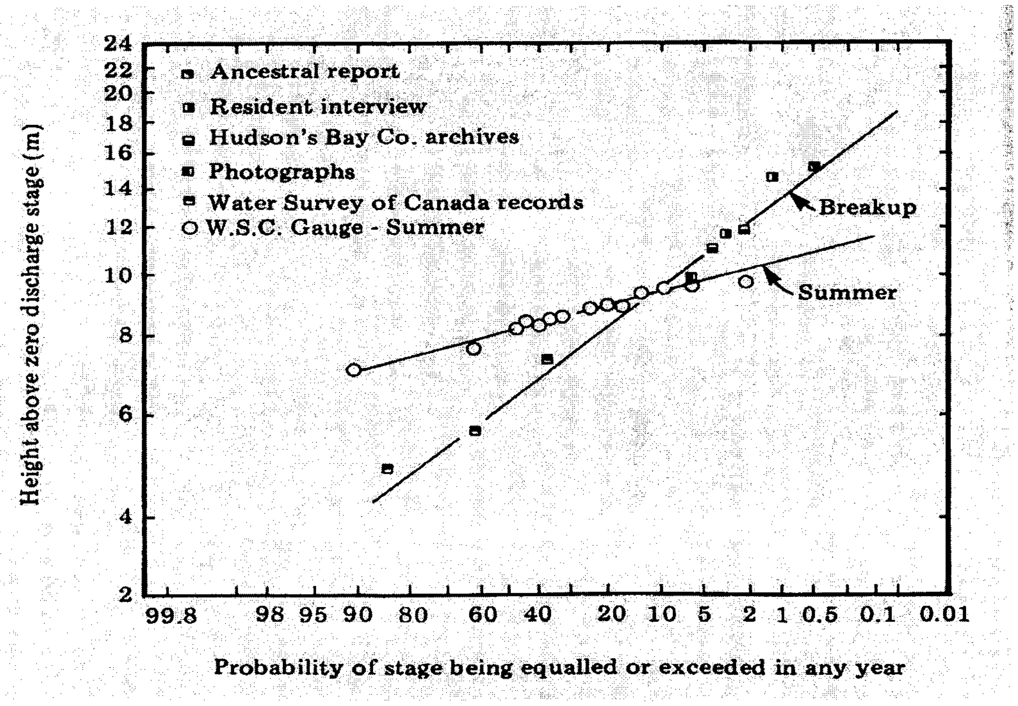

Figure 1-1: Flood frequency comparison between open water and ice jam flood events for the Athabasca River at Fort McMurray (adapted from Gerard and Karpuk, 1979).

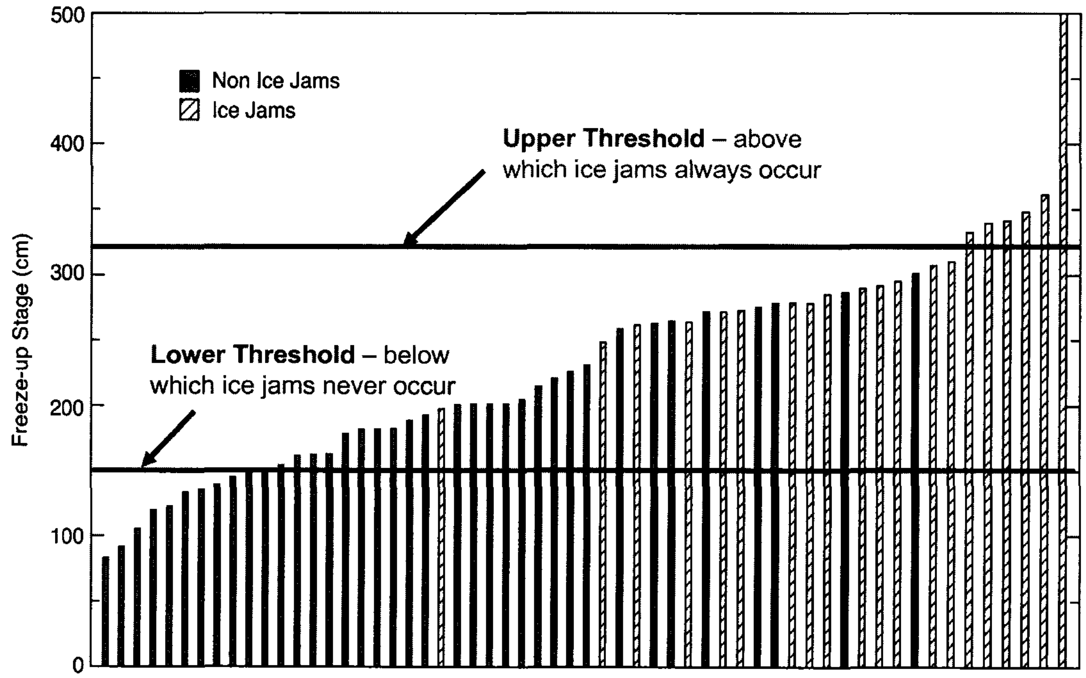

Figure 1-2: Single variable threshold model for Yenisel River, Russia (adapted Shuliakovskii, 1963, as reported by White, 2002).

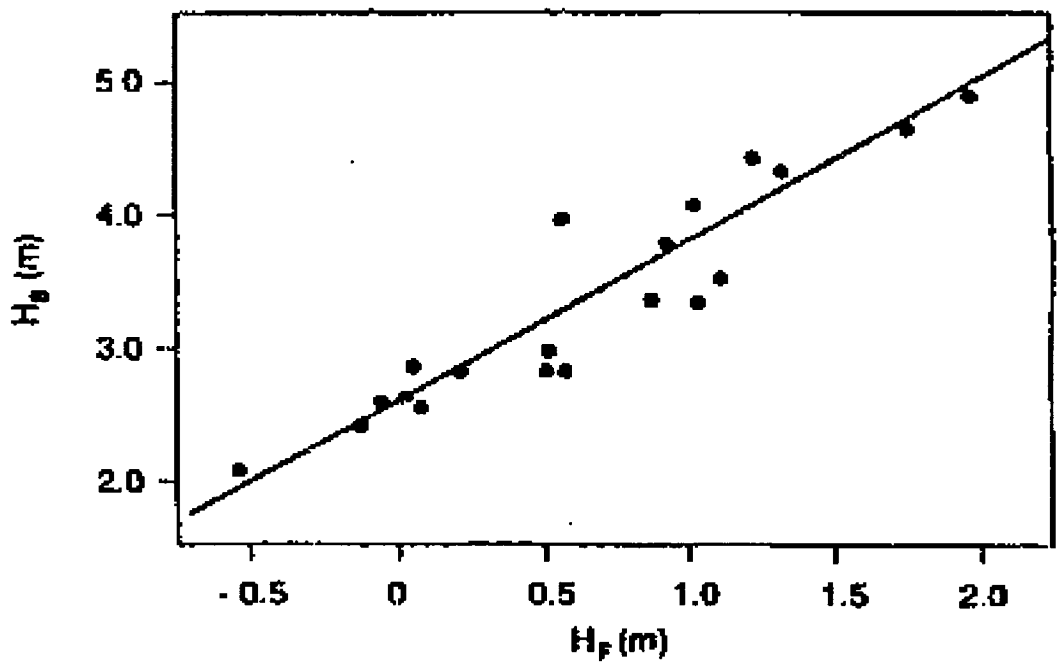

Figure 1-3: Single variable linear regression model to predict the first ice movement based on freeze-up water levels (adapted from Shuliakovskii (1963), reported by Ashton (1986)).

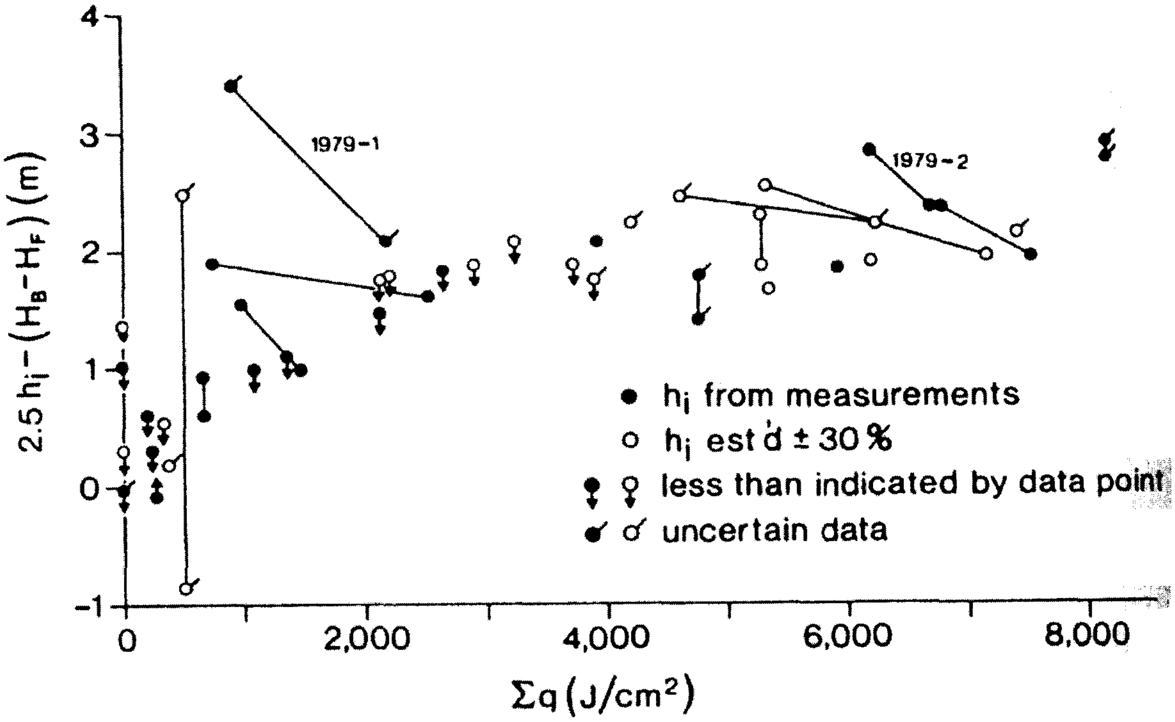

Figure 1-4: Multiple variable linear regression model to predict water level at river breakup (adapted from Beltaos, 1984).

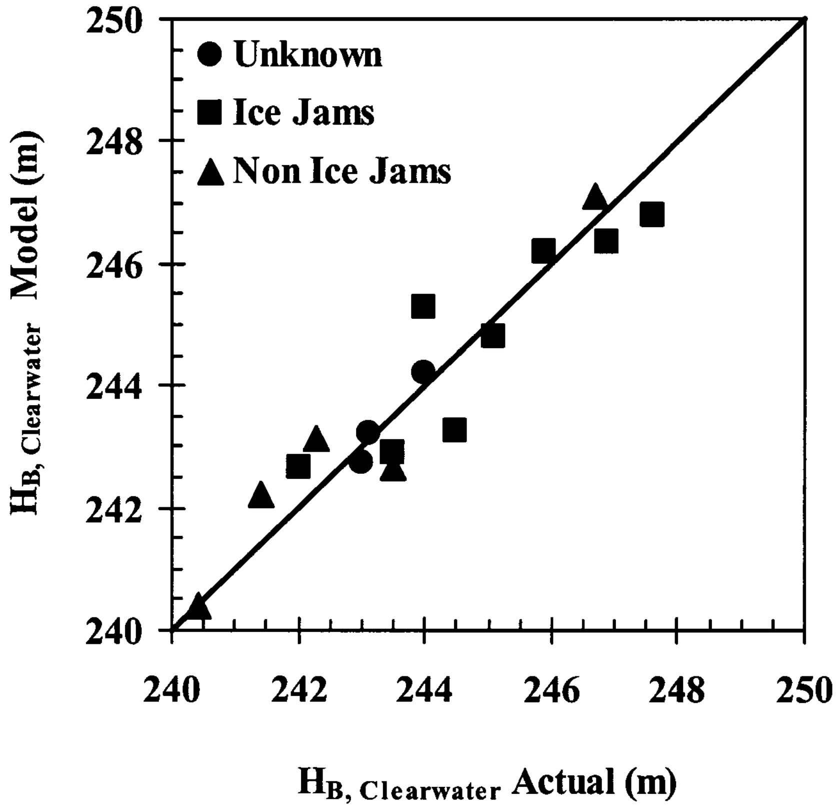

Figure 1-5: Multiple linear regression model of the maximum water level at river breakup for the Athabasca River at Fort McMurray (adapted from Robichaud, 2003).

Table 1-1: Multivariate threshold models for the Missouri River near Williston North Dakota (adapted from Wuebben et al., 1995).

Variable	Lower Threshold	Upper Threshold	Weight
AFDDmax (F days)	1700	2600	2
Qmax (m^3/s)	708 or 2548	850 xi 1982	1
Julian Day of AFDDmax	150	165	1
Julian Day of Qmax	155	170	1
Julian Day of AFDDmax - Julian Day of Qmax	-8 or 10	-5 xi 7	2
Lake Sakakawea stage (m MSL)	559.3	560.8	1
Total snowfall (cm)	50.8	101.6	2
Timing of snowfall	12.7 cm after JD=90	25.4 cm after JD=90 or 12.7 cm after JD=120	1

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Chapter 2: Forecasting Breakup Water Levels at Fort McMurray, AB, using Multiple Linear Regression[1]

2.1 INTRODUCTION

Some of the most extreme river flooding situations in Canadian history have occurred as a result of river ice jams, particularly during river breakup. Ice jams can produce rapid increases in water levels as water flow is impeded by its obstructive effects, or as water is suddenly released from storage behind an ice jam during release. Large competent ice floes carried with these floodwaters increase the potential danger of the situation.

Each spring, numerous rivers across Canada are monitored closely, because of the potential risk to property and lives should an ice jam form during the river breakup process. Fort McMurray, located in north-eastern Alberta, is one example of a community where the river is actively monitored each spring to advise on the river ice breakup progress. The community has a history of river ice jams resulting in flooding. The earliest documented river breakup flood event on the Athabasca River at Fort McMurray is described in a letter from Henry J. Moberly dated April 25th, 1875, which captures both the emotional distress and economic loss associated with a large ice jam (Blench and Associates Ltd. 1964).

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[1] This chapter has been accepted for publication. Mahabir, C., F..E. Hicks, C. Robichaud, and A. Robinson. 2006. "Forecasting Breakup Water Levels at Fort McMurray, AB, using Multiple Linear Regression". Canadian Journal of Civil Engineering (in press).

"On the 20 Instant about 2 hours after daylight, the river suddenly gave signs of breaking up and in half an hour from that time the water had risen about 60 feet, and the whole place was flooded – the water and ice passing with fearful rapidity and carrying off everything before them. We had just time to escape to the hill, in our immediate vicinity, with the families, bedding and a little Provisions and Ammunition, and to throw up stairs the Furs and most of the valuable property, when the water was already rushing through the Fort. From the time the river first gave signs of starting hardly half an hour elapsed before there was 5 feet of water in the highest building in the Fort, and the Interpreter's house was carried bodily away and dashed to pieces in the Woods; the Workshop and Men's houses have been almost destroyed."

It is clear that there was no indication that an extreme river breakup event was imminent. Over 100 years later, the ability to forecast such extreme events has changed little. In 1977, an ice jam caused flooding to the Lower town site of Fort McMurray, resulting in damage claims totaling an estimated $2.6 million (Alberta Environment 1985). In 1997, an ice jam again caused millions of dollars in damage and, again, there was little warning of the potential severity of river breakup. Minor flooding has also occurred several times in the last decade, and although these smaller events have only resulted in minimal damage to residential and commercial properties, expenses are still incurred by those government agencies responsible for monitoring the river and for preparing for the potential of a much more severe event. Clearly there is a significant need, both from safety and economic perspectives, to have the ability to forecast the occurrence of high water levels at Fort McMurray during the breakup period.

Research into forecasting river breakup forecasting began over 50 years ago with simple single variable models and quickly lead to multivariate models. Early work in this field was led by Shulyakovskii (1963) who viewed river breakup to be the result of deteriorating ice thickness and increases in river flows. Although Shulyakovskii's theory of river breakup was simplistic, he did recognize the importance of the energy cycle in river ice processes and atmospheric circulation. Shulyakovskii quantified the concept of forecasting maximum stage rise during river breakup, as a function of several variables including the original thickness of the ice cover, the characteristics of the ice cover where the ice jam occurs, snow depth on the ice cover prior to ice melt, change in water level between the commencement of snow melt and the time of ice jam formation, negative air temperatures in the ice breakup period, total heat input per unit surface of the snow-ice cover in the region of the ice jam, the total heat input per unit surface of the snow cover in the region of flood formation during ice jamming and the difference in time of breakup between the main river and its large tributaries. Both threshold models and regression models have evolved from this basic functional relationship.

Threshold methods attempt to establish lower or upper limits for a particular event. A reasonably successful single variable threshold method model was provided by Shulyakovskii (1963) for the Yenisel River, Russia. However, there is no evidence in the literature of any other successful single variable threshold models for breakup. Robichaud (2003) examined 16 parameters for the

Athabasca River and was unable to establish a single reasonable threshold model. Multivariate threshold models have been applied with modest success (for example, Galbraith, 1981 and Wuebben et al. 1995). However, specific additional variables and weighting factors required made these models highly site specific. In addition some of the required input parameters, such as date of breakup and rate of heat transfer, are difficult to predict in advance, thus reducing the practicality of these models for operational forecasting purposes.

White and Daly (2002) used stepwise selection of meteorological and hydrologic parameters to identify statistically significant input variables and then applied discriminant function analysis to predict ice jam occurrence. Massie *et al.* (2000) developed an artificial neural network to produce a daily forecast of jam/no jam that required 22 input variables. The most significant limitation of all of these models is that, while they do provide an assessment of the potential for ice jam occurrence, they cannot provide a prediction of the anticipated flood levels that might accompany an ice jam occurrence.

Single and multiple regression analyses have been applied to the problem of breakup water level prediction with moderate success. For example, Shulyakovskii (1963) used the freeze-up water level to forecast the water stage at the first ice movement. Beltaos (1984) used accumulated incoming heat to the ice cover to forecast the stage at breakup initiation, where the stage was a function of freeze-up levels and ice thickness. Doyle (1987) determined that regression equations based on hydrological and meteorological variables held potential for modeling the severity of river ice breakup but concluded that only with the development of a more extensive database could the greater statistical confidence be gained. Using multiple linear regression, Robichaud (2003) established that an indicator of the severity of river ice breakup could be established for the Athabasca River at Fort McMurray, based on six hydrometeorological parameters.

This purpose of this current investigation is to report the development of an extensive database of hydrometeorological variables relevant to ice jam formation on the Athabasca River at Fort McMurray, and to explore the potential application and limitations of multiple linear regression for forecasting peak water levels associated with river ice breakup at this site.

2.2 SITE DESCRIPTION

Figure 2-1 illustrates the Athabasca River Basin from its headwaters to the location of interest, immediately downstream from Fort McMurray. The Athabasca River is the largest, unregulated river in the province of Alberta (Seneka, 2004) with a drainage basin, as measured at the Water Survey of Canada gauging site below Fort McMurray, of 133,000 km^2. The Athabasca River originates in the Columbia Icefields in Jasper National Park and flows more than 1400 km in a northeastwardly direction across the province to its delta at Lake Athabasca. The Athabasca River flows eastward out of the Rocky

Mountains into the farmlands. It loops southwards from Hondo to the Town of Athabasca, making a dramatic turn northwards at the town. About 140 km upstream of Fort McMurray, the Athabasca River is deeply entrenched in a narrow meandering valley. Starting in this reach, series of rapids marks the transition from the cretaceous shale to the Paleozoic limestone and dolomite (Andres, 1980). As the river flows northwards, it passes over Stony, Pelican and Grand Rapids. The river sharply turns east and flows through another series of rapids (Brule Rapids, Long Rapids, Crooked Rapids, Rock Rapids, Cascade Rapids, Mountain Rapids, Moberly Rapids) before reaching Fort McMurray. At Fort McMurray, the dramatic change in the physical properties of the river channel is responsible for the frequent formation of ice jams in this reach. The flow of the river is changes direction from northeast to north. The slope reduces to 0.00014 which is less than a quarter of the river bed slope estimated by Malcovish et al. (1988) for the reach above Fort McMurray. Numerous sand bars and islands are distributed through the channel. It has been hypothesized by Smith and Fisher (1993) that the dramatic change in the river channel is a result of the drainage of the ancient Glacial Lake Agassiz into the Athabasca River through the Clearwater River which enters the Athabasca River immediately downstream of Fort McMurray.

These dramatic changes in the physical properties of the river in the vicinity of Fort McMurray are responsible for the frequent formation of ice jams at this particular site. The Clearwater River has its confluence with the Athabasca

River immediately downstream of Fort McMurray, and it is the restriction of Clearwater River outflows, because of ice jams on the Athabasca at or downstream of this confluence, which is the primary cause of flooding in Fort McMurray.

Basin hydrology is a very relevant factor in river ice breakup processes for this reach. Because the Athabasca River flows northwards, river breakup occurs in the southern basin first and progresses northwards. While the headwaters of the basin remain snowbound until late May due to the mountainous topography, the mid-basin can generate significant runoff resulting in a river ice breakup moving from upstream to downstream.

2.3 HYDROMETEOROLOGICAL DATABASE DEVELOPMENT

After the major flood resulting from the 1977 ice jam on the Athabasca River at Fort McMurray, considerable attention was focused on developing breakup monitoring programs for this site. Many groups have been involved in observations and research regarding river ice on the Athabasca River including: Alberta Environment (AENV), Alberta Transportation (AT), Alberta Research Council (ARC), the University of Alberta (UA), and the Regional Municipality of Wood Buffalo (RMWB).

While many groups have worked independently, Doyle (1987) and later Robichaud (2003) were the first to collect data from the sources named above into a database. Robichaud's (2003) effort was the most comprehensive up to that time, starting with the 1875 account and continuing through until 2001, to create a single database with a detailed description of documented qualitative descriptions, quantitative data and published research associated with breakup on the Athabasca River at Fort McMurray. While the most obvious and readily available quantitative data were incorporated into that database as variables, preliminary analyses suggested that there were still many processes which might be better represented by alternative variable selections. For example, in that original study (Robichaud 2003), air temperature was only considered at Fort McMurray and not in the mid-basin where the majority of the spring runoff snowmelt originates. Therefore, a major component of the present study was to extend Robichaud's (2003) database, resulting in a comprehensive data set describing 106 hydrometeorological variables relevant to river ice breakup at Fort McMurray. All variables, include those collated by Robichaud (2003) are provided in Appendix A with a brief explanation as to why they were selected for the database.

2.3.1 Time of River Ice Breakup

The timing of river ice breakup through the Fort McMurray river reach is not a major priority for model development because it has historically been relatively consistent. As shown in Figure 2-2, the mean breakup date is April 19 and over 75% of river breakups have been documented to have occurred within a week of this date. Almost 90% of the historical river breakups occurred by April 26, a week after the mean date.

2.3.2 Water Level and Discharge

The severity of river breakup can be quantified in terms of the maximum water level that occurs at a specific location. For this study, a forecast of the maximum spring breakup water level would be most valuable for the reach of the river near the Clearwater River confluence. Flooding typically occurs in Fort McMurray when flow out of the Clearwater River is obstructed, usually by ice jams on the Athabasca River, though also occasionally by shear walls remaining after passage of large ice runs . A key limitation of the data available to Robichaud (2003) was that the maximum water levels at breakup were typically recorded only at other sites within Fort McMurray, and simplified assumptions had been made in transposing these water levels to the Clearwater River confluence. Friesenhan (2004) conducted an extensive modelling effort analysing historical ice jams at Fort McMurray, providing additional water level estimates at the confluence for these historic ice jams based on hydraulic modelling, and this new information has been incorporated into the database. Figure 2-3 presents the collated record of maximum observed breakup water levels on the Athabasca River at its confluence with the Clearwater River for the period of record investigated (1972 to 2003). Insufficient information resulted in no water levels for 1973, 1975 and 1976. It is estimated that the relative accuracy of these values is ±0.5m (based on the accuracy to which these levels can be measured in the field). Figure 2-3 also summaries data collected and distinguishes the years when ice jams occurred within ten kilometres of Fort McMurray.

From the early work of Shulyakovskii (1963) to the modern research (Robichaud 2003), both fall and spring water levels and flows have been found to be associated with the potential for ice jam formation during river ice breakup. For example, fall water levels influence the level at which the ice cover forms and, on the Athabasca River near Fort McMurray, can indirectly affect the thickness of the ice cover (since hummocky ice covers tend to be associated with higher flows at freeze-up). Spring (pre-breakup) water levels provide an indication of the volume of water available to contribute heat to melt the ice cover from the underside, the potential to lift and move the ice cover before thermal melt can occur, and the magnitude of the jam that can occur (Beltaos 2003).

Two Water Survey of Canada (WSC) gauging stations were selected for investigation of water level and flow data. The Athabasca River at the town of Athabasca (WSC site 07BE001) has a drainage area 74,600 km^2 and is located in the middle of the basin downstream of the major sub-basin for snow melt contribution (~380 km upstream of Fort McMurray). The WSC gauging site, Athabasca River below Fort McMurray (07DA001), located approximately 3.5 km downstream of the Clearwater River confluence, represents a drainage area of 133,000 km^2. In most cases, the flow data published in the WSC record is estimated during periods of ice cover, and these discharge estimates are typically highly unreliable during periods of variable ice cover, such as during freeze-up and breakup. Therefore, measured water levels were used directly in the development of the regression database. Characteristics of river freeze-up that were investigated at each of these stations included: the water level prior to river ice formation, the water level after an ice cover had formed, the change in water levels during ice cover formation, and the maximum daily river flow during October. Figure 2-4(a) illustrates an example for 2002, illustrating how these various freeze-up water levels were determined from the gauge records. Winter and spring river flow characteristics that were investigated at each station included: the water level on March 1 prior to spring thaw, the rate of change in water level prior to ice movement, the water level at which the first ice movement was visually noticeable, and the maximum water level that occurred during river breakup. Figure 2-4(b) provides an example for 1989.

2.3.4 Heat Exchange (Air Temperature, Solar Radiation)

The energy involved in heat exchange is a key component which drives many of the complex processes that influence river ice, and is a key factor in the likelihood of a thermal versus a dynamic breakup. For example, the rate of heat influx to the basin influences the rate of snowmelt which, if it occurs quickly and amounts to a significant amount of runoff, can lift and possibly even break an ice cover, thus contributing to the potential for ice jam occurrence. Conversely, the magnitude and timing of heat input directly to the ice cover contributes to its thermal decay which, if significantly progressed prior to the arrival of dynamic influences (such as those provided by significant runoff events), can reduce the likelihood of ice jam formation.

Given the available data applicable for this site, the most practical approach for quantifying cumulative heat input to the ice cover was deemed to be the linear heat transfer approach, which has been used successfully by a number of other researchers for river ice breakup (Andres 1988; Hicks *et al.* 1997). In this approach, all temperature dependent components of the energy budget are assumed to be linearly related to air temperature. Thus a daily index of cumulative heat input to the system can be determined based on consideration of daily incoming solar radiation and mean daily air temperature, using the following formula:

[1] $\phi = \phi_s + h_{is}\, T_a$

where:

- ϕ is an index of daily cumulative heat input, W/m^2
- ϕ_s is the incoming solar radiation measured over a single day, W/m^2
- h_{is} is the linear heat transfer coefficient between the air and the ice (or snow) interface, $W/m^2/°C$; and
- T_a is the mean daily air temperature, °C.

Using equation [1] cumulative heat input was calculated for Fort McMurray based on temperature data collected by Meteorological Services Canada (MSC site 3062693 YMM) and a combined record of solar radiation from the Meteorological Services Canada (1972 to 1996), private data provided to the

University of Alberta (1997), and from the University of Alberta (UA) meteorological site (all transposed to the UA site by Robichaud (2003) to provide a single homogeneous data set). A linear heat transfer coefficient of 8 $W/m^2/°C$ was selected, based on calibrated results for the Mackenzie River at the outlet of Great Slave Lake (Hicks *et al.* 1997), which was the geographically closest site reported in the literature. This coefficient was not refined further, since it was taken as a constant for the period of record, and thus any refinement in the value taken would not have an impact on the results of regressions obtained using cumulative heat input as an input variable. Figure 2-5(a) presents the average daily cumulative heat input at Fort McMurray from 1974 to 2003 calculated on varying numbers of days prior to river breakup. The database also contains the total cumulative heat input based on a varying number of days prior to river breakup. Total cumulative and average daily heat inputs are included for several accumulation dates that correspond to a varying total of positive degree days. Heat inputs were also calculated based on a March 1 start date as shown in Figure 2-5(b).

In addition to the combined heat input calculation, air temperature and solar radiation were also considered separately, as it was believed that the individual variables might be a sufficient indicator of river ice breakup when combined with other parameters. Air temperature and solar radiation data were included from the sites previously described, as well as for mid-basin sites. A continuous record of air temperature data was established for Whitecourt using a combined record of data from Meteorological Services of Canada (MSC) sites 3067372 and 3067370 (the station name change represents a slight change in the location of the gauge in 1978). For mid-basin solar radiation, the closest continuous record was established for Stony Plain by combining the record from MSC sites 301222F, 3012208, and 3062244. Gaps in the solar radiation record made it necessary to establish several regression relationships between stations. Missing solar radiation flux data was also estimated from the sunshine data available at the same location with relationships that compared favourable to those found by Hicks *et al.* (1993) for Fort Providence, NWT. A regression analysis was performed against the long term MSC station Edmonton Municipal Airport to confirm the validity of combining the stations into a single continuous record.

Air temperature data were also used to determine accumulated degree days of freeze-up and thaw as possible index variables relevant to a regression. The degree days of thaw (positive degree days) were evaluated because of their identified relationship to the ripening of snow packs (Hinkler *et al.* 2002), the weakening of ice covers by thermal deterioration (Ashton 1986) and other processes which may indirectly influence river breakup.

To provide an index variable for melt effects, cumulative degree days of thaw were calculated for the Fort McMurray and Whitecourt stations independently, starting with the first three consecutive positive degree days. In an attempt to avoid a premature start (e.g., during mid-winter thaws), an alternative starting criteria was also investigated. This involved basing the starting point on a minimum total value of accumulated consecutive degree days (e.g., 10 °C-days), rather than on a specified number of days. A starting date was also determined as the day when the degree days accumulation remains positive as shown in Figure 2-6. Finally, the accumulated number of degree days for 3, 5, 10, 15 and 20 days prior to river breakup were determined.

The cumulative degree days of freezing (negative degree days) were considered over the entire winter as an indication of winter severity and thus, possibly, an indirect index of thermal ice growth. Negative degree days were also calculated for the spring breakup period as well, as it was believed that periods of cold weather occurring during breakup might be significant to the likelihood (or lack) of ice jam occurrence.

2.3.5 Soil Moisture (Groundwater, Precipitation)

Both fall and spring soil moisture conditions have the potential to indirectly affect river ice breakup severity. River stage in the fall, which is directly related to basin soil moisture conditions, can influence the level at which the initial ice cover forms. Basin soil moisture conditions in the spring can lead to potential variations in the quantity of snowmelt that reaches the river system, since wet soil will freeze, possibly inhibiting infiltration in the early spring period.

It is difficult to acquire direct measurements for basin scale soil moisture because of its temporal and spatial variability (Flores *et al.* 2004). For this reason, many hydrological models rely on either indexes or coefficients to simulate soil moisture as physical processes. In this study, soil moisture was represented by seasonal precipitation accumulations (from May 1 until October 15), using precipitation data from MSC sites in Fort McMurray (3062693 YMM) and Whitecourt (3067372 YZU), located near the Pembina River Basin. Figure 2-7 illustrates this data. Annual groundwater levels and fluctuations were also considered as a possible indicator of the level of the spring water table. After investigation, provincial groundwater well Devon #2 (LSD 8-12-51-26 W4M) was selected based on its length of record and suitability as a soil moisture indicator. Monthly water levels, changes in monthly water levels, and seasonal (3 month) changes in water levels were considered.

2.3.6 Ice Thickness

The thickness of an ice cover influences the time it takes to decay thermally, the resistance the ice cover has to fracture and movement, the volume of ice available to form a jam, and the thickness and roughness of any ice accumulations that do form (thus indirectly affecting potential ice jam levels). For this investigation, ice thickness data from the measurements by WSC for the Athabasca River below Fort McMurray (site number 07DA001) weres evaluated. As well, the ice thickness information from several sites in the immediate vicinity of Fort McMurray was available from the Regional Municipality of Wood Buffalo. The selection of ice thickness data for this study was reported by Mahabir *et al.* (2004).

2.3.7 Snow Water Equivalent (SWE)

The amount of snow available to generate spring runoff can be an important factor in the likelihood of breakup severity. Without a source of increased river flows to lift and fracture an ice cover, and then carry the flows downstream, the ice is more likely to sit in place and melt thermally. Snow falling on the ice cover itself provides insulation again thermal ice growth in early winter (tending towards thinner ice covers) and protection against thermal deterioration in late winter and early spring (thus potentially increasing the likelihood of dynamic breakup).

For this investigation, both manual and satellite measurements of SWE were considered. Provincial snow course data is collected manually by AENV in the Athabasca River Basin during the first week of March and April each year. As illustrated in Figure 2-1, this data are collected over most of the basin, though not in the immediate vicinity of Fort McMurray. The plains snow course data (representing the mid-basin) are considered to have the largest impact on river breakup in Fort McMurray, because the snowmelt peak from the Rocky Mountains typically occurs more a month after breakup. The Theissen polygon method was used to weight the data from these snow course stations to produce a basin average SWE for each year of record for each of the monthly measurements (see Figure 2-8(a)).

The use of passive microwave data obtained from satellite has been explored over the last decade as a means to develop estimations of SWE over large scales (Gan 1996). While there is still discussion as to the accuracy of the current algorithms, there is potential for this method of measurement to provide data for areas not covered by traditional snow course surveys. Therefore satellite data was considered as a possible input variable in this study. Gridded data, provided by Environment Canada were used to develop basin average SWE, using ArcGIS to determine an average over that portion of the basin covered in the Theissen polygon analysis of the snow course data. Figure 2-8(b) illustrates the data obtained by this method.

2.3.8 Climate Indices

The successful applications of El Nino/Southern Oscillation has established the scientific credibility of the effectiveness of using sea surface temperatures as an index for large scale climate conditions (Ramussen and Wallace 1983). While no direct link to river ice breakup has yet been established in general, several factors such as snowpack and streamflow have been linked to climatic indices

(Hamlet and Lettenmaier 1999). Based on the work of Maurer *et al.* (2004), who examined the relationship of several climate indices to runoff, snow, and soil moisture data for North America, it was determined that the Pacific Decadal Oscillation (PDO) would be the most appropriate index for the Athabasca River Basin and midwinter index values are appropriate. For this investigation, the PDO value for January was investigated as a potential indicator of river ice breakup jam occurrence.

2.3.9 Database Summary

As mentioned earlier, a total of 106 variables were investigated in the development of this database. Although the period of record was 1972 to 2004, not all variables were available for all of the years in this period. Consequently, the length of record (in years) varies, depending upon which variables are considered.

2.4 STATISTICAL ANALYSIS

Developing statistical models begins with conceptualizing relationships between known input characteristics (the explanatory variables) and the desired output parameter. Without a priori knowledge, a statistical method could relate data where no possible physical relation could exist. A statistical modeling approach to forecasting river breakup seeks to determine which environmental variables are the best predictors, without explicitly characterizing the physical processes involved, and establishes a mathematical function for the relationships. In statistical models, the explanatory variables may be directly related to the maximum water level at breakup or may simply be useful as indirect indicators. For this investigation, single variable regression models were explored and did not produce any satisfactory relationships to the maximum water level during spring breakup. This is consistent with the findings of other researchers including Beltaos (1997), Wuebben *et al.* (1995), and Robichaud (2003).

Multiple linear regression is a well known and used multivariate method. A member of the dependence methods, multiple regression is a tool that attempts to predict or determine the dependence of one variable based on a set of predictor variables. The size of the data set and multicollinearity are two major limitations that make it impractical to directly apply multiple linear regression analysis to the 106 variables that are to be investigated. Thus, the limited data set size and the potential interdependence of the variables must be carefully considered. As all regression equations require that there be more data points than variables to define a unique solution, the number of variables that can be considered in any multivariate model is limited by record length, n (up to 30 years in this study, depending upon the variables considered).

Multicollinearity is a problem that occurs when strong relationships exist between the explanatory variables. Not only does multicollinearity make it difficult to distinguish the unique effects of each predictor, but multicollinearity also leads to highly unstable estimated regression coefficients (Dillion and Goldstein 1984). Unstable regression coefficients are a particular problem, as standard error estimates become extremely sensitive to small changes in data points.

2.4.1 Data Reduction

The issues associated with record length and multicollinearity necessitated data reduction in order to determine the most suitable set of data for the regression analysis. To decrease the number of variables available for the multiple linear regression analysis, data reduction methods were applied through a series of progressive steps using Pearson Correlation analysis. Correlation coefficients (e.g., R) and the coefficient of determination (R^2) provide a normalized measure of the strength of the linear relationship between two variables (1 indicating perfect correlation, 0 indicating no correlation). Alpha, α, is traditionally used to symbolize the acceptable risk of a false positive and is directly related to the confidence level. Using the SigmaStat Statistical software (1997), it was determined that a sample size of 30 would provide an 80% chance of detecting a correlation of 0.500 or greater with a confidence (α) of 95%. A stronger correlation (0.600) with similar α value and detection power would require a minimum sample size of 20 values.

Data reduction was first applied between independent variables that measured the same physical feature but by different methods (e.g., SWE measured by manual snow courses versus those by satellite passive microwave algorithms). Relationships identified with a coefficient of determination greater than an arbitrarily selected threshold of 0.60 resulted in one of the variables being removed from the data set. The removal was also somewhat based on practical considerations, in that the variable with the most potential for future use was kept. That is, the variable that was deemed easier to obtain, or with more potential for application at other sites, was selected. This process resulted in a reduction of independent variables from 106 variables to 35.

There is a reasonable possibility that variables across categories could be correlated as well. For example the total freezing degree days may be related to the annual ice thickness if the ice thickness was dominated by thermal ice growth. To investigate this possibility, variables were clustered into three groupings based on seasonal relationships, and relationships between the variables in each group were investigated. Variables related to fall antecedent conditions are soil moisture as indicated by summer rainfall, and river water levels and flows that occur prior to, during or after ice cover formations. Variables that are measured during the winter are the total degree days of freeze, ice thickness, climate index, soil moisture (as indicated by groundwater wells early in the year), and accumulated snowpack. Variables that cannot be determined before spring include the degree days of thaw, cumulative solar radiation, cumulative heat flux and river water levels prior to, during, and after river ice breakup. The only correlated data, based on these seasonal groupings, was for the spring data. Specifically, the water level on the Athabasca River at the town of Athabasca prior to river ice movement, was found to be correlated to the intensity of the daily heat received (total accumulated heat prior to river breakup, divided by the number of days heat accumulated prior to breakup). Based on this analysis, the independent variable data set was further reduced to 34 variables (Table 2.1).

Table 2.2 shows the resulting 34 independent variables investigated, with records lengths varying from a minimum of 24 years to a maximum of 32 years. The dependent variable (maximum observed breakup water level at the Clearwater confluence) is also shown in the Table 2 for convenience.

2.4.2 Multiple Linear Regression Analysis

In the multiple linear regression analysis, standard tests available in SigmaStat (1997) were used to check for normality (Kolmogorov-Smirnov test), constant variance (Spearman rank correlation), and independence (Durbin-Watson Statistic). Variance influence factors, Cook's Distance, and DFFITS statistic were used to determine the influence of individual data points on the regression equation. An adjusted coefficient of determination, R^2_{adj}, was chosen to report the goodness of fit, because, unlike the familiar R^2 coefficient of determination,

R^2_{adj} accounts for the number of independent variables and reflects the degrees of freedom.

In terms of breakup water level forecasting, a model based exclusively on data available in the fall and/or winter is highly desirable, in that it would allow for a long lead time in terms of preparation for a flood. Although expectations were limited, to be complete, a multiple regression analysis was conducted on the data identified as available in the fall. As seen in Figure 2-9(a), a satisfactory relationship was not found ($R^2_{adj} = 0.27$, $n = 22$ years). Similarly, there were no linear relationships that would allow the winter data to exclusively predict the maximum water level at river breakup (Figure 2-9(b), $R^2_{adj} = 0.10$, $n = 23$ years). Furthermore, no relationship to maximum spring breakup water levels could be found for the combined fall and winter data sets (Figure 2-9c,$R^2_{adj} = 0.25$, $n = 22$ years).

Using only the spring data, a multiple linear regression relationship could be established to predict the maximum water level at river breakup, with an $R^2_{adj} = 0.67$ and a standard error of 1.0 m (Figure 2-9d, $n = 22$ years). This regression relied on seven variables, which included (1) the number of consecutive degree days of freezing recorded at Whitecourt within days of river breakup, (2) the number of accumulated degree days of freeze recorded at Fort McMurray prior to river breakup, (3) the average daily solar radiation received at Whitecourt prior to river breakup, (4) water levels recorded at Fort McMurray prior to any ice movement, (5) changes in water levels at Fort McMurray, (6) water levels at the Town of Athabasca prior to spring melt and (7) the precipitation recorded at Fort McMurray the previous summer.

To provide an assessment of the accuracy of this equation, the jackknife method was used. This method estimates the bias of an equation by successively removing one data value from the original data set and then recalculating the regression formula based on the remaining data (Quenouille 1949). The results of the jackknife method showed that a wide variation in regression coefficients occurred only when one of the extreme years (in terms of high water levels at breakup) was omitted from the data set. The resulting error in the predicted value of the maximum water level at breakup with these equations was consistently over 2 metres, with a maximum error of 3.5 m (which occurred when the highest water level at breakup, or the most extreme data point, was omitted from the data set).

Since a strong relationship could not be found with a combination of fall and winter data that would allow an extended seasonal lead forecast, a model with all variables was developed. With the assistance of regression variance influence factors listed previously, two data points (1987 and 2000) were removed as outliers, and a multiple linear regression model was created with the remaining data. The year 2000 had a low water level during river breakup and 1987 had average water levels. These years were modelled reasonably with only spring variables, many of which have been removed from the final model. In low to average years, some spring variables that are not influential in major breakup events, could play a larger role in determining the maximum water level at breakup. Figure 2-10a illustrates the goodness of fit of the resulting model which requires data for 8 variables from all three seasonal groupings. This model has an R^2_{adj} =0.84 and a standard error of 0.7 m (n = 14 years):

[2] $H_B = -257.044 + (0.00463\ P_{YMM}) - (0.000899\ DDay_{total}) - (4.832\ \Delta gw) - (0.0486\ SWE) - (0.0182\ DDay_{10}) + (0.0508\ S_{avg}) + (8.502\ \Delta h/t) + (2.078\ H_{Bo})$

where:

H_B = maximum water level attained on the Athabasca River at the Clearwater River confluence during spring river ice breakup, m

P_{YMM} = soil moisture index: precipitation recorded from May 15 until October 31 at Fort McMurray (mm)

$DDay_{total}$ = measure of the intensity of the winter cold: number of degree days of freeze-up from November 1 until spring breakup (°C-days)

Δgw = measure of early spring runoff: change in groundwater levels from January 1 until March 1 (m)

SWE = average SWE in the basin, as determined from satellite data for the entire basin (mm)

$DDay_{10}$ = intensity of cold weather immediately before breakup: number of degree days of freeze-up 10 days prior to river breakup (°C-days)

S_{avg} = intensity of the solar radiation in the mid-basin: daily average solar radiation from March 1 until river breakup, as measured at Whitecourt (W/m^2)

$\Delta h/t$ = Rate of water level increase as measured below Fort McMurray prior to major ice movement (meters/day)

H_{BO} = Water level as measured below the town of Athabasca prior to spring runoff (m)

Again the jackknife method was used to investigate the stability of the equation, and in this case, relatively smaller variations in the coefficients occurred. Figure 2-10(b) presents the range of modelled values produced by the multiple linear regression equations that were determined in the jackknife analysis. The largest error that occurred in any of the regression equations in the analysis was 1.6 m.

2.4.3 Additional Considerations

One of the major problems with this analysis is that the two years with the highest spring breakup water levels (1977 and 1997) were missing data required for variables in the final regression equation. This limited the validation of the model for extremely high events. Therefore, the potential for substituting available variables in the regression effort was explored, replacing the correlated variables from the more limited data records. It was found that, in some cases, correlated variables could be substituted to create a new multiple linear regression equation that had comparable accuracy to the model presented in equation [2]. For example, the change in water levels prior to the first ice movement of ice on the Athabasca at Fort McMurray is correlated to the absolute water level prior to the first ice movement at the same location. In this case, the new equation has an R^2_{adj} =0.88 and a standard error of 0.6 m; however, it was found to be less stable based on a jackknife analysis. No strong relationship could be found for the variables available in both 1977 and 1997. When limited to the variables that are available for 1977 or 1997, equations with an R^2_{adj} = 0.60 and R^2_{adj} = 0.36 and standard errors of 1.2 m and 1.6 m, respectively, were found. Essentially, no reasonable model could be developed with data available in both 1977 and 1997.

Some variables that were valuable in the regression equations did not have immediately obvious links to a known physical process. For example, it is not intuitively clear why the number of negative degree days prior to river breakup would be important; however, it might be indicative of temporary strength increases in the ice cover, or merely reflective of a change of thermal state of the ice away from an isothermal (0°C) condition. Interestingly, the original work by Shulyakovskii (1963) also identified the negative degree days prior to breakup as a key factor in the formation of river ice jams.

2.5 SUMMARY AND CONCLUSIONS

Spring river ice jams pose a potential threat to many communities in Canada. The rapid water level rise associated with ice jams allows for few mitigative measures once a jam has occurred. Models that provide an indication of risk prior to river ice breakup are a desirable planning tool.

A comprehensive database was created for investigating ice jams on the Athabasca River at Fort McMurray, Alberta. The database contains 106 hydrological and meteorological variables with data from 1972 to 2004 representing the extent of the river basin that could contribute to river ice jams. The quality of several of the variables has been recently improved based on studies by other researchers.

Dependant variables were reduced by Pearson Correlation analysis. Several multiple linear regression models were developed and evaluated with a jackknife approach to assess the stability of the equations. The maximum water level at spring breakup could be modeled by several combinations of variables. The best model, as determined by an adjusted R^2 criteria, consisted of a combination of hydrological and meteorological variables representing fall, winter and spring conditions.

In terms of forecasting breakup related water levels, the models developed in this paper are the most successful statistical models to date for this site, demonstrating the importance of an extensive, high quality database. The length of data collected in the database spanned 32 years; however, not all variables were available for all years. The better regression equations included variables that were not available for the major ice jam event in 1997, although a model could be developed for the 1977 which was the highest water level in the database resulting from an ice jam. While multiple linear regression models provide a means of predicting maximum water levels prior to river ice breakup at this site, the historical availability of variables is a limiting factor in evaluating the ability to model extreme events.

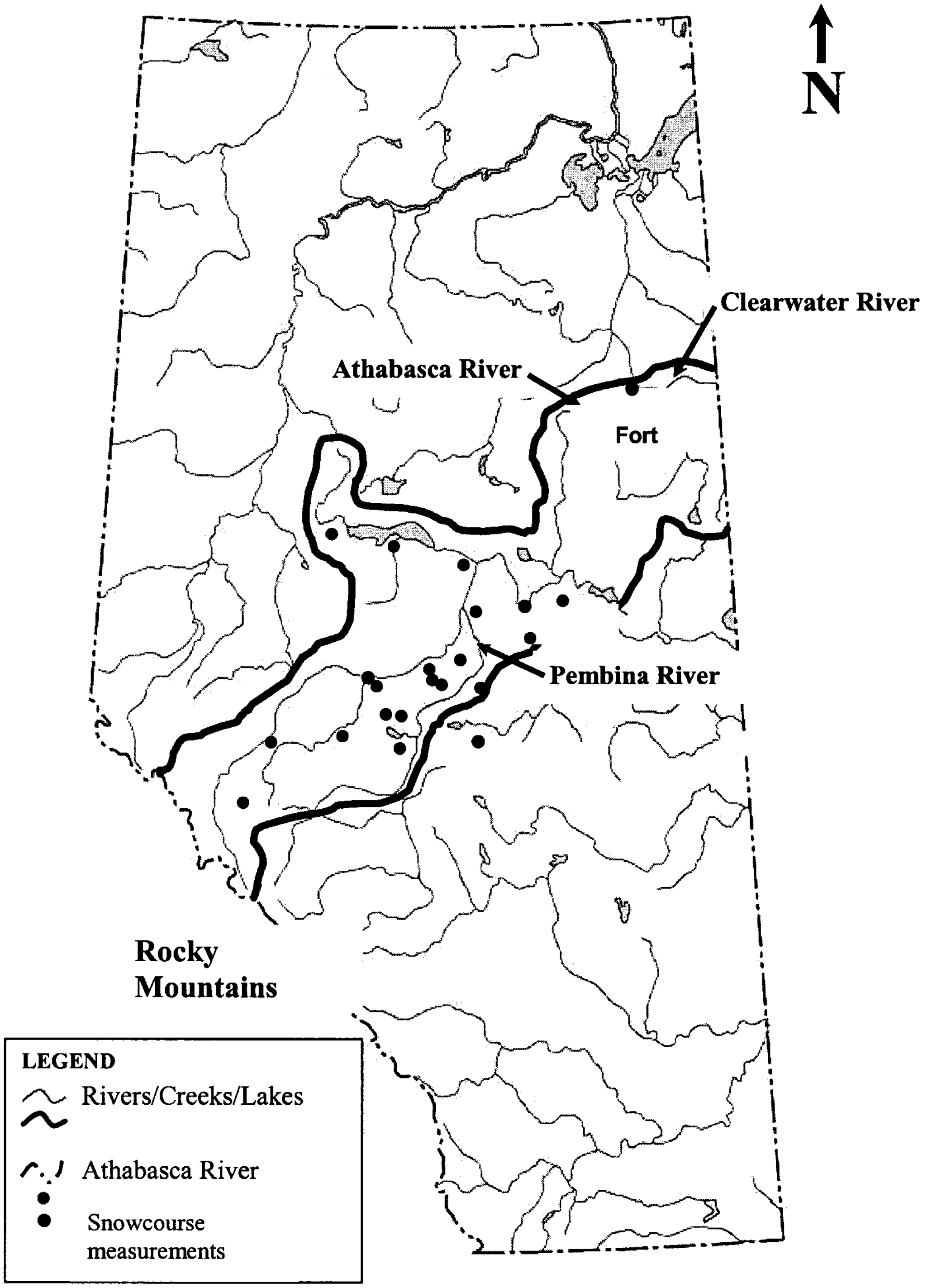

Figure 2-1: Athabasca River Basin.

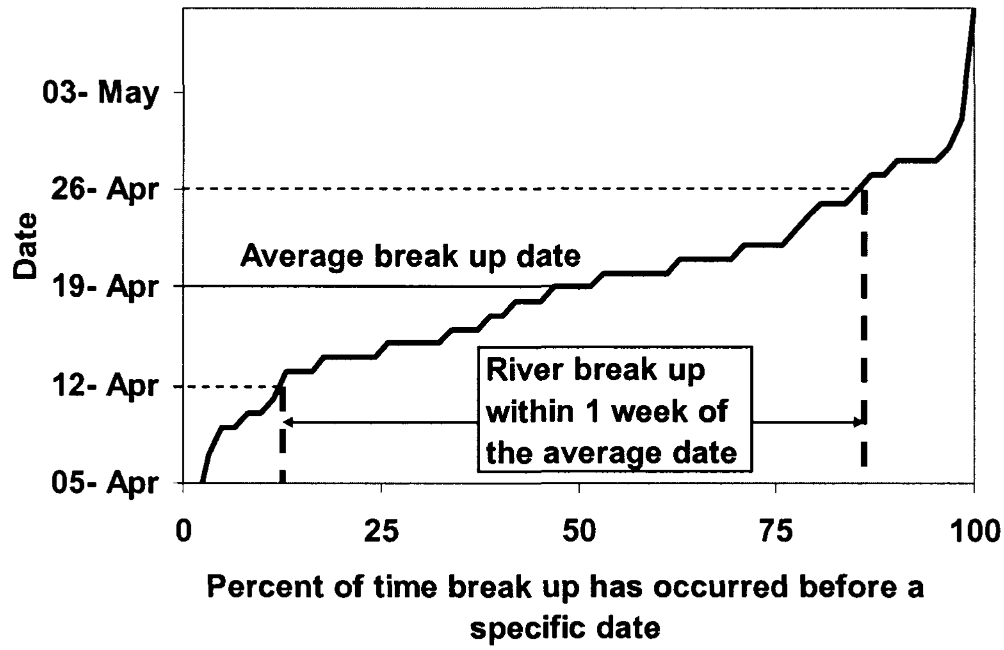

Figure 2-2: Distribution of the date of river breakup on the Athabasca River through the Fort McMurray River reach.

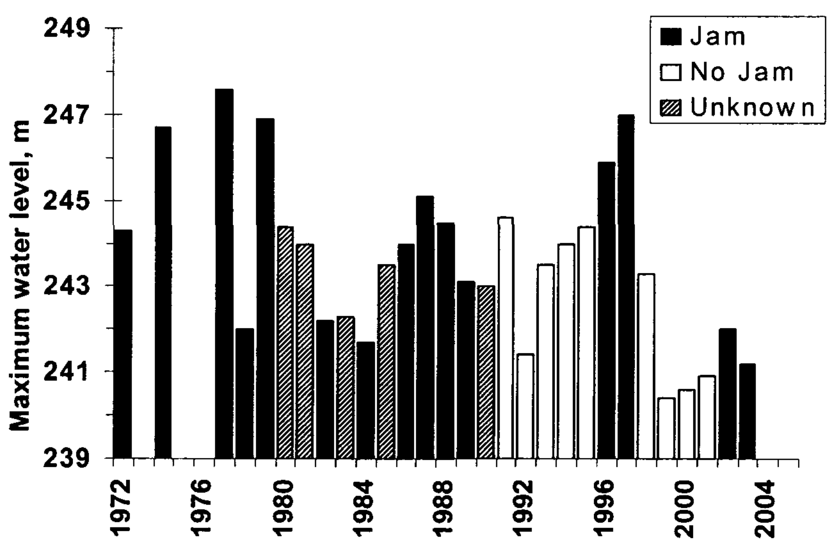

Figure 2-3: Maximum water level recorded at the Clearwater River confluence during spring breakup.

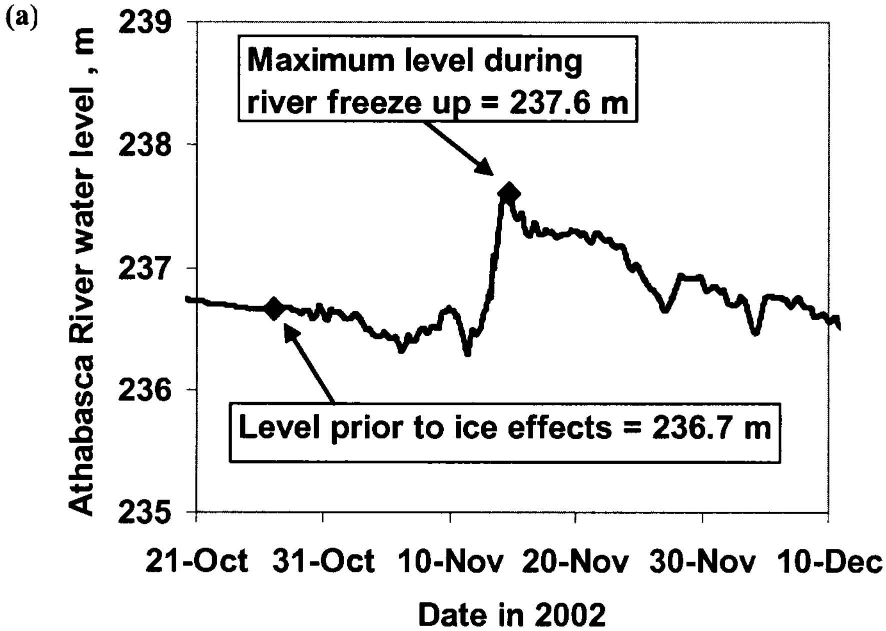

Figure 2-4a: Hydrograph for river freeze-up of the Athabasca River at the Town of Athabasca indicating relevant water level points for 2002.

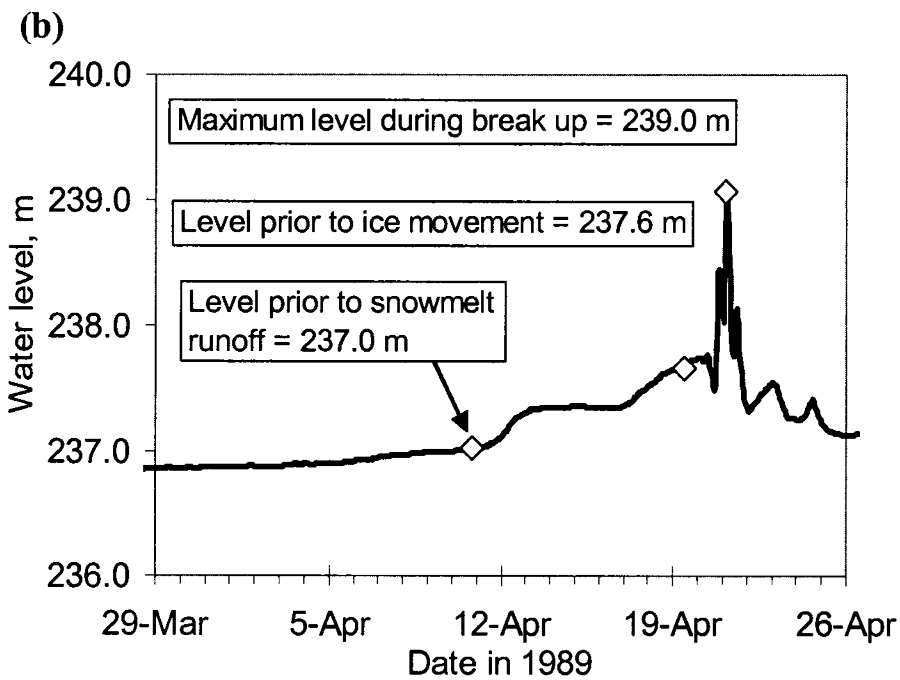

Figure 2-4b: Hydrograph for river breakup of the Athabasca River at the Town of Athabasca indicating relevant water level points for 1989.

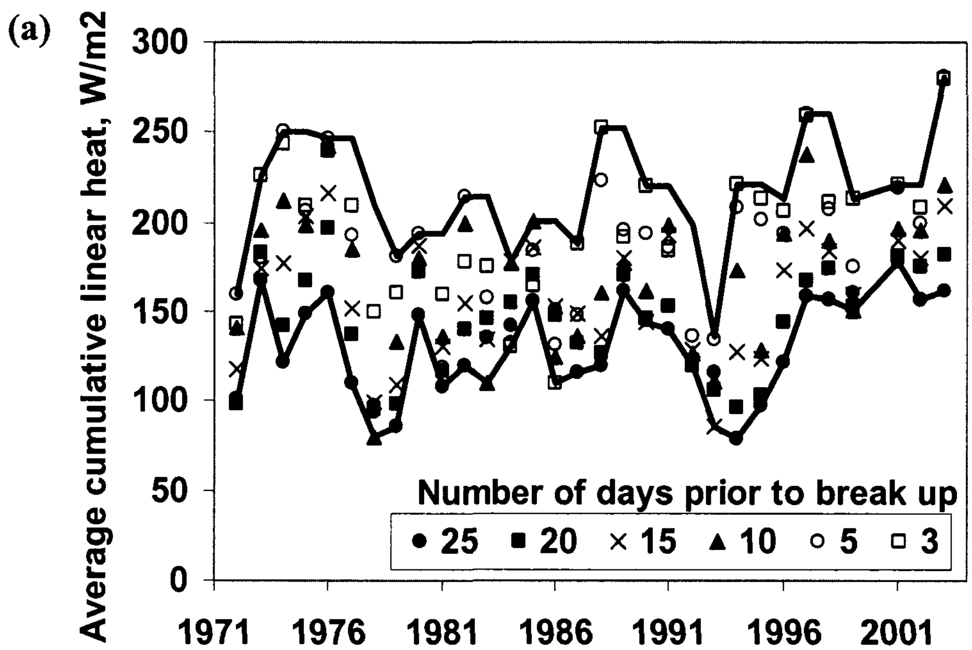

Figure 2-5a: Range of average cumulative linear heat for Fort McMurray based on varying time periods prior to river breakup.

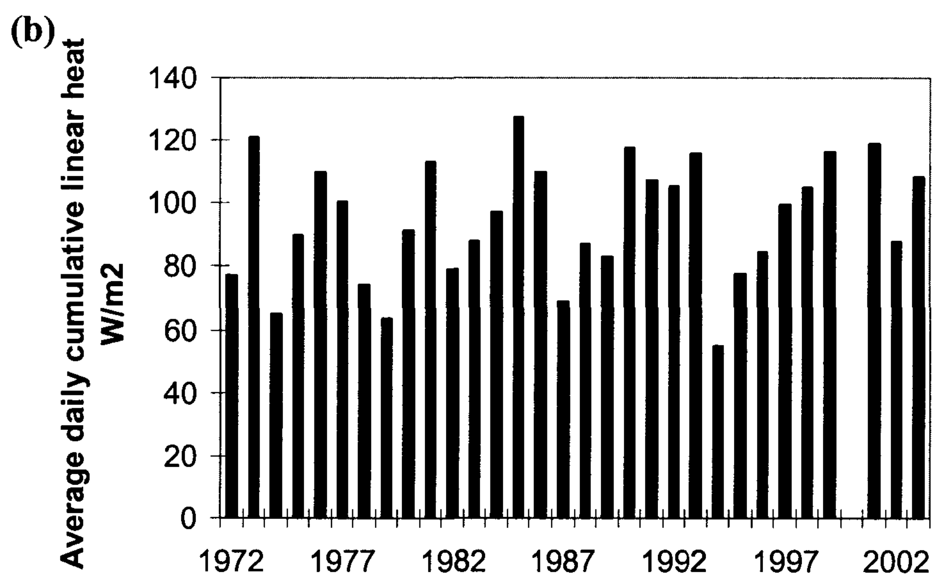

Figure 2-5b: Average daily cumulative linear heat for Fort McMurray from March 1 until river breakup occurs.

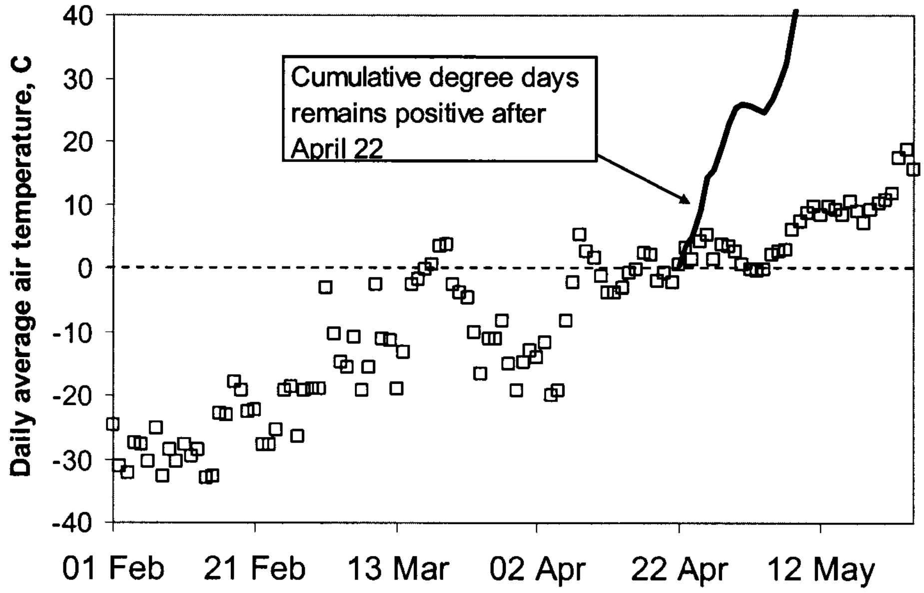

Figure 2-6: 1979 Fort McMurray example of accumulation start point determined as the day that the accumulated degree days remains positive.

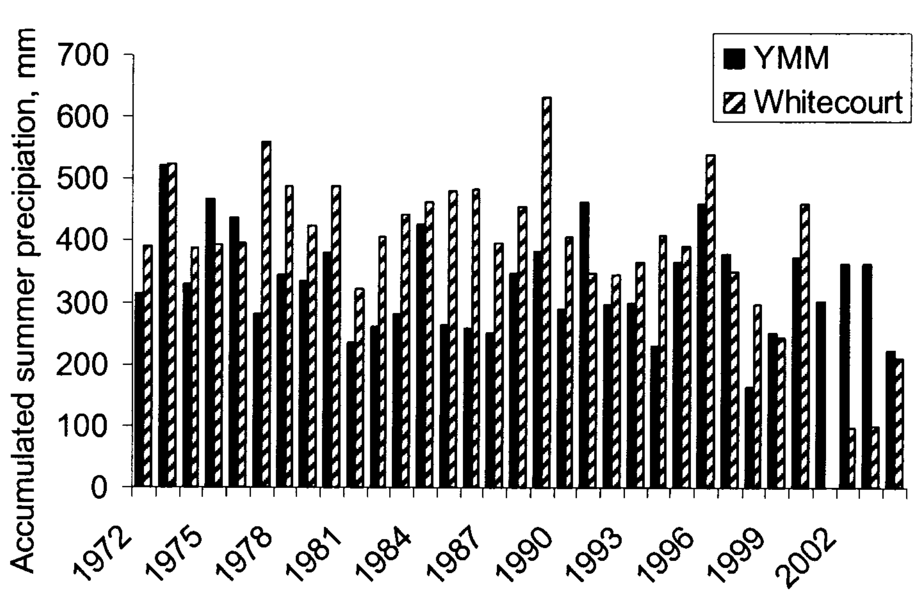

Figure 2-7: Accumulated precipitation from May 15 to October 31 for Fort McMurray and Whitecourt (2002 precipitation data not available for Whitecourt).

(a)

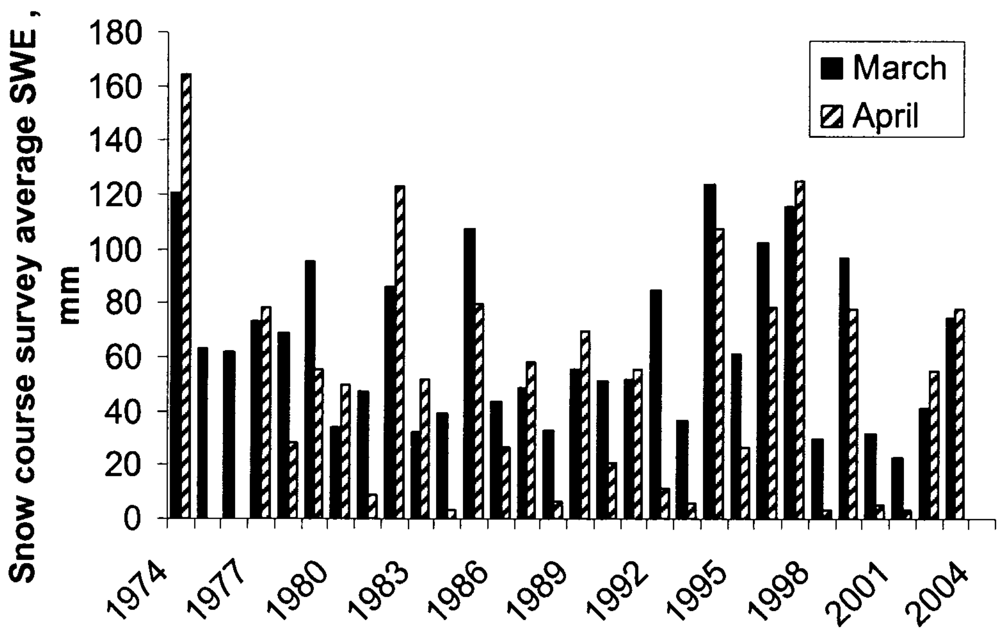

Figure 2-8a: SWE as measured by manual snow course surveys in March and April from 1974 to 2003 (measurements for April 1975 and 1976 not available).

(b)

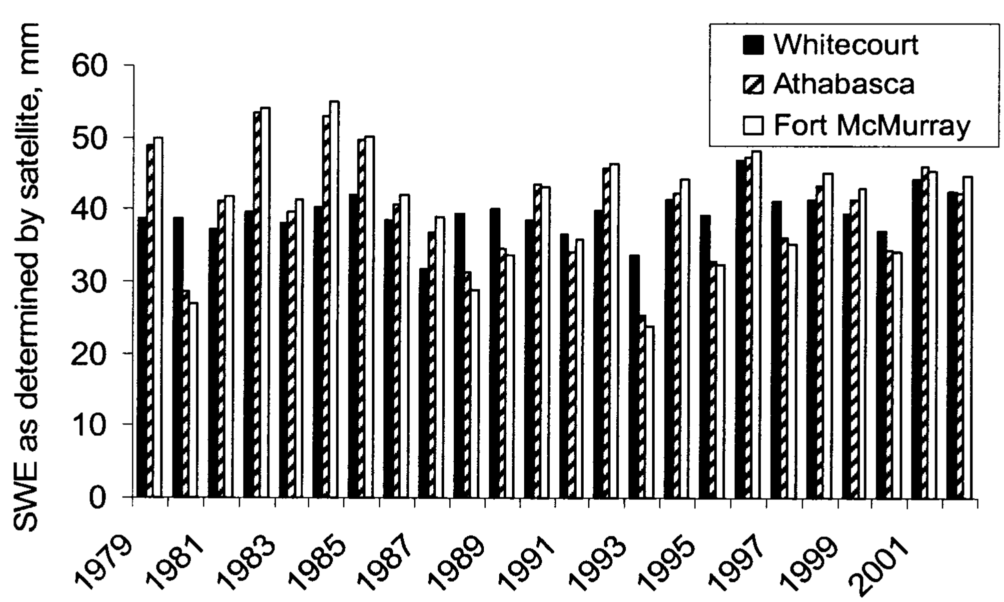

Figure 2-8b: SWE as measured by satellite for the Athabasca River Basin to Whitecourt, Athabasca and Fort McMurray from 1979 to 2002.

(a)

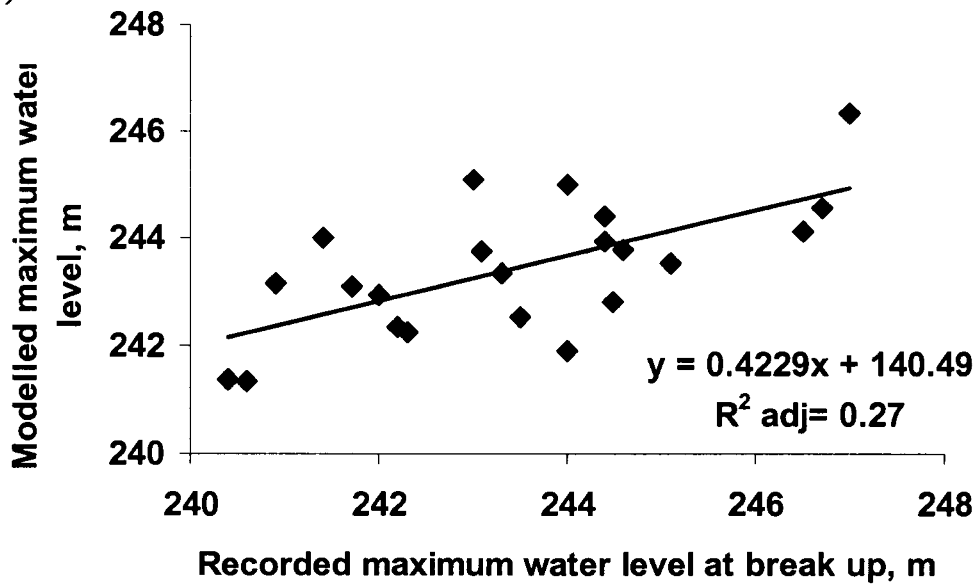

Figure 2-9a: Variables available in fall used to model maximum water levels during spring breakup.

(b)

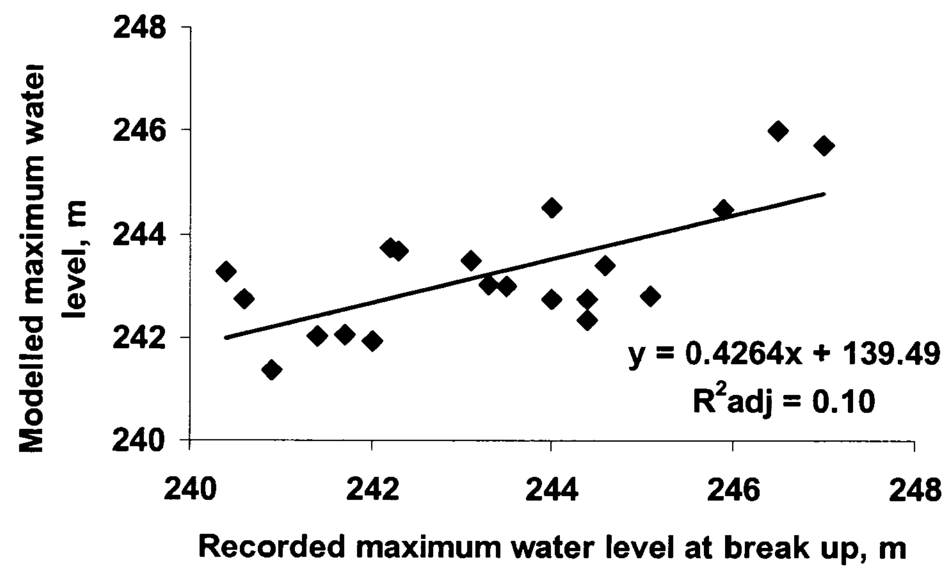

Figure 2-9b: Variables available in winter used to model maximum water levels during spring breakup.

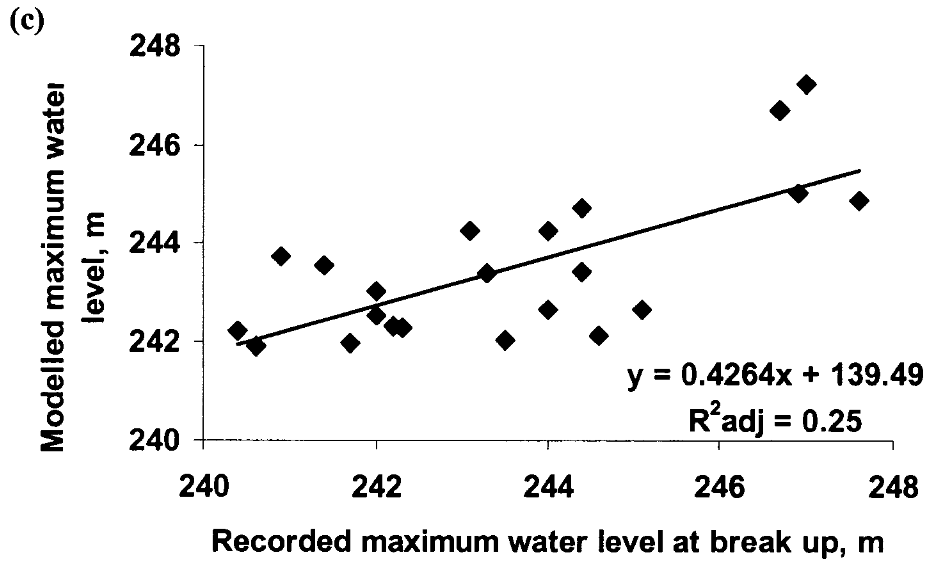

Figure 2-9c: Variables available in fall and winter used to model maximum water levels during spring breakup.

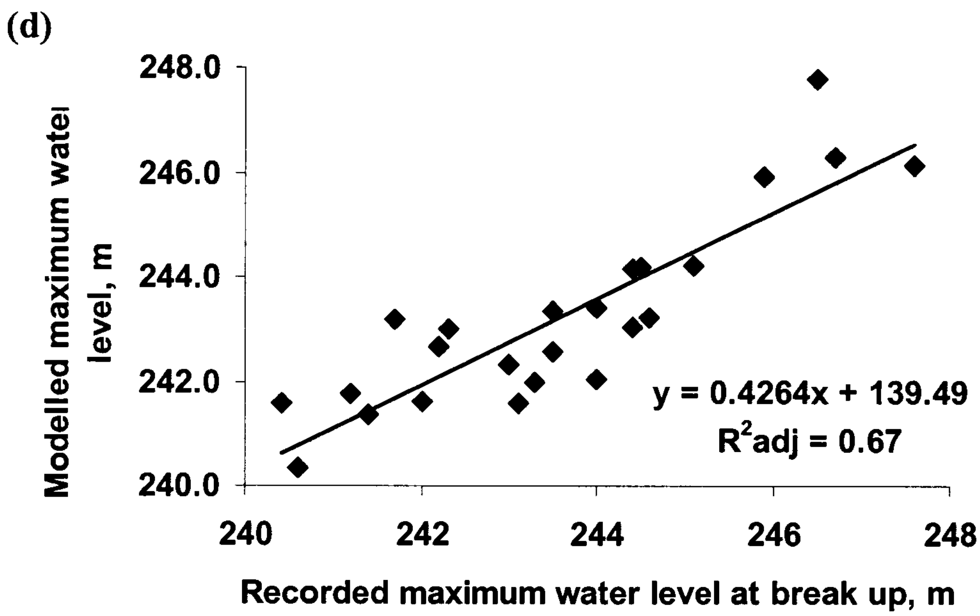

Figure 2-9d: Variables available in spring used to model maximum water levels during spring breakup.

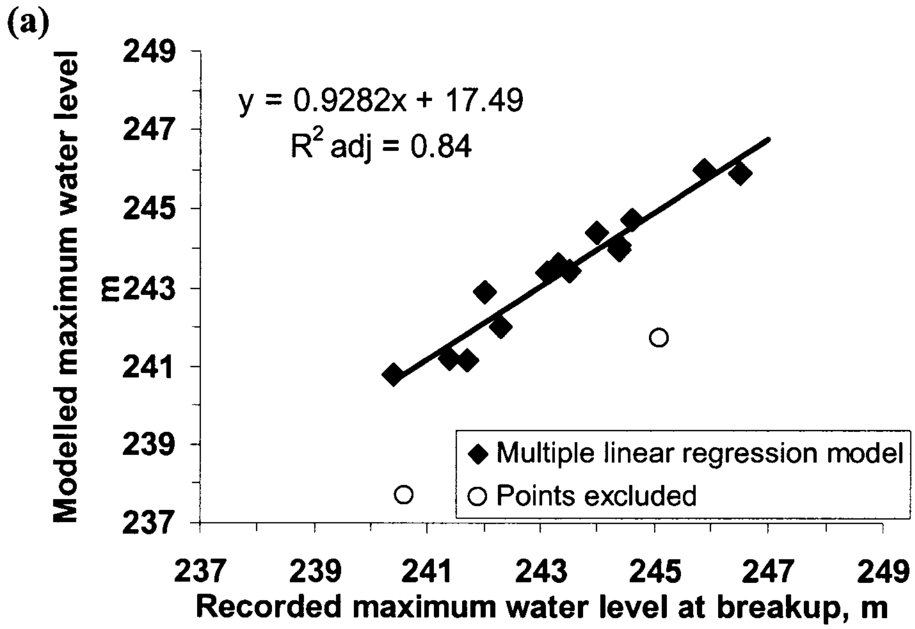

Figure 2-10a: Combination of fall, winter and spring variables used to model maximum water levels during spring breakup.

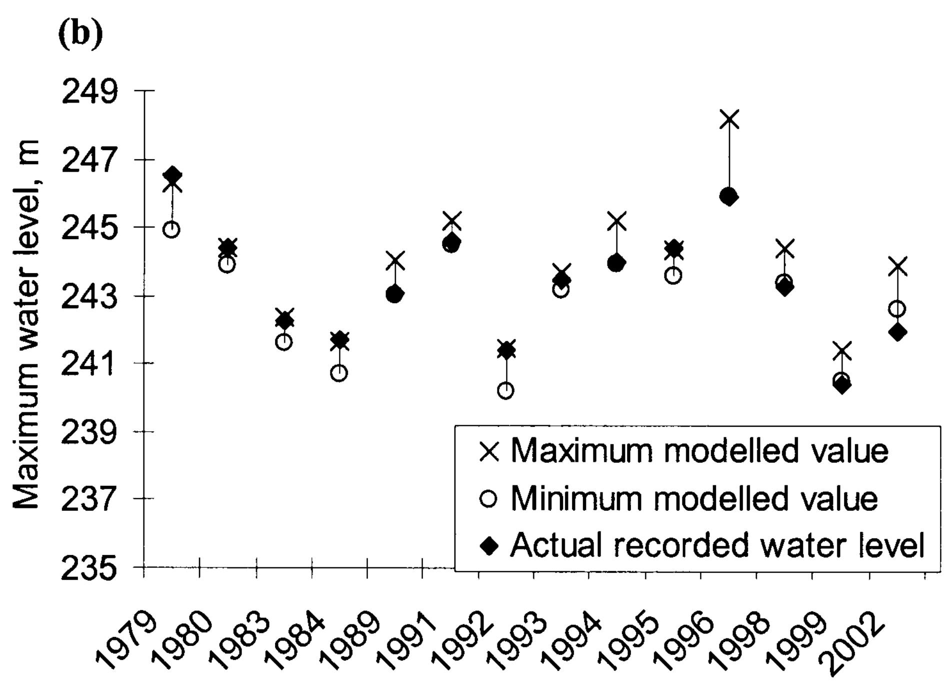

Figure 2-10b: Combination of fall, winter and spring variables used to model maximum water levels during spring breakup

Table 2.1: Data reduction by variable type

Variable Type	*Original Number of Variables*	*Non-Correlated Variables*
SWE	6	2
Degree Days (Freeze and Thaw)	46	8
Ice Thickness	7	3
Solar Radiation	7	4
Climate Index	1	1
Linear Heat Flux	20	4
Soil Moisture	7	4
Surface Water Levels	19	8

Table 2.2: Logical indicator groupings

Grouping	*Characteristic (number of variables)*
Winter Severity Indicator	Degree Days of Freeze (1)
	Ice Thickness (3)
	Climate Index (1)
	Soil Moisture –groundwater levels (2)
	Snowpack (3)
Fall Antecedent Conditions	Soil Moisture- precipitation (2)
	Surface Water Freeze-up Levels and flows (5)
Spring Severity Conditions	Degree Days of Thaw (7)
	Solar Radiation (4)
	Linear Heat Flux(4)
	Surface Water Pre-breakup and Breakup Water Levels (3)

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Chapter 3: Neuro-fuzzy River Ice Breakup Forecasting System[2]

3.1 INTRODUCTION

The spring breakup period is often a time of severe flood threat for many northern communities. The clearing of the winter ice cover can vary between two extremes: one innocuous, where the ice cover deteriorates due to meteorological influences and simply melts in place; and one quite threatening, where a large snowmelt runoff wave lifts and breaks the ice cover resulting in ice runs and ice jams. Ice jam formation and release events are among the most dangerous types of flood risk situations, primarily because the sudden congestion of a river channel with ice can result in dramatic and rapid water level increases. Water can rise several meters in a matter of minutes, inundating flood prone areas with little or no warning, and providing very little time to perform even the most basic mitigation measures. As a result, flood damages are usually high; the U.S. Army Corps of Engineers (2004) estimates that ice jam damages in the United States alone amount to more than $100 million annually.

A number of researchers have developed predictive methods for breakup ice jam forecasting but, due the complex interactions between hydrometeorological influences and ice mechanical properties, only limited progress has been

[2] This chapter has been accepted for publication. Mahabir, C., F..E. Hicks, and A. Robinson. 2006. "Neuro-fuzzy River Ice Breakup Forecasting System". Journal of Cold Regions Science and Technology (in press).

achieved to date using purely deterministic approaches for modeling dynamic river breakup. Until now, the majority of river breakup forecasting tools have been statistically based, including threshold models (e.g. Shulyakovskii 1963; Wuebben et al., 1995), multiple regression models (e.g. Beltaos 1984; Mahabir et al. 2006), and discriminant analysis models (Zachrisson (1990) and White and Daly (2002)). Massie et al. (2001) developed an artificial neural network (ANN) to produce a daily forecast of jam/no jam. Some of the common criticisms of these earlier models are that they are site specific, prone to false positive results, provide only qualitative assessments (jam/no jam) and require data available only days before river breakup, limiting the practical lead time for potential forecasting applications.

Belonging to the same family of soft computing methods as ANNs, but not based exclusively on recorded data, fuzzy logic is another non-linear method that has potential for application in river ice breakup forecasting. Zongfu (1992) first proposed the idea of using fuzzy logic for predicting ice jam occurrence and Mahabir et al. (2002) first applied it to develop a promising preliminary model for the Athabasca River, Canada, which produced a qualitative prediction of breakup water levels, showing few false positives for moderate events and no false positives for major events. Shouyu and Honglan (2005) used fuzzy logic to optimize an ANN in an attempt to predict the timing of breakup on the Yellow River, China forecasting the breakup date within seven days of actual for the five validation years (but also reporting that over 90% of the time river breakup is within seven days of the median breakup date).

Fuzzy logic is a form of artificial intelligence that is ideal for incorporating generalized knowledge. With fuzzy logic, linguistic descriptions are used to represent inputs, to evaluate input sets based on defined rules, and to provide a linguistic assessment of the resulting set. Pioneered by Zadeh (1965), fuzzy logic has been effectively used in combination with other soft computing methods for predictive water resource related sciences. One of the primary advantages of fuzzy logic over traditional mathematics is that it is enables the modeler to incorporate a conceptual understanding of cause and effect relationships describing the process to be modeled. This is ideally suited to the river ice breakup flood forecasting application; while it is not yet possible to model the complex hydrometeorological interactions leading to the occurrence of ice jams in a fully deterministic manner, many heuristic "rules of thumb" do exist. For example a high spring runoff would be expected to increase the likeliness of an ice jam occurrence.

Fuzzy logic has also been combined successfully with other forms of modeling to produce hybrid models that incorporate the advantages of both parent models. For example, Nayak et al. (2005) found that a neuro-fuzzy model had superior performance to both fuzzy models and ANNs for long lead forecasts in rainfall runoff process models. For river ice breakup modeling, combining fuzzy logic with the learning ability of ANNs in a neuro-fuzzy model provides the potential to combine available heuristic knowledge with limited recorded data in model development. A hybrid neuro-fuzzy model combines the modeling advantages gained with fuzzy logic with the ability to learn from the limited historical data that is available.

This paper details the development of fuzzy logic and neuro-fuzzy models for river ice jam flood forecasting. It provides insight into the application of fuzzy logic to predicting the severity of river ice breakup and the ability to use ANNs to make optimal use of the limited data so typical in this application. The potential for both linguistic assessments and quantitative predictions are explored. A prototype model is developed and alternate selections in model design are compared.

3.2 SITE DESCRIPTION AND PREVIOUS MODELS

The Athabasca River is the largest unregulated river in Alberta, Canada. It has its headwaters in the Rocky Mountains and flows in a northeasterly direction across the province to the Peace Athabasca Delta as shown in Figure 3-1. The drainage basin, as measured at the Water Survey of Canada gauging site just below Fort McMurray, is 133,000 km^2 with the majority of the basin area located south of this gauge site. Because the southern reaches tend to produce snowmelt prior to significant ice deterioration in the northern reaches, ice jams frequently occur in the vicinity of Fort McMurray. A data set was developed for studying river ice breakup in this basin and specifically at Fort McMurray. Mahabir et al. (2006) provide a description of the location of relevant meteorological and hydrological measurement sites. Available variables include antecedent precipitation, solar radiation, basin snow water equivalent (SWE), river flows and water levels, groundwater data, air temperature data, ice thickness measurements and documented descriptions of river breakup.

Mahabir et al. (2006) also present a multiple linear regression model for the purpose of forecasting the maximum water level attained on the Athabasca River at Fort McMurray during spring river ice breakup. It is based on the following eight input variables:

1. a soil moisture index: based on cumulative precipitation recorded from May 15 until October 31 at Fort McMurray (mm);
2. a measure of the intensity of the winter cold: based on the number of freezing degree days from November 1 until spring breakup (°C-days);
3. a measure of early spring runoff: based on the change in groundwater levels from January 1 until March 1 (m);
4. the average SWE in the basin: as determined from satellite data for the entire basin (mm);
5. the intensity of cold weather immediately before breakup: number of freezing degree days for the 10 days prior to river breakup (°C-days);

6. the intensity of the solar radiation in the mid-basin: based on daily average solar radiation from March 1 until river breakup, as measured at Whitecourt (W/m^2);
7. the rate of water level increase as measured below Fort McMurray, prior to major ice movement (meters/day); and
8. the water level as measured below the town of Athabasca (upstream) prior to spring runoff (m)

That regression model has an $R^2_{adj} = 0.84$ and a standard error of ±0.7 m but, through jackknife analysis, it was shown to have the potential for errors of up to ±1.6 m. A total of 14 points were modeled, with several years discarded because of insufficient data (Figure 3-2). This included the two highest water level years on record (occurring in 1977 and 1997) when flooding actually occurred. Two data points, 1987 and 2000, also had to be removed as outliers. Since no reasonable model could be developed with data available in both 1977 and 1997, the regression model could not be demonstrated to adequately model a flood event. Clearly another approach was needed and this was the motivation for this investigation.

Most types of measurements have inherent limitations in accuracy based on the measurement equipment. Apart from the inaccuracies associated with the actual measurement itself, data error can occur when extrapolating point measurements to determine basin average conditions. Other important processes, such as heat transfer, are estimated through simplifications of complex processes. Precise quantitative data are not available for some of the most critical data such as the water level at breakup which is often estimated to the nearest half a meter due to the hazardous conditions that exist along the river bank during river ice jam occurrence. In addition, data collected over decades by several different groups and agencies could involve variations in precision. For example, the maximum water level at breakup may have been taken as the actual water level, the top of the ice along an in-situ ice jam, or the estimated shear wall height. Fuzzy logic has been shown to be a particular good modeling approach for data sets such as this, that have limited accuracy that cannot be easily resolved with additional data collection. Errors resulting from measurement uncertainties and extrapolation are less influential in fuzzy systems compared to traditional mathematical models. Bardossy et al. (1990) and Revelli and Ridolfi (2002) successfully applied fuzzy set theory to accommodate measurement uncertainties in their analysis.

3.3 HYDROMETEOROLOGICAL DATABASE DEVELOPMENT

The basic components of Mamdani fuzzy expert systems involve fuzzification of the input variables, application of a fuzzy operator, implication from an antecedent to the consequent, aggregation of the consequents across the rules and, potentially, defuzzification (interpretation of resultant fuzzy set to a crisp or unique number). A basic description of the components is presented here with more details provided in relation to aspects that were found to be important to river ice modeling. Several books such as Tsoukalas and Uhrig (1996) and Nelles (2001) can provide the reader with more detail on the components and mathematics of fuzzy logic and expert modeling systems.

3.3.1 Fuzzification

Fuzzification is the process by which linguistic descriptive terms with logical meanings such as 'low', 'average' or 'high' are used to describe the input variables. By this process, a defined quantity (e.g. 40 mm of SWE in a snowpack) is redefined in terms how representative it is of a magnitude concept, such as a 'low' snowpack. Membership functions are logical linguistic descriptors which evaluate each input quantity in terms of how well it is suited to each specific linguistic term. The membership functions are defined over the full range of possible values with the shape and number of the membership functions selected based on expert opinion, statistical distributions, or simple logical groupings. Figures 3-3(a) and (b) show example triangular and mixed-triangular/trapezoidal shaped membership functions for the SWE of a snowpack respectively, and illustrate that a single input value can belong to more than one membership function. Figure 3-3(a) specifically illustrates Standard Membership Functions, for which membership groupings have simply been spread evenly over the range of possible values. 3-3(b) shows Statistical Membership Functions which have been based on historical occurrences of the variable defining 'low' and 'high' as above or below the 25^{th} and 75^{th} quartiles of the data. This definition naturally implies the trapezoidal shaped membership functions illustrated.

3.3.2 Application of a Fuzzy Operator

The selection of a fuzzy operator governs the interaction of the input variables with the familiar linguistic terms of "AND" or "OR". For most applications, the independence or interdependence of the input variables with respect to the physical process being modeled governs the selection of "AND" or "OR" respectively. Most river ice breakup forecasting methodologies are based on traditional mathematics, such as regression analysis, which do not allow variables to be considered with the logical "OR" relationship that is associated with correlated variables. While it is recognized that fuzzy logic provides this opportunity, this paper will follow the traditional ice modeling approach of considering only "AND" relationships between variables with little or no known correlation.

3.3.3 ***Implication from an Antecedent to the Consequent***

A rule base is developed to define the implication from an antecedent combination of input variables to the consequent, or outcome, membership functions. Rules can be set based on historical evaluations, expert knowledge, or a combination of both. Rules follow the format of an *if-then* statement such that

"*If* condition X AND/OR condition Y - *then* condition Z". Conditions X and Y describe the state of the input variables, while condition Z describes the state of the output variable(s).

Because of the transparency of the rule base it is possible to have an expert, or a team of experts, determine the rules and degrees of support for each rule without implicit knowledge of fuzzy modeling. The degree of support in the rule base can range from 0 to 1 to reflect differing views of these experts. For example, the degree of support for the outcome of a rule with high agreement between experts would be higher than the degree of support for a rule where the outcome is more uncertain, due to differing views among the experts. De La Garza and Ibbs (1990) report on several techniques for expert knowledge elicitation; Bardossy and Duckstein (1995) provide information for the construction of rule bases with both logical and statistical foundations.

If sufficient historical data is available, Artificial Neural Networks (ANNs) can be used to extract data for the rule base, creating a hybrid neuro-fuzzy model. ANNs perform repetitive evaluation of the known results and incrementally strengthen/weaken the influence of the rule on the modeling result, referred to as the 'degree of support' in fuzzy models, or the 'neuron weighting' in ANNs. As with many iterative solutions, precautions must be taken to avoid undertraining or overtraining the rule base.

The size of the rule base can be a limiting factor in the development of a fuzzy logic system, as the rule base increases substantially with the number of input variables. For a model where each rule has only a single possible output, a complete rule base requires that a rule be defined for every combination of antecedent conditions. For example, if a process is defined by two input variables, each described by three linguistic terms, then 2^3 (or 8) rules would constitute the complete rule base. If multiple outcomes or outputs are defined for identical inputs (through rule weighting), then the number of rules required increases by a factor equal to the number of possible results for each rule. For example, if the output variable has five linguistic descriptors for the previous example, and all are possible from any rule combination, the number of rules required is 5 x 2^3 (or 30) rules.

The sets of data from the evaluation of each rule are combined through the aggregation of the consequents across the rules. A common method used in fuzzy logic in conjunction with the 'AND' operator, and applied in this research, is 'Maximum'. In terms of aggregation, Maximum is a function that combines the maximum value attained by any rule evaluation into a single resultant set.

3.3.4 Defuzzification

Defuzzification is the process of evaluating the resultant set, often for the purpose of describing the result as a single crisp value. Features of the resultant set are analyzed in the defuzzification process to produce the optimum description of the result. The method of defuzzification is often the most sensitive process in a fuzzy model (Fayek and Sun, 2001). With evaluation methods such as 'Centroid' (selection of the set centroid), the properties of the resultant fuzzy set are extracted. Other methods evaluate properties of the range at which the resultant set achieves the highest membership. For example, 'Mean of Maxima', commonly abbreviated as MOM, selects the average value in the highest membership range. Figure 3-4 illustrates the defuzzifacation of a resultant set with Centroid and MOM defuzzification methods producing crisp, quantitative results of A and B respectively. Roychowdhury and Pedrycz (2001) provide mathematical descriptions of these defuzzification processes, as well as strategic approaches to the selection of defuzzification methods within a design system.

3.4 PROTOTYPE FUZZY LOGIC MODEL

3.4.1 Variable Selection

While the multiple linear regression model (Mahabir et al., 2006) had its limitations, the variables it identified as key to modeling river breakup should provide a reasonable basis from which to consider variables for a nonlinear model, as highly influential variables should play a role in both models. The variables in this fuzzy logic prototype model were therefore selected from that multiple linear regression model. It logically follows that the variables should be considered independent, as this was a criterion for retention in the regression model. This leads to the selection of "AND" as the logical link between variables.

The use of eight input variables, as found to be important to the multiple linear regression analysis (Mahabir et al., 2006) was not practical for this prototype fuzzy logic model. If each of the eight variables had three linguistic descriptors (three membership functions which, in this paper, are described by the linguistic terms "low", "average" and "high"), then 3^8 or 6561 rules would be required for just a simple rule base (i.e. one in which the result of a rule was defined as a single linguistic term and not a weighting of multiple terms). In this application, a particular value of any variable may belong to up to two of the three linguistic input/output terms (e.g. Figure 3-3, a particular value of SWE may belong to both low and average, or to both average and high, to different degrees). This dual membership results in rules related to both possible variable states being activated by a single set of data points. By multiplying the number of variables by the maximum number of linguistic terms with membership, the maximum number of rules that can be evaluated per set of data can be determined. A model with eight variables could have up to 16 rules activated per data set (i.e. per year, in our case). Thus with 30 years of data, a maximum of 480 rules could be evaluated if each case activated a unique rule. Although this sounds like a large number, it is not sufficient to formulate and validate a model requiring 6561 rules.

Clearly a reduction in the rule base was required and this is typically achieved by reducing the number of input variables. This can be done either by simple deletion, or by combining multiple basic variables into more complex input variables (e.g. temperature and snow accumulation might be combined into a single variable representing the severity of the winter). As this is the first application of fuzzy logic to river ice breakup forecasting, the prototype model was made as transparent as possible by retaining the actual variables rather than by employing combination variables. Thus the number of input variables was reduced, from eight to four. This reduced the required rules to 3^4 (or 81) rules in a partial rule base where each set of initial conditions (antecedent) has a unique outcome (consequent), or 3 x 3^4 = 243 rules, in a rule base where the output variable has three possible linguistic descriptors and each antecedent can produce any consequent.

The criterion for selecting those input variables that would be retained was straightforward and practical: those with the longest lead time were retained since this would result in a model with the maximum lead time between the forecast and the event. Specifically, only those variables that were available in the fall or late winter were used in the fuzzy models, while those known only a few days before breakup were not. The retained variables evaluated in the prototype fuzzy model are thus: an index of soil moisture (previous summer's precipitation at Fort McMurray); a measure of the intensity of winter cold (number of freezing degree days during the winter); a measure of early spring runoff (change in shallow groundwater levels from January to March); and later winter SWE in the basin (measured from satellite data for the entire basin). The variables used in the multiple linear regression model, but not considered for the fuzzy models are: the intensity of cold weather immediately before breakup, as measured by number of degree days of freeze-up 10 days prior to river breakup; the intensity of the solar radiation in the mid-basin (Whitecourt), measured as the daily average solar radiation from March 1 until river breakup; the rate of water level increase as measured below Fort McMurray prior to major ice movement; and, the water level as measured below the town of Athabasca prior to spring runoff. Elimination of these variables facilitated the development of a model with 3 to 4 weeks lead time prior to river breakup.

3.4.2 Membership Functions

The membership functions for each variable were created based on the available historical record from 1972 to 2004. Three membership functions, namely 'low', 'average' and 'high', were used to define each variable and two approaches were employed for developing these membership functions. This first involved the development of Standard Membership Functions, which were heuristically based on historical data. In this case, the membership functions were evenly distributed over the plausible range, which was determined as the historical range ±10%, considering physical restrictions (e.g. negative quantities of most physical measurements are not possible). The range for the output variable, the maximum breakup water level at Fort McMurray, was defined as ±10% of the difference between the historical maximum and minimum values (since it would be inappropriate to use ±10% of the geodetic elevations, as the site is approximately 250m above sea level). All Standard Membership Functions had linear interpolations between 0 and 1 membership values. This produced membership functions similar to those illustrated in Figure 3-3(a). For the second approach, Statistical Membership Functions were defined with the 'average' linguistic term being the mean value, and the 'low' and 'high' membership functions being below the 25th percentile or above the 75th percentile of historical data, respectively. This produced membership functions similar to those illustrated in Figure 3-3(b).

If the definition of the membership function is based on historical statistics, one would expect that a non-linear transition in membership would be more logical, as this is frequently seen in natural populations (hydrographs, duration curves, etc.). However it might be argued that, if the membership definition is based on expert knowledge or thought, it may be more reasonable to have linear properties in the membership function as this is more reflective of basic reasoning, especially in applications such as this which are complex and data limited. In order to investigate the possible importance of this question, the effects of transition limb shape were also investigated by changing the nature of the membership functions in the expert knowledge prototype model from the linear membership functions shown in Figures 3-3(a) and (b) to non-linear interpolative cubic spline membership functions where the transition from a membership value of 1 to a membership value of 0 is non-linear.

3.4.3 Expert Knowledge Rule Base

For this prototype model the rule base was completely created based on the author's experience and the 20 years of data available for model validation. Although it is acknowledged that the expert opinion rule base may benefit from increasing the number of experts participating in the development of the rule base it should be noted that, unlike many other fields of study where it is possible to get a statistically significant sampling of experts' opinions, expertise on river ice breakup processes on the Athabasca River at this site is limited to about 5 to 10 professionals. Therefore, at best, only a limited enhancement to the rule base development could possibly be realized by employing more experts in the development of the rule base, as no statistical analysis of the varying opinions could be achieved. Therefore input from additional experts was not pursued at this time. The expert knowledge rule base was created within the *fuzzy*TECH® software system, version 5.54 (2001). The complete rule base consisted of 81 rules with the degree of support for each rule being 1. The rule base is located in Appendix C. From the developed rule base, we learn that precipitation and the negative degree days are more influential in causing severe breakups than groundwater or SWE.

3.4.4 Results of the Prototype Expert Knowledge Fuzzy Logic Model

Figure 3-5(a) show the quantitative results comparing the output from the expert knowledge fuzzy logic model to the observed values for both the Standard and Statistical Membership Functions, using the Centroid method of defuzzification. Both models were effective at qualitatively predicting high water levels (i.e. separating low concern water levels from high concern water levels. However, neither model produced particularly accurate quantitative water level predictions. Additionally, the statistically defined membership functions tended to direct the model towards an average value of the output range, likely due to the fact that definition of the input variables was not well defined at the extreme ends of the range. It was further found that this fuzzy logic model was not sensitive to the shaping of transition limbs of the membership functions.

A further test was conducted using the MOM method of defuzzification with the Standard Membership Functions (Figure 3-5(b)). While the MOM method did not produce satisfactory quantitative results, it did provide a clear qualitative distinction between the years when flooding occurred and those when it did not.

By extracting three points (years) for calibration, representing the occurrence of 'low', 'average' and 'high' water levels, the prototype model could be recalibrated manually. This involved an iterative process of adjusting the rules until the results for these three calibration years were optimized. Although the calibration process was time consuming, as Figure 3-6 illustrates it resulted in an improvement in the quantitative forecasts for most years. Excluding the four validation years with poor performance (1982, 1987, 1992, and 1995), the coefficient of determination, R^2, was calculated as 0.71 for this model (for the relationship between observed and modeled values). Since there is no basis to exclude these points, the ability of the expert knowledge fuzzy model to provide quantitative results appears limited.

3.5 PROTOTYPE NEURO-FUZZY MODEL

To reduce the subjectivity of the prototype model, ANNs were explored for training the rule base with *fuzzy*TECH® software. Through backward propagation with random supervised training, the degree of support for each rule and the distribution of the membership functions could be determined. (The degree of support is equivalent to rule weightings in an ANN for this application.) A complete rule base containing all possible outcomes was generated with random weightings for each rule. All training was initiated from Standard Membership Functions evenly distributed across the identified variable range. Initially some difficulties were encountered in calibrating this neuro-fuzzy model, because of inconsistencies in the data (e.g. similar inputs causing different outputs) and due to the fact that the majority of the available data was at the low range of breakup water levels. To address this problem, fuzzy cluster analysis which is part of *fuzzy*TECH® software, was used to identify discrepancies contained in the data. Fuzzy clustering is a method of preprocessing the data to remove redundant or conflicting data to increase the speed of the training (Tsoukalas and Uhrig 1996). In the case of the latter, expert knowledge must be used to decide if the removal of data is warranted for training purposes. By this process, conflicting data was identified for 4 of the 20 event years (1982, 1997, 2000 and 2001). These years were therefore not used for model training, but were instead reserved for the model validation.

Eight of the 16 years of consistent data were used for the training of the neural network, including three years that resulted in low water levels during spring river breakup, three years with average water levels and two years with high water levels during breakup. The remaining eight data points from the consistent data subset were then used for verification. This subset included one year with a high water level. Several combinations of this grouping or "bagging" of training versus validation data were tested, and performance of the resulting neuro-fuzzy model was found to be relatively similar for the different combinations. Results for the 'optimum' neuro-fuzzy model are presented in Figure 3-7, ($R^2 = 0.88$ for the relationship between observed and modeled data). The figure also shows the excluded (contradictory) data for information purposes. The dashed lines (±0.5m) represent the target accuracy of the model (reflective of the accuracy to which ice jam related water levels can be measured at the site).

One possible strategy to improve the model might be to use Statistical rather than Standard membership functions; however, this was tested and was not found to provide any significant improvement in results. Another approach would be to train the output membership functions in addition to the rule base. However, this was tested and it was found that the performance of the neuro-fuzzy model was only marginally improved as a result. The ANN moved both the upper and the lower output membership functions to the extremes of the ranges, indicating that it was having difficulty in resolving a quantitative relationship with only three defined (linguistic) output terms. The number of linguistic membership terms could be increased to five (normally an odd number of terms is used). However, because of the limited data available, this option was not pursued as the number of rules in the database would have increased from 243 (3×3^4) to 405 (5×3^4), and the data were not sufficient to support such an extensive rule base.

One area of concern with the neuro-fuzzy model was that the automated rule weightings in the rule base did not appear rational. For example, a particular rule could indicate an 'average' result, while a similar rule with a linguistic input variable that would be expected to increase this outcome, would predict a 'low' result. These types of discrepancies could be the result of insufficient data available for complete training of the rule base. This is actually one advantage of the neuro-fuzzy model over ANNs alone, since this type of logical evaluation of the model would not be possible with a non-hybrid (pure ANN) model. The potential for improving the performance of the neuro-fuzzy model is an aspect for future research in that it may be beneficial to allow the ANN to train only a portion of the rule base and considerable interpretation or modification of the rule base after training could be performed.

3.6 DISCUSSION OF RESULTS

3.6.1 Type of Membership Function

For both the Expert Knowledge Fuzzy Logic model and the Neuro-fuzzy trained model, performance was not improved by altering the definition of membership functions from the Standard Membership Functions to Statistical Membership Functions. Likely this is somewhat due to the fact that none of the variables used in the model were highly skewed; therefore the Statistical Membership Functions did not vary significantly from the Standard Membership functions. While the Standard Membership Functions require less data to implement and performed equally as well as the Statistical Membership Functions, more research would be required to draw any conclusions. It was also found that the fuzzy logic model was not sensitive to the shaping of transition limbs of the membership functions.

3.6.2 Rule Base Creation

These model results indicated that both expert knowledge and ANN training are beneficial in developing the rule base. Reasonable qualitative forecasts could be achieved for this site when the rule base was developed from expert opinion only, whereas using ANNs to train the rule base improved the quantitative modeling of breakup water levels. For the latter case (i.e. the neuro-fuzzy model) it is interesting to note that the ANN improved the model performance primarily in the lower years. Because low water levels at breakup are most common, the ANN has more examples to train at this end of the scale. In contrast, there is more heuristic (expert) knowledge regarding the cause and effect factors surrounding large events, as these are the events of primary concern and thus more time has been focused on studying them. This suggests that, by combining the knowledge from experience with the interpretation provided by the ANN, an optimized rule base could conceivably be created. There are many techniques for establishing a rule base in a neuro-fuzzy model such as only allowing selected rules to be trained or training all rules and later having an experienced person adjust rules where sufficient training was not available. The promising results obtained here clearly suggest that further study is warranted to provide an optimized approach.

The heuristic knowledge held in the rule base of fuzzy models may be a valuable tool to river ice modelers, allowing the development of forecasting models for sites where statistically based models are not practically feasible (due to data limitations). If it is reasonable that similar physical "rules" would apply at another location, knowledge gained at one site may be transferred to another site by means of a fuzzy rule base. This potential for transferability between sites is a clear advantage of fuzzy based modeling over more statistical, site specific methods.

3.6.3 Model Performance

From a qualitative forecasting perspective, the prototype Expert Knowledge Fuzzy Logic model, with rules based exclusively on experience, was able to correctly identify three years out of twenty in which ice jam flooding occurred (1979, 1996 and 1997). Unlike many other river breakup forecasting models, false positives did not occur. The poor quality of quantitative results from this model is similar to the preliminary results reported by Mahabir et al. (2002), based on an expert system with three variables.

Extracting three years of data for calibration, improved the prototype Expert Knowledge Fuzzy Logic model performance. Should a larger data set be provided for manual calibration, it is likely that the model results could be even further improved. Although the quantitative modeling results were still inadequate, the model produced excellent qualitative results if the criteria were to distinguish between years when ice jam flooding occurred and years when it did not. This example provides encouragement that the application of fuzzy logic may be practical at sites where the data is too limited to apply ANNs for training but for which several years of calibration data are available. In such cases, although quantitative forecasts might still not be practical, such a model could provide a long lead forecast of the relative risk of flooding (i.e. a qualitative forecast) which could be very useful for emergency preparedness planning purposes.

Figure 3-8 presents a comparison of the optimal quantitative model developed in this study (the neuron-fuzzy model) to the multiple linear regression model developed by Mahabir et al (2006). While the performance of both models is similar for the years evaluated, it is significant to note that a clear advantage of the neuro-fuzzy model is that it requires half as many input variables, which allowed an additional six years to be modeled, including one of the years in which flooding actually occurred. This is significant because it is the first model for this site that is able to model, given the limited data available, a year when flooding occurred. Furthermore, the neuron-fuzzy model is based only on variables known well in advance of breakup, providing several weeks lead time. In contrast, the earlier regression model (Mahabir et al. 2006) required input data known only a few days before the actual breakup event.

3.7 CONCLUSIONS

Fuzzy logic modeling appears to provide a promising new tool for forecasting flood levels associated with breakup ice jams. Using data from the Athabasca River basin, both fuzzy and neuro-fuzzy expert systems were successful in producing qualitative models for predicting the severity of water levels associated with the spring breakup. From this research, it appears that the development of reliable qualitative risk assessment models may be feasible at locations that do not have an extensive database, potentially providing several weeks advance warning of the expected severity of breakup.

The quantitative results of the neuro-fuzzy model developed for the Athabasca River at Fort McMurray were found to be as accurate as a previous multiple linear regression in modeling water levels at breakup for this site. However, a significant advantage of this neuro-fuzzy model is the fact that it requires only half the number of input variables (four versus eight, as compared to the regression model) and all are known several weeks in advance of breakup. This is significant in that it represents the first accurate long term forecasting model for river breakup water levels.

Future studies should focus on the development of models integrating the use of both expert knowledge and ANNs in developing the rule base. Additionally, testing the transferability of model logic to more data limited sites would be worthwhile. Because of the deterministic nature of fuzzy logic based models, they provide the ideal platform from which to explore the potential effects of climate change on increasing or decreasing the risk of ice jam related floods in future.

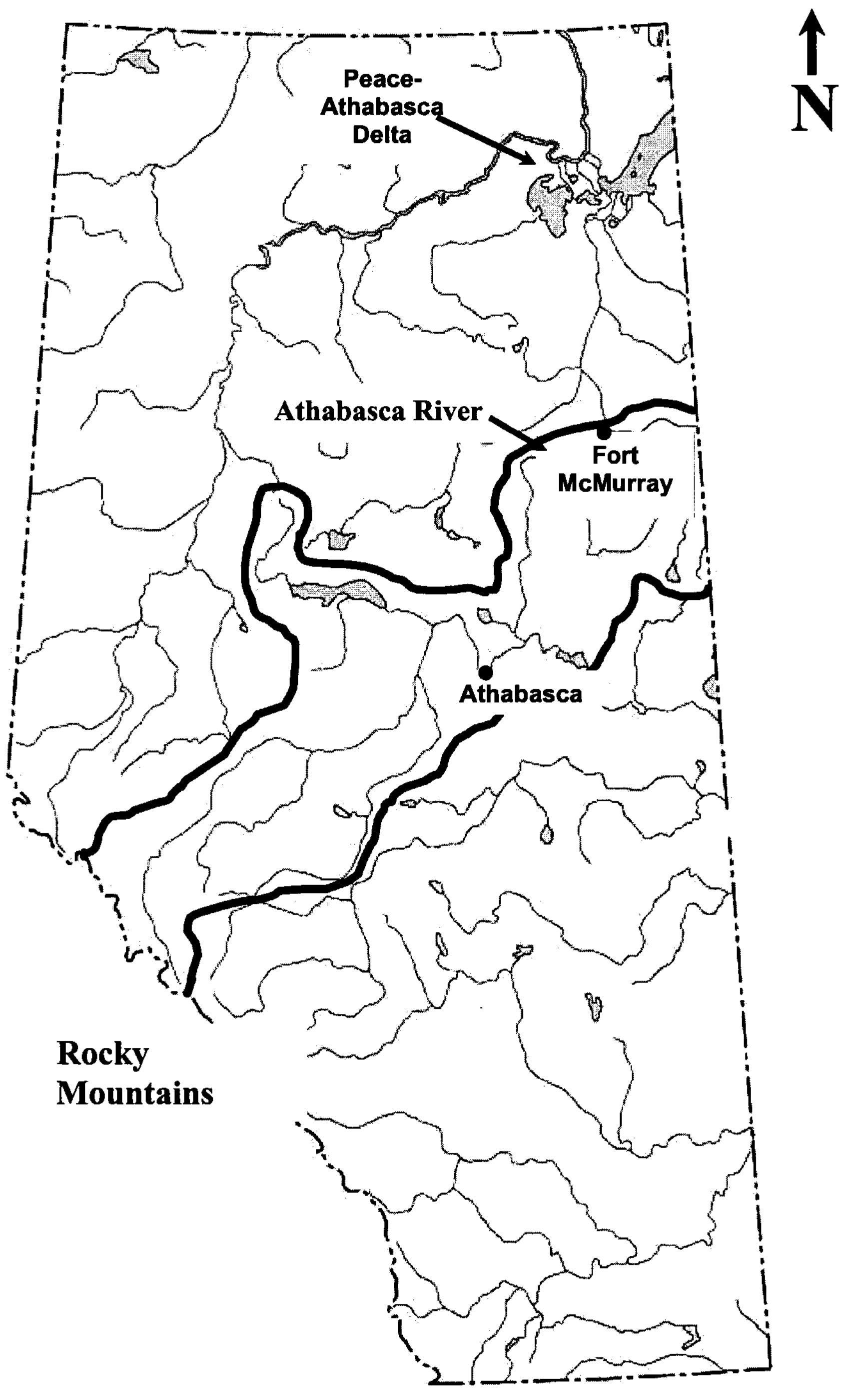

Figure 3-1: Location map for Fort McMurray in the Athabasca River Basin in Alberta, Canada.

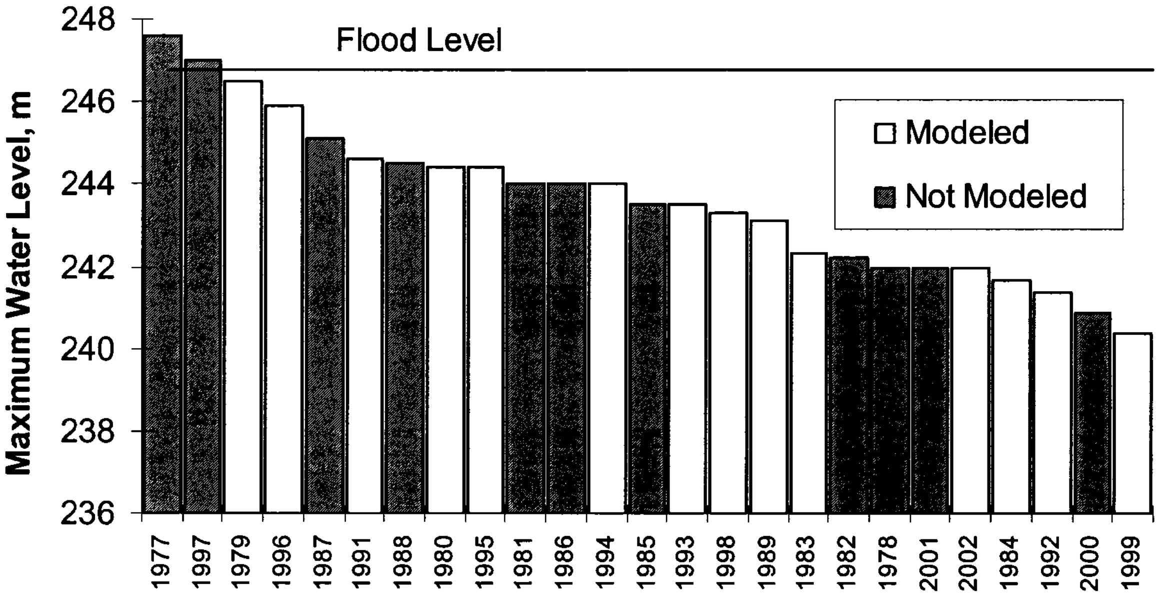

Figure 3-2: Events considered in multiple linear regression model for the Athabasca River at Fort McMurray, AB.

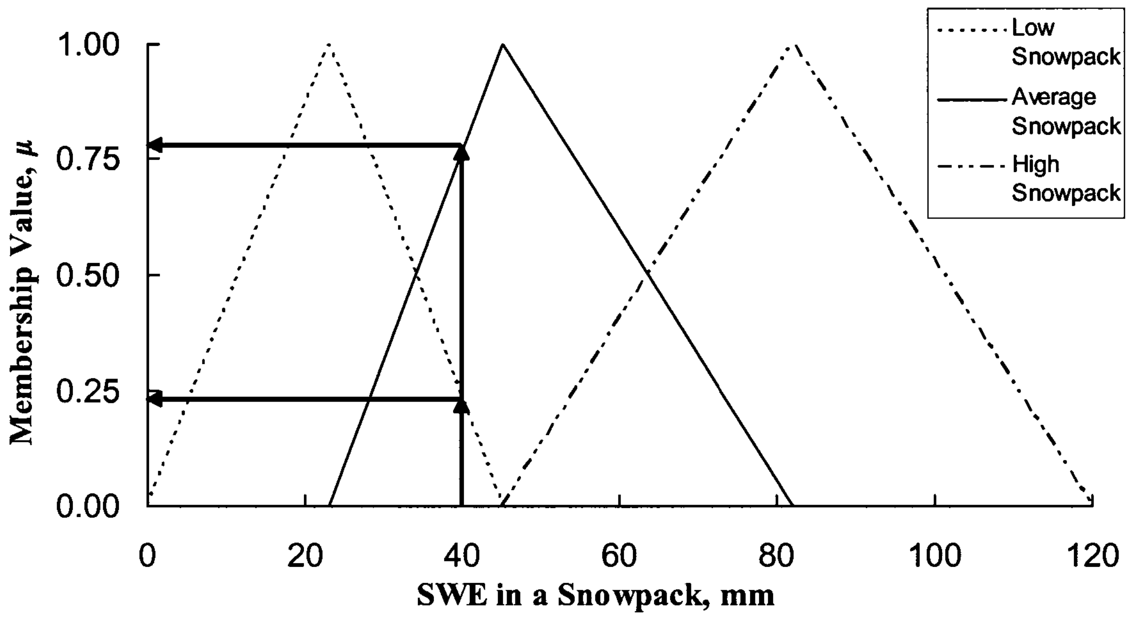

Figure 3-3 (a): Translation of a measured quantity to linguistic variable represented by triangular membership functions.

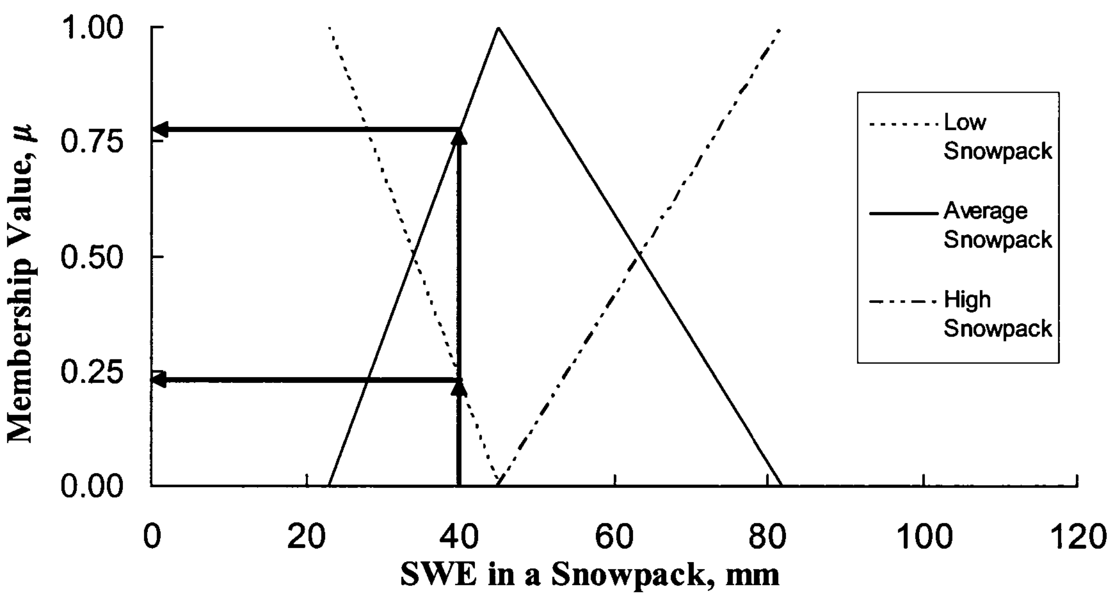

Figure 3-3 (b): Translation of a measured quantity to linguistic variables with trapezoidal and triangular membership functions.

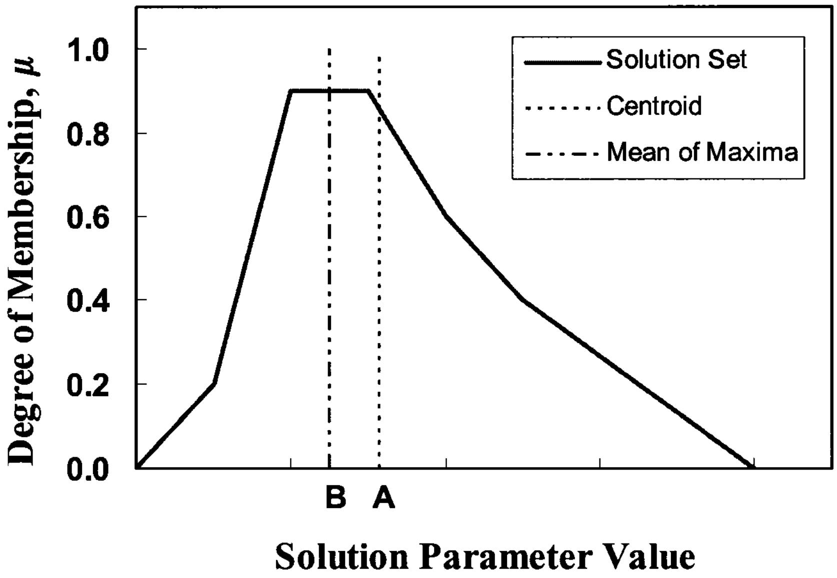

Figure 3-4: Defuzzification of a resultant set by (A) Centroid and (B) Mean of Maxima methods.

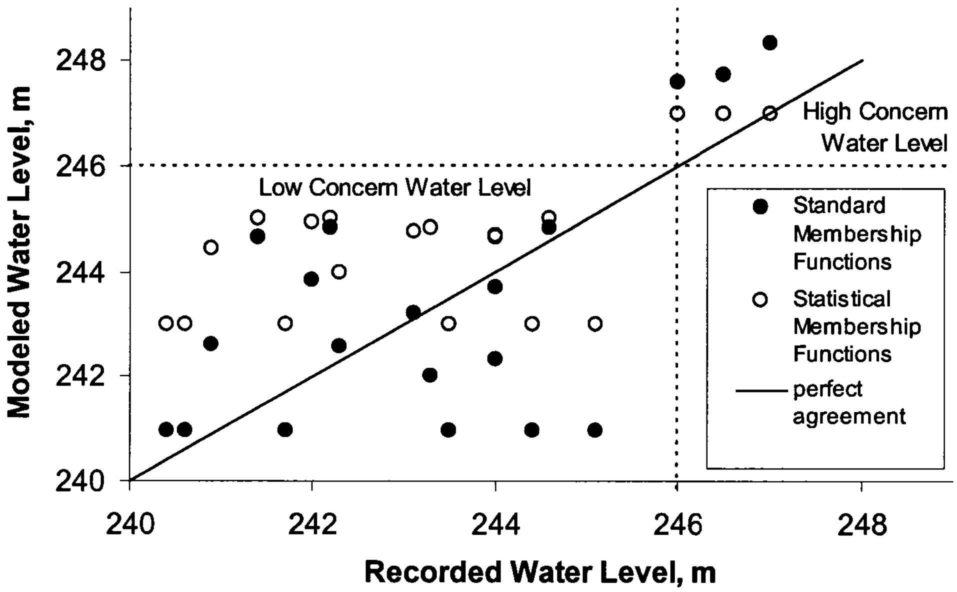

Figure 3-5(a): Results of expert knowledge based fuzzy logic model for both Standard and Statistical Membership Functions (Centroid method of defuzzification) for the Athabasca River at Fort McMurray, AB.

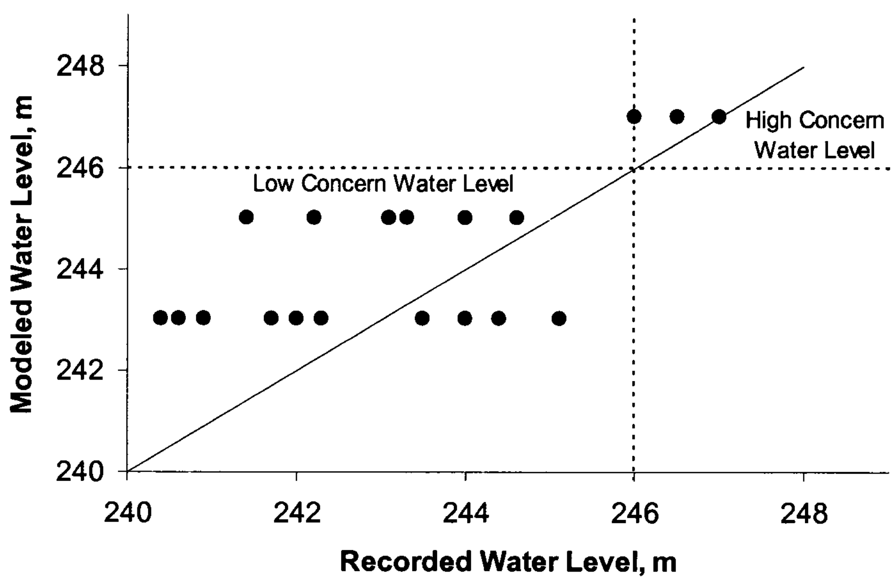

Figure 3-5(b): Results of expert knowledge based fuzzy logic model with MOM method of defuzzification (using Standard Membership Functions) for the Athabasca River at Fort McMurray, AB.

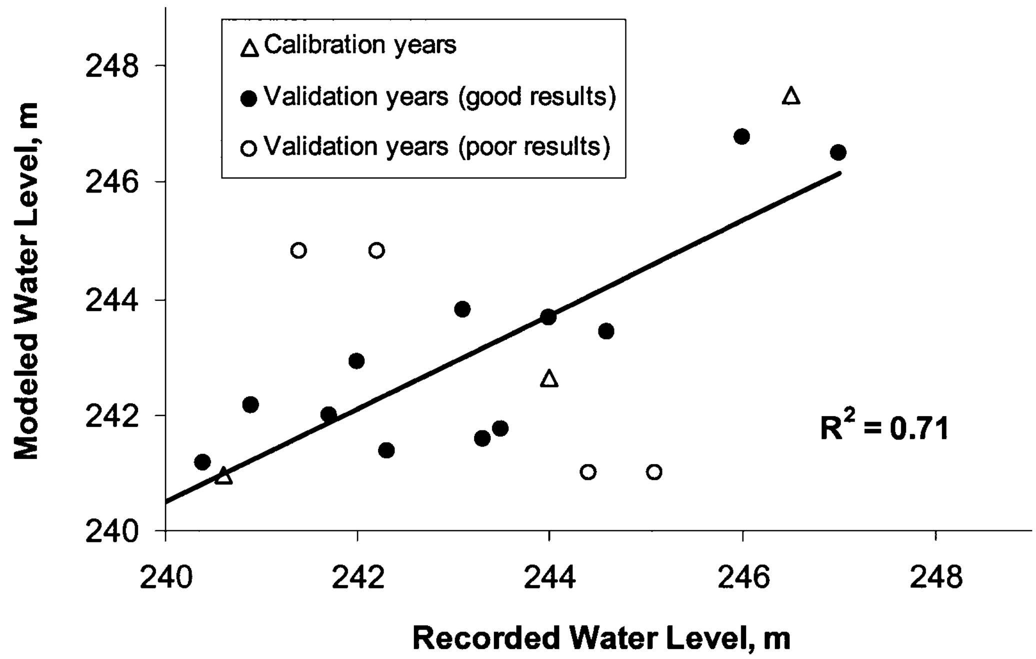

Figure 3-6: Expert knowledge fuzzy logic model calibrated with expert knowledge and three years of calibration data (trend line shown is for the best validation years, which excludes the 4 years with poor results) for the Athabasca River at Fort McMurray, AB.

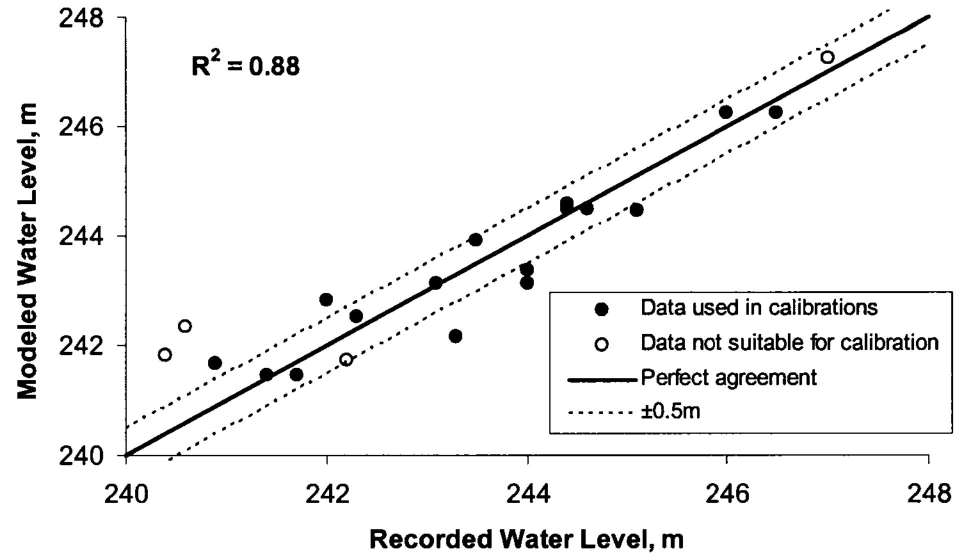

Figure 3-7: Neuro-fuzzy model of maximum water levels during spring breakup on the Athabasca River at Fort McMurray, AB (dashed lines indicate ±0.5m from line of perfect agreement).

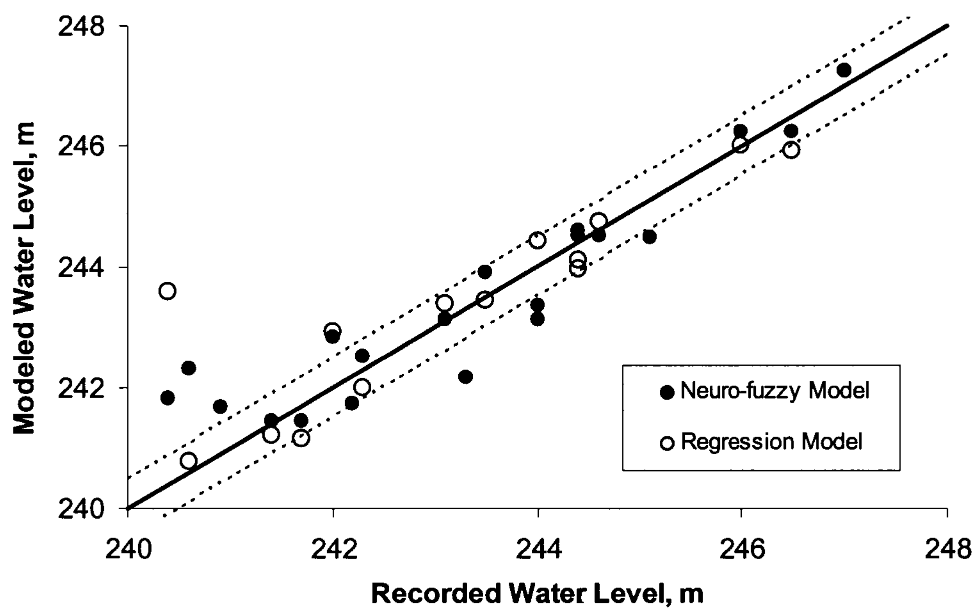

Figure 3-8: Comparison of multiple linear regression model and neuro-fuzzy model of maximum water levels during spring river ice breakup for the Athabasca River at Fort McMurray, AB.

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Chapter 4: Transferability of a Neuro-fuzzy River Ice Jam Flood Forecasting Model[3]

4.1 INTRODUCTION

Each spring, river ice breakup brings the threat of severe damages and risk to life to many northern communities, due to ice jam related floods. As development continues in northern Canada and Alaska, the potential impact of severe ice jams continues to increase. Because ice jams develop quickly and leave little time for mitigation, advanced warning of an impending event is highly desirable. Unfortunately, at present, there are limited modeling tools available for assessing the potential risk of ice jam flood occurrence. Furthermore, a shortage of long term monitoring and the sparse data networks are often cited as primary limitations in the development of river ice jam flood forecasting models. Since river breakup is an annual event, several years of consistent monitoring are required to establish even a small set of data for a river basin. This is particularly true in northern Canada where the population is sparse and quantitative data related to ice jam occurrence is limited. Typically, most financial and human resources go towards dealing with ice jam flood events as they occur, rather than establishing the database and models necessary to predict them. Therefore, reliable models that could be transferred between sites would be highly advantageous to northern communities threatened by ice jam floods.

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[3]This chapter has been submitted for publication. Mahabir, C., F..E. Hicks, and A. Robinson. 2006. "Transferability of a Neuro-fuzzy River Ice Jam Flood Forecasting Model". Journal of Cold Regions and Technology.

Considerable advances have been made in the last decade towards river ice breakup forecasting, as documented by Morse and Hicks (2005). White (2003) provides a review of the developing science of river breakup forecasting. Beltaos (2003) provided criteria to classify river breakups as thermal (less dangerous) or mechanical (associated with ice jams). While river ice breakup continues to be documented through journal articles (Jasek, 2003) and government reports (Robichaud, 2005), much of the data needed to develop a deterministic process based model is not being collected due to the logistics and safety aspects involved in measuring these dynamic events. As a result, most river ice breakup flood forecasting models have been site specific in nature (e.g. Gerard and Stanley 1992, Wuebben et al. 1995; Belatos 2003, Robichaud 2003).

Recently, soft computing methods have been applied successfully to river ice breakup modeling. Zongfu (1992) suggested a conceptual basis for a fuzzy logic based model that could be used to predict the potential of an ice jam occurrence. Massie et al. (2001) also modeled the potential of jam occurrence but applied Artificial Neural Networks as the computational engine in the model. Mahabir et al. (2002) provided preliminary results for fuzzy logic based model which modeled the severity of ice jams in qualitative terms of flood or non-flood events. Shouyu and Honglan (2005) were able to model the date of breakup at several locations in China with a site specific fuzzy optimized neural network.

Artificial Neural Networks (ANN) are essentially blackbox models which, when used alone as the basis of a model, should not be applied at sites other than those for which they are trained. However, when combined with fuzzy logic in the form neuro-fuzzy models, the logic in the model may be transferable to another site, as the neural network aspect is limited to being a rule training tool in conjunction with heuristic knowledge. Mahabir et. al (2006b) reported successful modeling of the maximum water level during spring breakup with such a neuro-fuzzy model developed for the Athabasca River in northern Alberta, Canada. The primary objective of this research is to investigate the feasibility of transferring fuzzy and neuro-fuzzy ice jam flood forecasting models to a different basin, specifically to the Hay River basin in the Northwest Territories, Canada.

Soft computing has also been identified as a potential tool for climate change analysis, providing an alternative to historical trend analysis. Changes in the climate and the current impacts in the north have been documented by Hinzman et al. (2005); Prowse and Beltaos (2002) stated that changes in meteorological conditions could result in significant changes in river ice breakup severity. Often climate change is evaluated only by observation of a current trend compared with historical data, as in Wolfe et al. (2005). Similarly for climate change related to river ice, evaluation methods have typically been limited to establishing trends or relating the statistical analysis of past occurrences, such as the study on ice cover timing and duration by Hodgkins et al. (2005). Soft computing has been used previously for evaluating the uncertainties in climate change scenarios (e.g. Scherm 2000). Huang et al. (1996) used fuzzy analysis to evaluate the impact of climate change on land use activities in the Mackenzie Basin, Canada. In addition to exploring the potential transferability of fuzzy and neuro-fuzzy river ice jam flood forecasting models between river basins in northern Canada, the fuzzy river ice jam flood forecasting model is also used to investigate the potential impacts of climate change scenarios for the Athabasca and Hay River basins.

4.2 SITE DESCRIPTIONS

The two rivers considered in this analysis of breakup ice jam flood forecasting model transferability are the Hay River, Northwest Territories, and the Athabasca River, Alberta, both located in northern Canada. Both rivers are unregulated and north flowing, with spring melt tending to occur in the upper reaches, supplying meltwater runoff to drive a dynamic breakup in the lower reaches while the ice cover is still strong and intact. Both rivers have steep sections, involving bed discontinuities, helping to drive the dynamic breakup and both rivers have a notable decrease in bed slope further downstream, adjacent to the community threatened by ice jam flooding. In contrast, the two rivers are different in scale, with the Athabasca River being considerably larger than the Hay River. Specific descriptions of each river are provided below.

Originating in the Rocky Mountains, the Hay River flows northeast through northern Alberta to the Northwest Territories as shown in Figure 4-1a. It is a natural river with no major manmade flow controls. Upstream of the Town of Hay River, dramatic discontinuities exist in the river bed in the form of Alexander Falls (33 m) and Louise Falls (15m). At the town of Hay River, on the southern shore of Great Slave Lake, the river bed slope flattens considerably, and the channel splits to form a small delta. The channel is entrenched over much of the distance downstream of the falls, with the bank height decreasing from about 30 m at Alexandra Fall to less than 5 m just upstream of the delta. The channel width averages from about 100 m in this reach. The river has a drainage basin of 47,900 km^2 at the Water survey of Canada (WSC) gauge just upstream of the delta (Hay River near Hay River, 07OB001). Spring melt waters from the upper (more southerly) portion of the basin typically initiate breakup, with the ice first breaking up in the reach downstream of the falls, due to dynamic influences; causing small ice jams to form in the delta channels. This is followed by ice runs resulting from breakup in the upper reach, which contribute ice to these jams, enlarging and pushing them towards Great Slave Lake which is still frozen. Generally this builds until the ice is released out onto the lake ice cover. However, if the delta becomes sufficiently congested with ice, flow into and onto the frozen lake can become impeded to the state that the resulting backwater from the ice jam will flood the Town of Hay River.

The Athabasca River also originates in the Rocky Mountains, making its way across the plains of north central Alberta in a northeasterly direction. Like the Hay River, the Athabasca is unregulated but is much larger, with a drainage basin of 133,000 km^2 at the WSC gauge at Fort McMurray, Alberta (Athabasca River below McMurray, 07DA001), and a typical width of 400 to 500 m. At the town of Athabasca (Figure 4-1b) the river turns north and becomes entrenched, turning east again before reaching Fort McMurray. The bed of the Athabasca River between the two communities is fairly steep, particularly for about 200 km upstream of Fort McMurray, and contains numerous rapids and bed discontinuities. Many of these involve drops of only a few meters; however, the largest, Grande Rapids, involves a drop of approximately 9 m in less than 1 km. Breakup on the Athabasca is typically triggered by runoff from the upper (southerly) portion of the basin, and along this 200 km upstream of reach it is characterized by the formation and release of numerous ice jams that typically progresses downstream to Fort McMurray in a cascading manner. The river bed slope decreases substantially at Fort McMurray, and this, along with the presence of numerous islands in the channel, make this a site of frequent ice jam occurrence. When ice jams on the Athabasca River block the outflow of the Clearwater River, a small tributary that joins the Athabasca River right at Fort McMurray, the community experiences flooding.

4.3 DATA

Complete and detailed ice jam flood forecasting databases for both the Athabasca River (Mahabir et al., 2006a) and the Hay River (Jasek, 1993) basins have been presented in previous publications and reports. This section describes only the data considered for the river ice breakup models considered in this study.

One of the largest challenges to river ice breakup modeling at Hay River is that the water level at breakup, the outcome to be modeled, is has not been consistently recorded over the years. Specifically, the locations of measurement and the agency performing the measurements vary throughout the years. In several years, water levels were not measured at all and only qualitative statements describing river breakup are available for assessment of the severity of the water levels. This lack of quantitative data is a major obstacle for many types of modeling, but such qualitative data can be of value in a fuzzy logic based model where qualitative outcomes can be part of a data set.

The fuzzy and neuro-fuzzy models developed by Mahabir et al. (2006b) for the Athabasca River were considered for evaluation of transferability to the Hay River. To provide a quantitative prediction of the expected maximum water level during spring river ice breakup on the Athabasca River, these models required four input variables: (1) a measure of expected snowmelt runoff (basin average SWE), as measured by satellite, (2) an index of antecedent basin moisture conditions (cumulative precipitation during the previous summer), based on measurements of precipitation at Fort McMurray, (3) an index of the severity of the winter (accumulated negative degree days), based on measured air temperature at Fort McMurray, and (4) an early indicator of the rate of spring runoff, based on the measured change in groundwater levels from January to April.

To evaluate the transferability of a model from one river basin to another, equivalent variables must be available at each site. For example, if precipitation is required in a model for site A, then precipitation must be measured at site B or a correlated variable for precipitation must be available. Similar variables were available in the Hay River basin for the first three input variables, but a suitable groundwater monitoring site with sufficient length of record was not available for the Hay River basin. Since no correlated substitute for the groundwater variable was found by examining the extensive database for Fort McMurray, it is unlikely that a reasonable substitute could be established in the relatively sparse database for the Hay River. Therefore a new prototype model was developed and tested, based on the three input variables available at both the Athabasca and the Hay River sites. Tables 4-1 and 4-2 present the final data sets used in this modeling effort. Years with incomplete data sets have been removed from the tables. Spring river breakup water levels for the Hay River are described in detail later in this paper.

4.4 MODEL PROTOTYPE DEVELOPMENT

The first step in this study was to develop a prototype model based on the Athabasca River data base. Three approaches were considered in developing the rule base for this prototype model. First a fuzzy logic model was developed, with the rule base developed purely based on expert knowledge. Second, the fuzzy-logic rule base was developed using ANNs trained with historical data, creating a neuro-fuzzy model. Finally, a prototype was developed, in which ANNs were initially used to train the rule base for moderate events, and then expert knowledge was employed to determine the rules for extreme events. Expert knowledge was also employed to overrule the rule base for the moderate events where necessary, in order to minimize or eliminate logical contradictions in the rule base created by the ANN. Each version of the prototype model is discussed below.

4.4.1 General Overview of Prototype Model Development Approach

Mahabir et al. (2006b) describe the basic components for a fuzzy and neuro-fuzzy river ice breakup model. Bardossy and Duckstein (1995), Govindaraju and Rao (2000) and Badiru and Cheung (2002) provide more extensive details on fuzzy, artificial neural networks and neurofuzzy modeling, respectively. The fuzzy and neuro-fuzzy models in this study consist of input variables expressed as linguistic terms, application of a fuzzy operator to determine the logical relationship between the input variables, a rule base describing the relationship between the antecedent conditions and the consequent, aggregation of the consequents from the all the rules, and defuzzification, which changes a fuzzy output set to a crisp, or unique, quantitative result.

Some design properties were consistently used in all of the models developed for this study based on Mahabir et al. (2006b). For example, the fuzzy operator "AND" was consistently used to describe the relationship between input variables. In terms of aggregation, Maximum, a function that combines the maximum value attained by any rule evaluation into a single resultant set, was used, as it is commonly associated with the fuzzy operator "AND". Defuzzification, the evaluation of the resultant set for the purpose of describing the result as a single point value, was performed with the Centroid Method (selection of the set centroid).

The goal of testing the potential transferability of the model to a basin with a less extensive data base resulted in design implications for the model. For example, input membership functions were simply constructed and evenly distributed over a plausible range since the Hay River data was too sparse to justify the logical formation of more complex membership functions (MBF), such as those based on statistical distributions or non-linear relationships. The plausible range consists of the minimum recorded value minus 10% (except where not physically possible due to negative values) and the maximum highest value plus

10% as described by Mahabir et al (2006b). Simple output membership functions, as shown in Figure 4-2, were similarly defined. No automated advanced shaping of input or output MBF was considered, such as ANN training of MBF distributions, since the logic of the formation of the MBF had to be consistent between the Athabasca River Basin (where sufficient data exists to apply this method) and the Hay River Basin (where the severely limited data precluded it).

4.4.2 Expert Knowledge Based Fuzzy Model Prototype

Since groundwater information was not available in the Hay River Basin, the potential to develop an expert knowledge based fuzzy model for the Athabasca River with only three of the four variables from the original model was explored. Figure 4-3 shows the results for a model calibrated with 3 years of data and combined with expert knowledge to determine the rule database. The quantitative accuracy of high events was reasonable, and although medium and low water levels were poorly modeled quantitatively, they were properly assessed qualitatively as non-flood event years.

Three areas of the fuzzy model design were explored in an unsuccessful attempt to produce improvement in terms of quantitative accuracy. Alternative designs included:

1. Increasing the number of years of calibration data presented to the expert from 3 to 5, with the addition of one low and one average event;
2. Increasing the number of linguistic descriptions (membership functions) from three to five for the input variables, then for the output variables and finally, for both the input and output variables; and
3. Using combinations of triangular and mixed triangular trapezoidal membership functions for input and output variables. Triangular and mixed triangular trapezoidal MBF are shown for the output variable, water level, in Figure 4-2a and Figure 4-2b.

The first modification to the design produced no significant improvement in the accuracy. Increasing the number of output MBF provided some minor improvements for the midrange event years, but no significant improvement to the overall performance of the model. Changing the shape of the output MBF from triangular functions to mixed triangular and trapezoidal MBF (as shown in Figure 4-2a and Figure 4-2b) had a significant impact, in that the range of the modeled results were extended. As a result, the lowest events were modeled better; however, the average events were modeled worse (as shown in Figure 4-4). In this figure, the "lower" limit of the prototype model is clearly visible as no points are below 241.7 m or the definition of the membership "Low". A similar limit would occur with the membership "High". For this reason, consideration should be given to mixed MBF despite the poor quantitative results for this model.

4.4.3 Neuro-fuzzy Logic Model Prototype

Mahabir et al. (2006b) provide details of the development of neuro-fuzzy models, using ANN exclusively to train the rule base in the fuzzy logic model. Here, two rule base configurations were considered in exploring the use of ANNs for determining the rule base of the prototype model. First the ANN was presented with a single possible outcome for each rule as defined by experience, and the ANN was allowed to train the degree of support for each rule. Second, a complete rule base was made available to the ANN to train, where all possible outcomes were possible for each rule. The degree of support for all rules was set to zero, as ANNs are known to train quicker with small initial values, and zero was selected so that untrained rules (or rules with no support) could be more easily identified.

To assist with training, fuzzy clustering was used to evaluate the dataset for similar and conflicting data. Conflicting data were not considered for training, and only one point from a cluster was considered as it is considered to represent all points in the cluster for training purposes. Eight points were selected for training based on providing a full range of scenarios represented in the data. A reasonable calibration could not be achieved exclusively with ANN training despite several combinations of training/verification data groupings, possibly due to the imprecise relationship between the input variables and the output variable. With all rules having all outcomes available for training, the model could be trained to data in the midranges, but performed poorly when presented with validation data. The poor performance, shown in Figure 4-5, may be related to not all combinations of possible input scenarios being represented in the data as there are a number of "untrained" rules which had no support. Rules with no support have no influence at all but whereas, by logical reasoning, they should be influential.

A neuro-fuzzy model was next developed with iterative calibration. Specifically, the extreme rules were determined based on expert knowledge and not made available for ANN training. The remaining eight data points were then presented to the ANN in random order for training. After training, the ANN rule base was examined and logical contradictions were removed since the rule base in the neuro-fuzzy model should be logical in that the degree of support shows an intuitive progression from rule to rule. Specifically, when contradictory rules were found, the degree of support for the rule was either reset to a low value to reinitiate training or, based on surrounding rules, set to either 0 or 1 and removed from ANN training altogether. Similarly to previous models, the rules which were not activated by the calibration data were logically defined based on surrounding rules.

Input and output variables were described by three evenly distributed mixed (triangular and trapezoidal) membership functions. Using mixed membership variable definitions increased the overall calibration time for the model compared to those model versions with purely triangular membership functions, with the additional time required because of the increased reliance on expertise to determine the rule base. Here again, better results were obtained as illustrated previously in the prototype model since the range of the output is extended. While the training dataset is modeled equally as well as when exclusive ANN training methods were employed, the validation dataset (containing data not presented during the training phase) is modeled better with a combination of both ANN training and experience to create the rule base. The final neuro-fuzzy prototype model results are shown in Figure 4-6, where it can be seen that out of 16 validation points, only two are modeled with less than $\pm$1.2 m accuracy. Figure 4-6 also shows that the results from the 3 variable model developed in this paper have similar accuracy to the 4 variable model developed by Mahabir et al. (2006b).

For the Athabasca River, two prototype models were created, an expert knowledge fuzzy model and a neuro-fuzzy model, to model the severity of spring breakup (the maximum water level that was recorded). Both models have identical mixed membership functions for input and output variables. The distinguishing feature between the models is the rule base. The expert knowledge fuzzy model consists of a rule base derived exclusively from expert knowledge. The neuro-fuzzy model consists of a rule base developed with both ANN training and expert knowledge. The expert knowledge fuzzy model provides a qualitative assessment of the severity of flooding during spring breakup in terms of distinguishing between years when flooding occurred and those when it did not. Quantitative estimates of water levels during low risk years (years when low water levels occur) are poor which limits the expert knowledge fuzzy model to providing strictly qualitative assessments. The neuro-fuzzy model provides a potential tool for making a quantitative assessment of the maximum water level at breakup.

4.5 TRANSFERABILITY OF THE PROTOTYPE MODELS

The next step in the investigation was to test the transferability of the expert knowledge fuzzy model and the neuro-fuzzy model prototype ice jam flood forecasting models developed for the Athabasca River, to the Hay River at the town of Hay River. Essentially this involved applying the design concepts developed for the Athabasca River site to develop membership functions for the Hay River input and output variables, with the transferability constraint of making no changes to the rule base. The reasoning is that if a rule base truly reflects logical, physically based relationships between the antecedent conditions and the consequent, then it should be independent of the site at which it is applied as long as the sites have similar relevant characteristics. Although the Hay River Basin is smaller in size than the Athabasca River Basin, both rivers are north flowing rivers originating at high altitudes with reach characterized by a series of rapids upstream of the investigation site. Since the rule base has already been calibrated and validated, it should not be necessary to recalibrate it for the new site. If viable, such a model transfer would be highly beneficial for sites with small data sets, such as the Hay River case, since it means that all available data could be used for validation purposes.

To transfer the prototype models, the membership functions for the Hay River input and output variables were first defined, based on the memberships functions defined for the Athabasca models. Specifically, the plausible ranges for the input variables were defined as $\pm 10\%$ of the lowest and highest values to create lower and upper range limits, respectively. Three membership functions representing the concepts of "Low", "Average" and "High" were then defined, with mixed triangular and trapezoidal membership functions distributed evenly over the plausible range of each variable.

4.5.1 Qualitative Assessment

Unfortunately, no single specific site within the Hay River delta has a continuous record of water levels or consistent descriptions of the severity of flooding. Therefore, to provide a comparison between the performance of the forecasting models for the Athabasca River and Hay River sites, a qualitative assessment of the models was conducted. This qualitative assessment evaluates the ability of the models to correctly identify logical grouping rather than specific quantitative results.

To form the basis for this comparison, a qualitative assessment was first done for the results for the two prototype models obtained for the Athabasca River. To create qualitative terms, the forecasting model output was defined simply in terms of flood severity, with membership functions of “Low”, “Average” and “High”. Using mixed membership functions (Figure 4-2b), “Low” was defined as 239 m to 243.5 m, “Average” as 243.6 m to 246.5 m and “High” as 246.5 m to 250 m. The results of the qualitative assessment of the model are compared to the actual occurrences in Table 4-3. Both the expert knowledge fuzzy model and the neuro-fuzzy model correctly identify the extreme flood events with no false positive results. However, the expert knowledge fuzzy model performed poorly compared to the neuro-fuzzy model for the lower events (i.e those events that produced non-flood water levels).

With limited knowledge of actual water levels, the assessment of the severity of flood events for the Hay River site was necessarily more subjective and required judgment. First, documented years with flood occurrences were separated from the years with no flood events. In total, 10 of the 24 years of record were identified as flood events. The remaining 14 (non-flood) years were simply classified as “Low”; however, classifying the 10 flood years as either “Average” or “High” was more difficult due to the sporadic nature of the water level record. As development occurs in the floodplain, a high water event will be perceived as being more severe as more damage actually occurs. Conversely, the relocation of buildings or construction of mitigation protection works can reduce the impact of an event that would have previously been reported as more damaging to the community. For example, in Hub (1997), the local newspaper, described that spring breakup as *"... damage was minimal... A newly constructed section of berm is being credited with saving West Channel homes"*.

To provide consistency for the concept of "High" severity flood years, only the most damaging floods were considered as "High" severity events, in a manner is similar to the logic used for classifying events on the Athabasca River. The classification was based on qualitative descriptions which clearly indicated that water levels were higher than previous years. In some instances direct quantitative comparisons were also possible; for example for the 1985 event Gerard and Stanley (1988) reported *"Early on May 7 a huge surge of water and ice was reported moving down the West Channel...within 15 minutes the Fishing Village was flooded, with water reaching a depth of over 1 m on the roadway."* By comparison, Gerard and Stanley (1988) described river breakup in 1981 as *"For the most part water levels were low during breakup, with some minor flooding..."*. In the end, the documented reports, as well as local knowledge, supported 1985 and 1992 as being the more extreme flood events on record; thus they were classified as two extreme ("High") flood years. Based on photographic evidence of flooding (Gerard and Jasek, 1990) 1989 was also classified as a "High" year, giving a total of 3 years within the "High" category. The remaining seven years in which flooding was reported were classified as being of "Average" severity.

Based on this qualitative assessment of the severity of river breakup, the transferability of the two Athabasca River models were tested for the Hay River and found to produce some encouraging results, as seen in Table 4-4. Firstly, the rule base created from experience on the Athabasca River was combined with the input/output linguistic descriptions of variables from the Hay River. The resulting expert knowledge fuzzy model was able to accurately identify all three "High" risk years, even with no site specific calibration of the rule base. Furthermore, the expert knowledge fuzzy model identified all extreme flood years with no false positive results. As was seen for the Athabasca River site, the expert knowledge fuzzy model was less successful at distinguishing between the "Low" and "Average" events (Table 4-4). However, the erroneous classifications were never off by more than one category in any year. The neuro-fuzzy model was not quite as successful as the expert knowledge fuzzy model in this case. Although no false positive results occurred for the "High" events, only two of the three were correctly identified. In fact, the neuro-fuzzy model tended to classify most years as "Average". Again, all erroneous classifications were within one category of the correct grouping. Based on these results, it appears that the expert knowledge fuzzy model, when transferred to another basin, can identify severe flood events, whereas the neuro-fuzzy model may not be as flexible. One possible explanation for this is that the rule base in the neuro-fuzzy model that resulted in good quantitative results at Fort McMurray has incorporated site specific information reducing the generalization of the rule base. However, it is also possible that this poorer performance reflects a lack of data at the Hay River site.

Both the expert knowledge fuzzy model and the neuro-fuzzy model produced similar assessments of the severity of river breakup on the Hay River for many years, as shown in Figure 4-7. Unfortunately water level data were not available for the Hay River basin for years when large differences between the degree of severity of river breakup was predicted by the different models. Interestingly, both models indicate that flooding would have occurred in 1989 where no information about river breakup is available. This signals a possible false positive event as one would expect that if flooding had occurred, observations would have been noted in local records.

4.5.2 Quantitative Assessment

It was also desirable to conduct a quantitative assessment of the transferability of the prototype models, specifically in terms of assessing their capability of predicting breakup water levels in the town of Hay River. Unfortunately, as mentioned earlier, there is no single site within the Hay River delta which is indicative of breakup levels, since ice jams can form in a variety of locations along either the East or West Channels, or both. Consequently, although water level measurements have historically been taken at a variety of sites in the delta during breakup, on many occasions and by a number of different agencies, the measurement sites were not always the same and the maximum water levels reported were not always necessarily the maximum water level that occurred. Although these significant data limitations for the Hay River site are typical of many ice jam flood prone communities in northern Canada, it means that only limited quantitative evaluation of the prototype models' transferability could be conducted.

For the expert knowledge fuzzy model, the severity of spring breakup determined by the model was compared with the recorded water levels for the Hay River and the East Channel in Figure 4-8a and for the West Channel in Figure 4-8b. Similarly, Figure 4-8c and Figure 4-8d show the results for the neuro-fuzzy model. In all four figures, the data appears scattered. If a quantitative model were possible, a linear relationship should exist between the modeled severity and the geodetic water level. It appears that the neuo-fuzzy model may not be transferable between river basins although a second set of quantitative water levels would be preferable to confirm this finding.

4.5.3 Discussion of Results

Despite the considerable differences between the two river basins, the expert knowledge fuzzy model has been shown to be a potential tool for qualitatively predicting severe river breakup events several weeks in advance, at a site previously thought to lack sufficient data for modeling purposes. The encouraging results of the transfer of the expert knowledge fuzzy model between the Athabasca and the Hay River sites provides not only an opportunity to forecast severe breakup events for annual flood preparedness, but also provides a research tool for exploring the potential changes in river ice breakup severity under scenarios such as climate change.

4.6 CLIMATE CHANGE ANALYSIS

Since the fuzzy models are based on logical rules and not statistical analyses, they should be suitable to model the impacts of climate change if the underlying physical cause and effect processes remain unchanged. To investigate this possibility, the Athabasca River at Fort McMurray and the Hay River at Hay River were both considered in an evaluation of the potential effects of climate change and climate variability on the risk of severe ice jam flooding events.

The climate change data selected for evaluation were based on the CGCM/A2 model results. A complete description of this model is available from Environment Canada (2006 website reference). Modelled air temperature, precipitation and snowpack SWE climate change prediction data were obtained from Environment Canada's data sets. Data for each basin was comprised of four data points in or adjacent to the river basins which were averaged to produce a single basin value. Simulated data for 1975-2005 were compared with the recorded values. As shown in Table 4-5, some of the recorded values differed significantly from the modeled data. For example, the results from the climate model provide an annual average precipitation of 391 mm from 1975 to

2005. Recorded data would estimate the annual average from 1979 to 2002 as 318 mm. This represents a 20% difference, which can be accounted for in the method of estimating basin averages (point source vs. gridded large scale model). The ratio between the recorded and the modeled values was applied to future climate change scenarios to provide a relative comparison of the changes due to the scenario.

As the expert knowledge fuzzy model was shown to be more reliable at determining severe water levels at breakup when transferred to another site, this model was evaluated for the Athabasca River and the Hay River for three future time periods: 2025-2050, 2051-2075 and 2076-2099. These time frames were selected so that each time period is similar in length to the number of years for which recorded data exists. The difference reported by the CGCM/A2 model between 1975-2005 and each of the future time periods for each variable was calculated. The ratios calculated in Table 4-5 were then applied to the differences to create a relative change from the recorded climate of 1975-2005.

For the Athabasca River Basin, the expert knowledge fuzzy model indicated a reduced potential for severe river ice breakups in all three future climate change time periods. The Athabasca River Basin had no events that were classified as severe for the first 25 year time period (2025-2050), as compared to two severe events recorded in the last 25 years. For 2051-2075 and 2076-2099, the model predicted no severe events due to low snowpacks and warm winters.

Based on the analysis for the Hay River Basin, climate change would be expected to first increase and later decrease the risk of severe spring river ice breakup events. Specifically, during the initial forecasting period (2025-2050), the late summer precipitation would be expected to increase, while only a small decrease in the snowpack and slightly warmer winter temperatures predicted. The expert knowledge fuzzy model interprets this to increase the potential of severe breakups from two (historical) to five (predicted) events in a quarter century. Dramatically, the model predicts no severe breakup events for the ensuing period (2051-2075), as significant warming is expected during the winter resulting in a reduced snowpack. For the final prediction period (2076 to 2099), the climate change model predicts and increase in fall precipitation, but the warming trend and consequent lack of snow expected governs the modeled outcome, and the expert knowledge fuzzy model predicts no extreme breakup events.

While this climate change analysis is interesting, particularly for the Hay River, there are many factors that this type of logic model does not consider. For example, river breakup on both of these basins occurs at a relatively consistent time of year. Therefore, SWE can be selected at a set date prior to river breakup and evaluated annually. However, if river breakup were to occur a month earlier, it might be appropriate to consider SWE a month earlier than that used in the current model, which would result in slightly higher average values.

Variables that change dramatically based on the month, such as daily average solar radiation, could also significantly change, which would be expected to impact the potential for severe events. Therefore, while more research is required to conduct conclusive climate change analyses, this effort does illustrate the potential for fuzzy logic models to provide a physically based approach to modeling climate change scenarios.

4.7 SUMMARY AND CONCLUSIONS

This study investigated the potential for transferring expert knowledge based fuzzy logic and neuro-fuzzy river ice breakup models between river basins, by testing the performance of prototype models developed for the Athabasca River, AB when transferred to the Hay River, NWT. Constraints on the availability of data were a limiting factor at both sites, as is the case for many rivers in sparsely populated areas.

Prototype expert knowledge based fuzzy logic and neuro-fuzzy models were developed for the Athabasca River site, building on previous research and with consideration for the potential availability of comparable data for the Hay River site. In the former case the rule base was exclusively determined based on expert knowledge, while for the neuro-fuzzy model the rule base was developed using a combination of Artificial Neural Network analysis (for the mind-range events) and expert knowledge (primarily for the extreme events). The latter model was found to provide excellent qualitative and quantitative predictions of the risk of ice jam flooding for the Athabasca River at Fort McMurray. A particularly promising feature of both prototype models was that they produced no false positive predictions of extreme ice jam flood occurrence, and were based exclusively on data available several weeks in advance of the breakup period, providing a long lead time forecast.

Qualitative results indicated that the expert knowledge based fuzzy logic model was transferable between basins, although it appeared to be reliable only for predicting the extreme ("High") flood events. Again, promising features of this model included the fact than no false positives were generated for extreme floods, and that it was based upon input data available several weeks in advance of breakup. The transferred neuro-fuzzy model was found to performed slightly worse that the expert knowledge based model for the Hay River. The fact that the high accuracy of the neuro-fuzzy model was not reproduced at the Hay River site, suggests that site specific physical factors play too large a role for the ANN rule calibration to be transferable. Neither model was particularly successful in providing quantitative predictions for the Hay River site. However this was not unexpected, given the sporadic nature of the water level data for this site.

This research confirms the positive potential for transferring fuzzy logic based models for indicating the severity of spring breakup at ice jam prone sites. This is a significant step towards providing flood preparedness at sites which were previously considered too lacking in data to model. Given the current lack of forecasting abilities in this area, even a qualitative model would be a significant improvement.

The expert knowledge fuzzy model was used to evaluate the potential impact of climate change on the severity of river ice breakup for both rivers. Climate change scenarios for these two sites produced different results. At Fort McMurray, the risk of ice jams continuously decreased with the progression of climate change effects. In the Hay River Basin, the frequency of severe ice jams increased for a period before waning. The increased risk was associated with the rate at which the long term trend in variables responded to changes in the climate. River breakup fuzzy logic based models provide the opportunity to evaluate climate change in areas were deterministic models have not yet been developed, and this potential should be explored further.

While further research is required, this research demonstrates the potential to extend river ice modeling into areas where there is insufficient data to support more traditional river ice breakup models. The transferability of the models should be tested at a site where the water levels are available for at least a decade. Ideally, the transferability of the models should be tested for several basins. While it may be several years before sufficient data sets are developed to evaluate transferability in detail, this research provides sufficient information to begin collecting data relevant to modeling the severity river ice breakup.

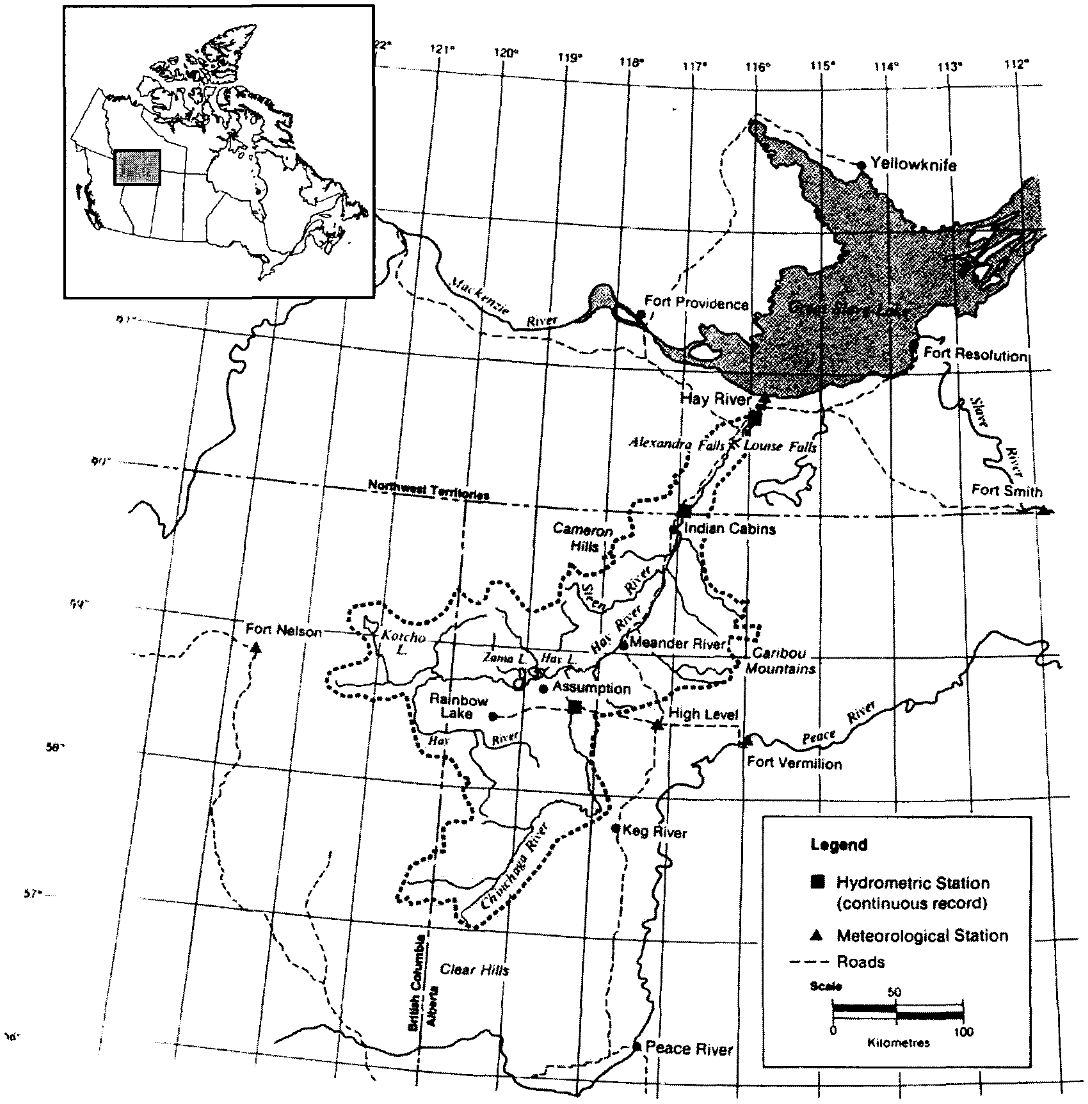

Figure 4-1(a): Hay River basin, NWT (adapted from Hicks, Gerard and Steffler, 1992).

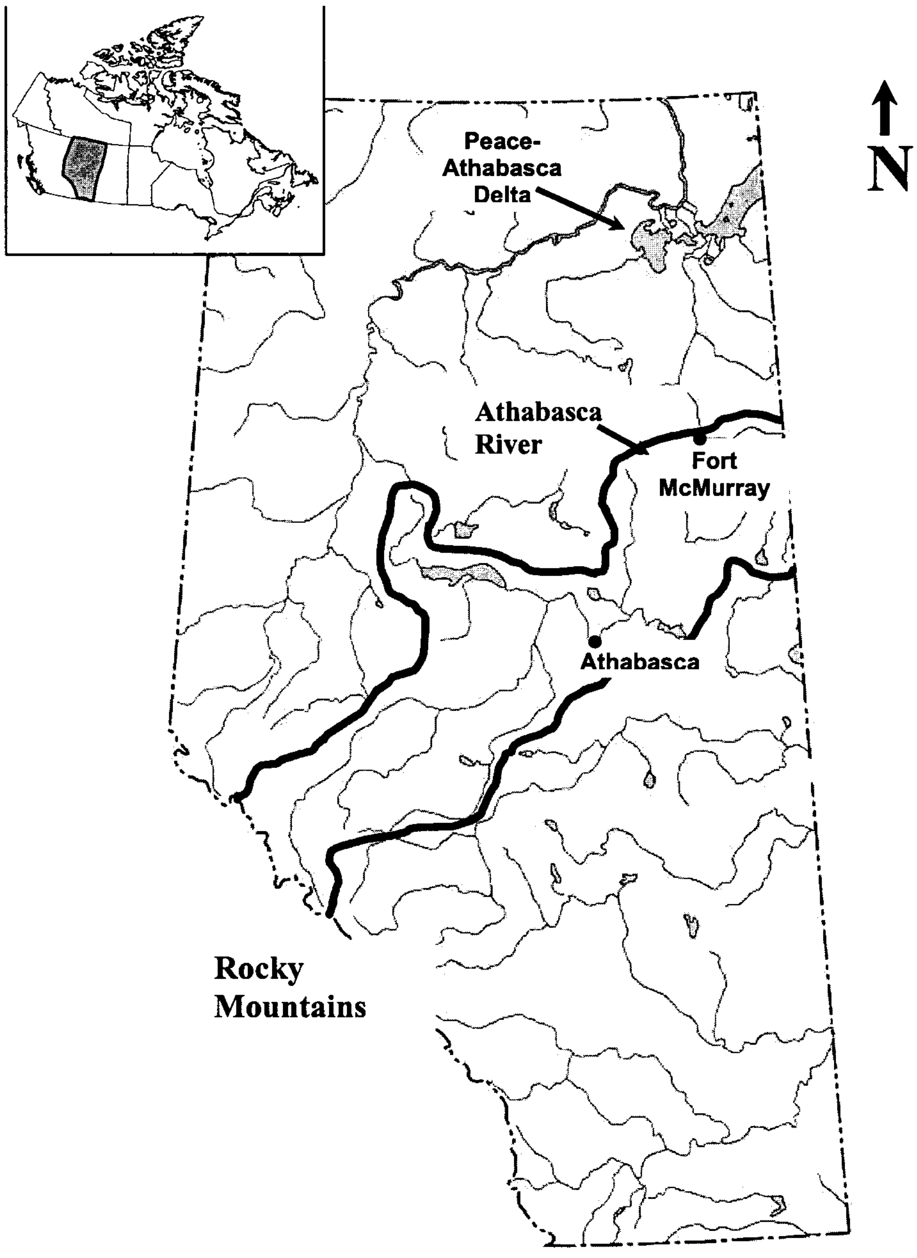

Figure 4-1(b): Athabasca River basin, AB.

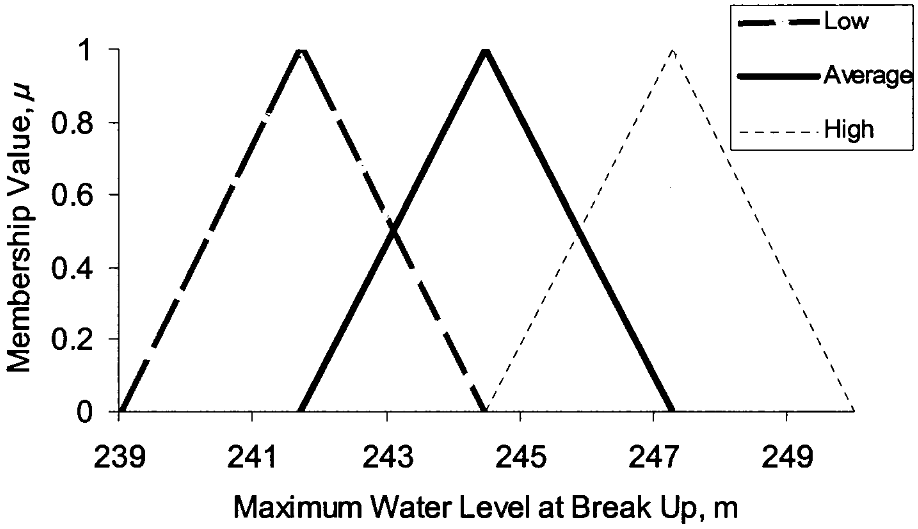

Figure 4-2 (a): Triangular membership functions with linguistic terms Low, Average, and High to describe the maximum water level at break up for the Athabasca River at Fort McMurray

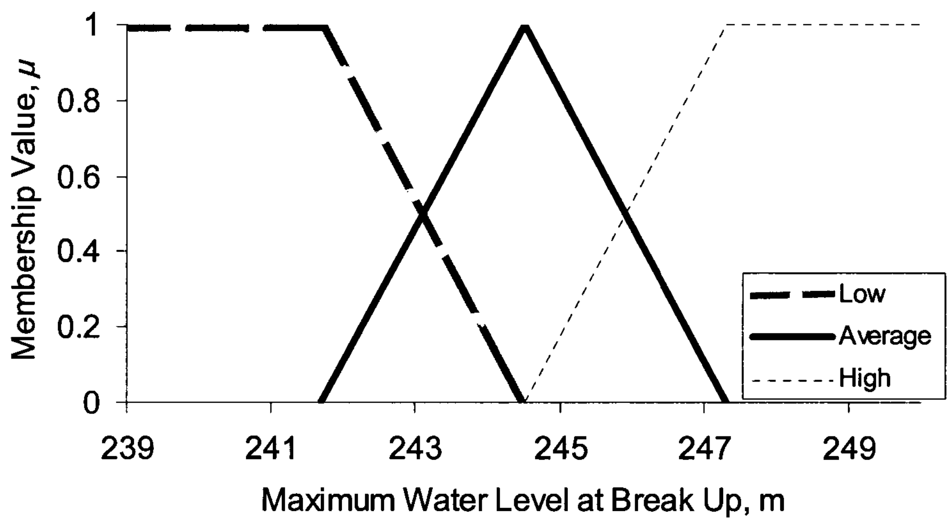

Figure 4-2(b): Mixed membership functions with linguistic terms Low (triangular membership function), Average (trapezoidal membership function), and High (trapezoidal membership function) to describe the maximum water level at break up for the Athabasca River at Fort McMurray.

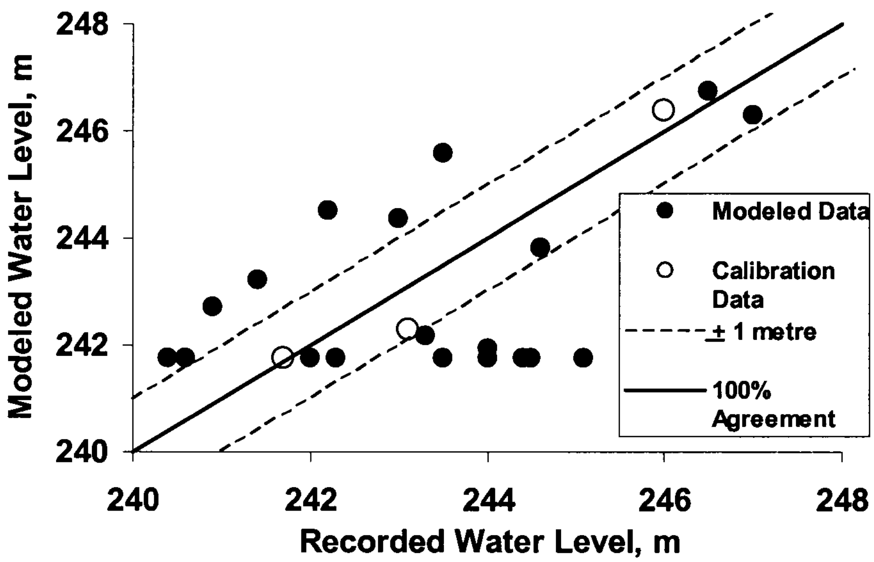

Figure 4-3: Experience based fuzzy model for the Athabasca River at Fort McMurray.

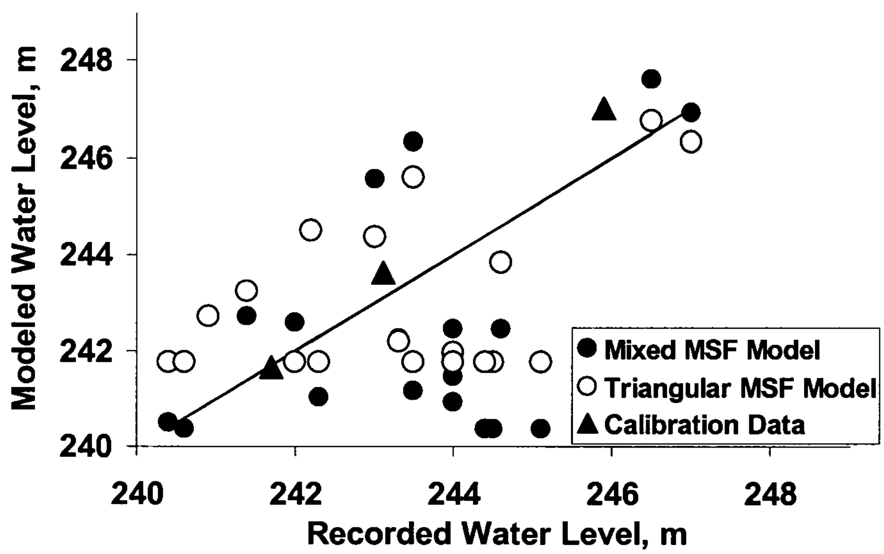

Figure 4-4: Modeled water levels for the Athabasca River for triangular output membership functions and for mixed triangular and trapezoidal membership functions.

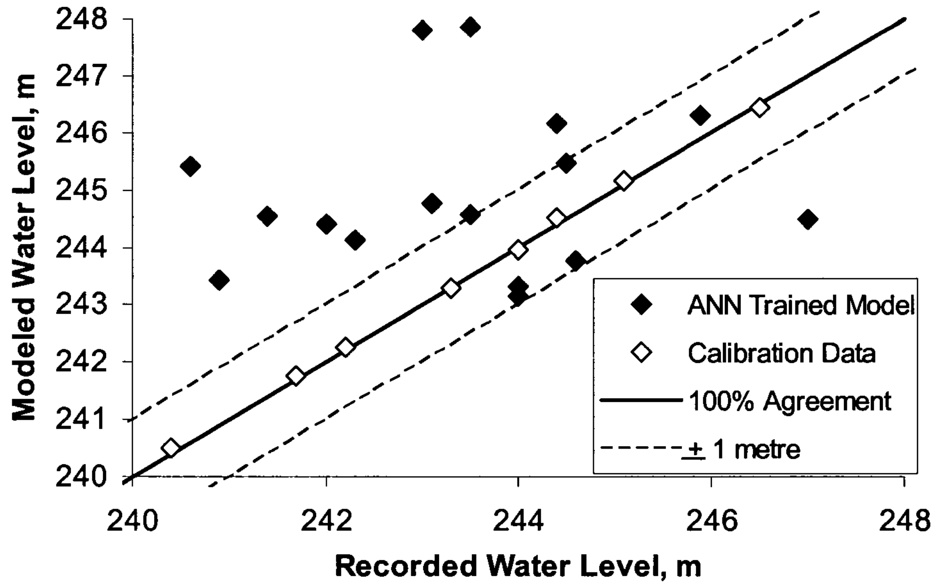

Figure 4-5: River breakup water level model for the Athabasca River with mixed membership functions and rule base trained exclusively by an ANN.

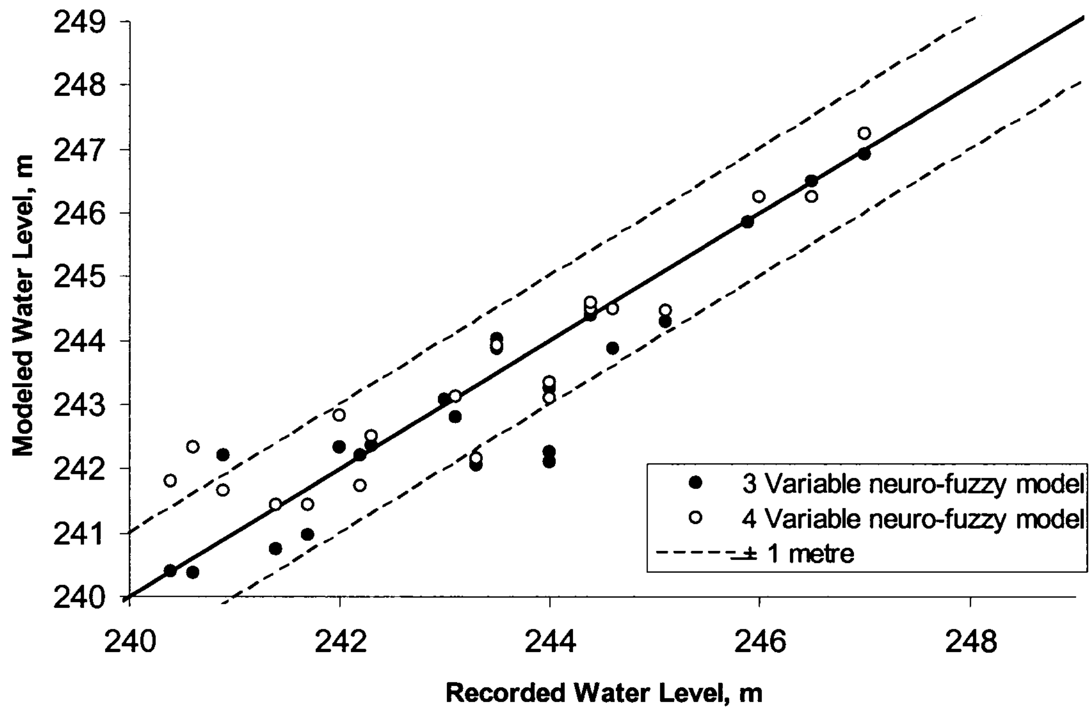

Figure 4-6: Performance neuro-fuzzy prototype ice jam flood forecasting model for the Athabasca River at Fort McMurray.

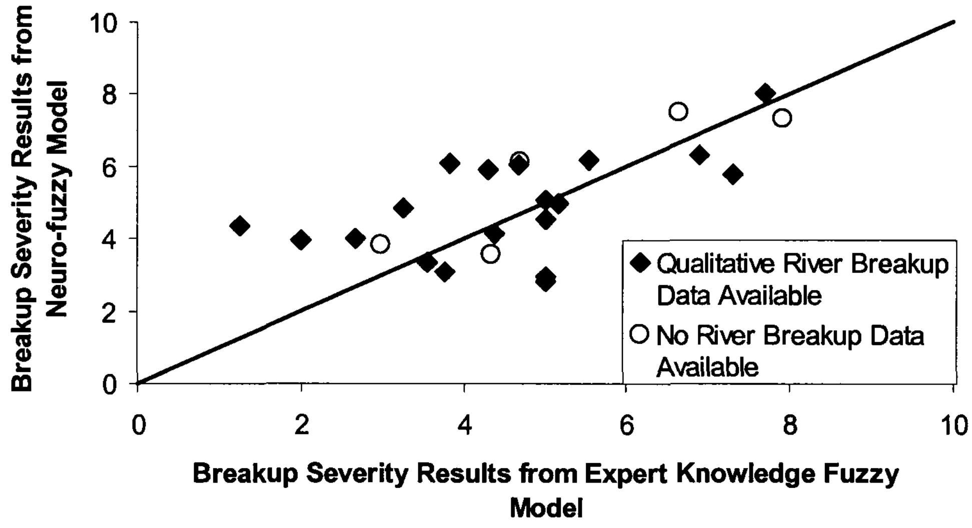

Figure 4-7: Comparison of modeled breakup severity between expert knowledge fuzzy model and neuro-fuzzy model for the Hay River.

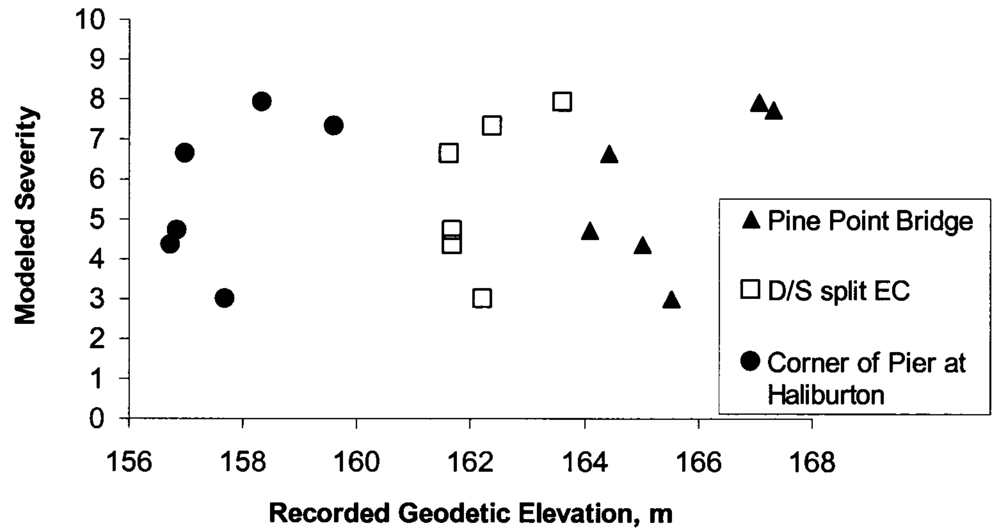

Figure 4-8a: Expert knowledge fuzzy model results for severity of water levels compared to geodetic water levels for the Hay River and the East Channel with series ordered from upstream to downstream.

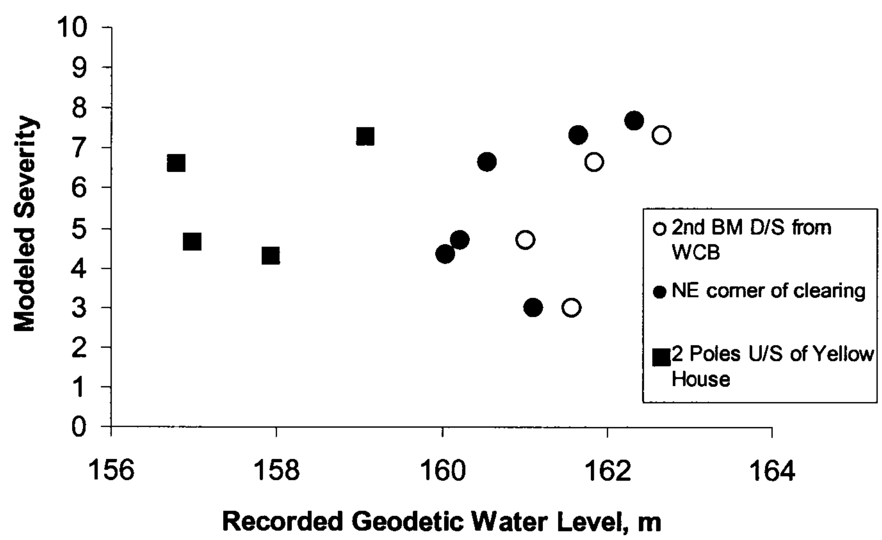

Figure 4-8b: Expert knowledge fuzzy model results for severity of water levels compared with geodetic water levels for the West Channel with series ordered from upstream to downstream.

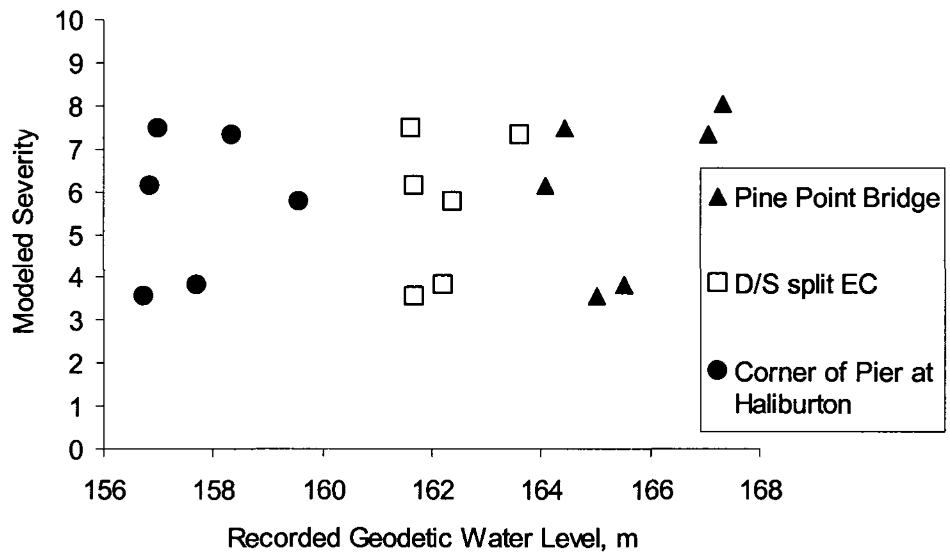

Figure 4-8c: Neuro-fuzzy Model results for severity of water levels compared to geodetic water levels for the Hay River and the East Channel with series ordered from upstream to downstream.

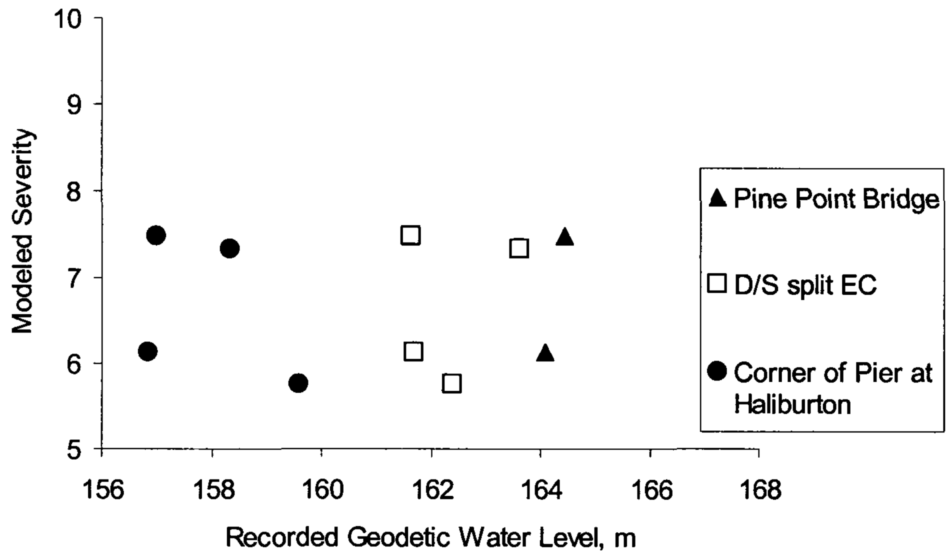

Figure 4-8d: Neuro-fuzzy Model results for severity of water levels compared with geodetic water levels for the West Channel with series ordered from upstream to downstream.

Table 4-1: SWE, Precipitation, Degree Day and Water Level Data employed to develop a prototype forecast model for the Athabasca River at Fort McMurray.

	Input Variables			Output Variable
Year	Accumulated Precipitation during previous summer (mm)	Accumulated Negative Degree Days (°C)	Accumulated Basin Average SWE (mm)	Maximum water level recorded during break up (m)
1979	345.8	-2663	50.0	246.5
1980	335.2	-1699	26.9	244.4
1981	380.1	-1539	41.7	244.0
1982	234.9	-2588	54.1	242.2
1983	260.8	-2034	41.4	242.3
1984	280.5	-1750	55.0	241.7
1985	425.5	-2288	50.2	243.5
1986	262.0	-1879	42.0	244.0
1987	258.0	-1489	38.9	245.1
1988	249.9	-1669	28.9	244.5
1989	347.5	-2157	33.8	243.1
1990	382.9	-2188	43.1	243.0
1991	289.0	-2244	35.9	244.6
1992	463.2	-1704	46.5	241.4
1993	295.3	-1830	23.9	243.5
1994	299.1	-2078	44.2	244.0
1995	228.8	-1857	32.3	244.4
1996	365.0	-2511	48.2	245.9
1997	460.1	-2445	35.3	247.0
1998	378.9	-1477	45.2	243.3
1999	162.9	-1747	42.9	240.4
2000	249.4	-1664	34.1	240.6
2001	373.3	-1768	45.3	240.9
2002	302.6	-2096	44.7	242.0

Table 4-2: SWE, Precipitation, and Degree Day Data employed to develop a prototype forecast model for the Hay River at the Town of Hay River.

	Input Variables		
Year	Accumulated Precipitation during previous summer (mm)	Accumulated Negative Degree Days (°C)	Accumulated Basin Average SWE (mm)
1979	149.9	-3548	72.5
1980	139.5	-2219	66.8
1981	211.1	-2502	71.1
1982	121.2	-3323	63.8
1983	160.2	-3403	69.5
1984	187.7	-2690	71.6
1985	287.6	-3233	68.4
1986	185.6	-2995	63.7
1987	185.5	-2399	62.9
1988	235.9	-2462	52.0
1989	368.6	-3075.3	68.67
1990	139.5	-3111.6	67.34
1991	250.1	-3229.7	69.03
1992	296.0	-2968	77.3
1993	174.7	-2328	64.1
1994	143.4	-3188	72.7
1995	107.8	-2730	70.9
1996	65.6	-4195	71.2
1997	181.9	-3090	67.1
1998	149.9	-3548	72.5
1999	139.5	-2219	66.8
2000	211.1	-2502	71.1
2001	121.2	-3323	63.8
2002	160.2	-3403	69.5

Table 4-3: Qualitative assessment results for the expert knowledge fuzzy and neuro-fuzzy models for the Athabasca River at Fort McMurray.

Flood Level		**Low**	**Average**	**High**
Actual Events		12	10	2
Expert Knowledge Fuzzy Model				
	Correctly Classified	6	5	2
	Incorrectly Classified	5	6	0
Neuro-fuzzy Model				
	Correctly Classified	12	9	2
	Incorrectly Classified	1	0	0

Table 4-4: Qualitative assessment results for the expert knowledge fuzzy and neuro-fuzzy models for the Hay River at the Town of Hay River.

Flood Level		**Low**	**Average**	**High**
Actual Events		14	7	3
Expert Knowledge Fuzzy Model				
	Correctly Classified	5	5	3
	Incorrectly Classified	2	9	0
Neuro-fuzzy Model				
	Correctly Classified	2	6	2
	Incorrectly Classified	1	13	0

Table 4-5: Comparison of recorded annual average data and average annual data from climate change model for 1975 to 2005.

		Recorded Annual Average	Modeled Annual Average	Ratio
Athabasca River Basin				
	SWE	41	85	0.48
	Precipitation	318	391	0.81
	Degree Days	-1974	-1141	1.73
Hay River Basin				
	SWE	69	77	0.90
	Precipitation	200	296	0.68
	Degree Days	-2924	-1560	1.87

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Chapter 5: Discussion and Conclusions

River ice breakup jams have the potential to create severe flooding in many northern communities and, in several cases, are the most extreme event on record. Flood mitigation measures in response to the formation of an ice jam are limited due to the rapid rise in water levels that are typical of a river ice breakup jam. The development of a river ice breakup model capable of identifying the potential risk associated with the annual river breakup prior to river breakup would have substantial benefit for emergency preparedness. The objective of this research was to develop a potential forecasting tool that, when implemented, would provide an indication of the severity of river ice breakup. To be beneficial for operation purposes, the extent of application of this forecasting tool would also need to be addressed.

As a first step in model development, a comprehensive database was created for the Athabasca River at Fort McMurray. This site was initially identified as a prototype model development site because water levels, the variable that would be ideal to model as an indicator of flood severity, had been monitored for over 25 years. The database included hydrometeorological data for the river basin from numerous sources including federal, provincial, and municipal governments.

With this extensive database, simple river breakup models were investigated. Multiple linear regression models had limited success. An equation relating eight variables to water level was developed with an R^2_{adj} =0.88 and a standard error of 0.6 m. The eight variables included (1) soil moisture index, (2) a measure of the intensity of the winter cold, (3) measure of early spring runoff, (4) average SWE in the basin, (5) a measure of the intensity of cold weather immediately before breakup, (6) the intensity of the solar radiation in the mid-basin, (7) the rate of water level increase as measured below Fort McMurray prior to major ice movement and (8) water level as measured below the town of Athabasca prior to spring runoff. Unfortunately, the model could not be validated with years when flooding actually occurred due to gaps in the data sets. No successful linear regression models could be developed with the data available during the most extreme flood years (1977 and 1997). Along with the drawback of being site specific in nature, the multiple linear regression equation that was developed also has limited practical application due minimal lead time that results from the selection of variables. For example, the rate of water level increase would be known only immediately prior to river breakup.

To take full advantage of the heuristic knowledge of river ice breakup, fuzzy logic was applied to the problem of river ice breakup modeling. Experience, or expert knowledge, was used to create the logical rule base stating the relationship between the input variables and the water level at breakup. It was necessary to reduce the number of variables in this expert knowledge fuzzy model due to the limited size of the data set available to validate the rule base. Variables retained from the multiple linear regression model and evaluated in the prototype fuzzy model are: an index of soil moisture; a measure of the intensity of winter cold; a measure of early spring runoff; and later winter SWE in the basin. Several model configurations were explored. The prototype fuzzy model was largely successful from a qualitative forecasting perspective as it was able to correctly identify three years out of twenty in which ice jam flooding occurred (1979, 1996 and 1997) but produced poor quality quantitative results. Unlike many other river breakup forecasting models, false positives did not occur.

To reduce the subjectivity of the development of the rule base, artificial neural networks (ANNs) were considered as a tool to determine the relationship between input and output variables in conjunction with expert knowledge. The quantitative results of the neuro-fuzzy model developed for the Athabasca River at Fort McMurray were found to be as accurate as a previous multiple linear regression in modeling water levels at breakup for this site. However, a significant advantage of this neuro-fuzzy model is the fact that it requires only half the number of input variables, all are known several weeks in advance of breakup. This is significant because it allowed six additional years to modeled making it the first model to quantitatively model actual flood event years. This is significant in that it represents the first accurate 6 week lead time forecasting model for river breakup water levels for this, or any, site.

The modeling ability of the fuzzy models was tested further by evaluating the potential to transfer a logical rule base to another river; in this case, the Hay River. Because of the limited variables available for the Hay River basin, the Athabasca River expert knowledge fuzzy and neuro-fuzzy models were redeveloped with only three input variables (without significant decrease in the model performance). The expert knowledge fuzzy model was able to qualitatively identify the two largest flood events for the Town of Hay River at Hay River based on the logical rule base created for the Athabasca River. However, the high accuracy of the neuro-fuzzy model did not transfer between the two sites. Given the limited water level data for the Hay River site, it was not possible to determine whether this was due the inapplicability of the neuro-fuzzy rule base or an issue of data inadequacy.

The expert knowledge fuzzy model was used to evaluate future climate change scenarios provided by Environment Canada for both the Athabasca and the Hay river basins. Three intervals of 25 years were evaluated beginning in 2025. Based on this preliminary analysis, extreme flood events during river breakup on the Athabasca River at Fort McMurray are expected to decrease as the climate warms. At Hay River, however, the number of extreme flood events during river breakup is indicated to increase between 2025-2050 (due to wetter basin conditions) but in the following time periods, the number of extreme events is expected to decrease. While the expert knowledge fuzzy model provides some insight into the potential river breakup scenarios, it does not account for severe river ice events such as freeze up or midwinter ice jam events.

5.1 CONTRIBUTIONS TO KNOWLEDGE

The database created to support the development of river ice breakup forecasting models is an asset to future model development for the Athabasca River Basin. It represents one of the most comprehensive databases for river ice breakup modeling for a natural river. The building of this database was time consuming but it illustrates the volume of information that may be available for river basins should a researcher wish to invest in assembling a database rather than just accepting the data that is readily available.

This research provides new methods for evaluating the severity of river ice breakup prior to the formation of an ice jam and increased our knowledge of the influential variables that lead to the formation of river ice jams. Models developed in this thesis are the first to provide quantitative forecasts of the maximum water level at spring breakup with weeks of lead time.

The fuzzy expert knowledge river ice jam flood forecasting model has been shown to be transferable between rivers. This creates the possibility of modeling in river basins that were once believed to lack sufficient data for river ice breakup model development. By clearly distinguishing flood event years from years when flood did not occur, a qualitative forecast can be developed with minimal data. This is the first river breakup forecast model that has successfully been transferred between river basins.

In this research, there was a progressive reduction of variables as the sophistication of the models increased. The database contained 116 variables. Linear regression modeling required 8 variables. Fuzzy logic models were functional with only three input variables. While the logic models do not indicate what the relevant physical process is that dictates the use of one variable over another, the implication of importance of input variables may provide insight for physical models as to which processes are dominant during years with severe ice jams. Further insight may be deduced from the developed rule bases; for example, in the Athabasca Expert Knowledge model, it was found that precipitation and negative degree days were more influential in causing severe breakups than groundwater or SWE. This is worthy of further study, in the context of increasing our understanding of the causative factors affecting ice jam severity, and illustrates a further (deterministic) application of fuzzy logic.

5.2 FUTURE RESEARCH

From this research, future research and operational river ice programs may benefit from identifying the necessary information required from data collection networks and monitoring programs in ice jam prone communities. The methods developed for river ice breakup modeling provide governments and communities with an important step towards river ice jam flood mitigation and may also assist deterministic river ice modelers to identify key processes (through the identification of critical variables) for river ice jam formation. Clearly fuzzy logic models have potential application in the field of river ice breakup modeling. This research has established the basic applicability of fuzzy logic to provide an indicator of the severity of river ice breakup.

The methods developed in this paper provide a basis to further refine and evaluate fuzzy and neuro-fuzzy modeling methods at other sites to establish a wider range of model application. Of particular benefit would be the evaluation of the models at a site with an established record of maximum water levels at river breakup.

For basin transferability, the limitations of the fuzzy expert systems should be explored further. The Hay River and the Athabasca River had very similar physical river characteristics but the point at which the rules within the rule base would become non-transfer is unknown. If a fuzzy model for a river in a different geographical setting was created, a comparison of relevant variables and rule bases could be beneficial in determining, not only the extent of transferability but also the influence of input variables in the river break up process at different sites.

APPENDIX A
Data

APPENDIX A (DATA)

List of Tables

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The data reported in this appendix is summarized by Mahabir et al. (2006).

A.1.0 SWE DATA

A.1.1 SWE SATELLITE DATA

Environment Canada provided SWE data as measured by satellite for the Fort McMurray and Hay River watersheds. Gan (1996) provides a background on passive microwave snow measurement by satellite. Basin average SWE values are presented in Table A-1-1.

A.1.2 SNOW COURSE DATA FOR FORT MCMURRAY

Snow course data for the Athabasca River Basin has historically been collected close to the first week in March and April each year. While some snow course data has been collected on in the middle of a month, the record is neither lengthy nor continuous. Based on the available snow course data, only the first of the month records were evaluated as indicators. Robichaud (2003) used a Thiessen polygon approach to estimate the total snow in the Athabasca River Basin based on the record for 18 provincial snow courses which included all of the upper and most of the middle river basin.

There are two major flaws in estimating a true basin average SWE based on the simple Thiessen polygon method presented by Robichaud (2003). Firstly, the entire area contributing to snowmelt in the river above Fort McMurray is not represented. Robichaud did not include the area surrounding Fort McMurray itself as there were no snow courses in the eastern portion of the river basin. The reason for the lack of snow course sites is that there have historically been no problems with spring runoff in this area of the province and therefore, resources have not been invested to quantity the SWE. Typically during river breakup, there is very little snow on the ground in the local area. However, there have been years where the local snowmelt contribution was significant enough to create diurnal patterns at the Water Survey of Canada gauge immediately downstream of Fort McMurray. The data collected during 2002 supports the theory that small local amounts of snow would not a play a major role during river breakup as it would likely melt prior to the arrival of the major snowmelt from the upper basin.

The second problem inherent in the Thiessen polygon method for approximating basin SWE is that the topography of the basin is not considered. It is well known that the volume of precipitation can very dramatically based on changes in elevation as well as slope aspect. Although mountain snow course sites are included in the analysis, they are weighted by the distance to the next snow course site and include no adjustments for elevation or aspect. Snowmelt from the Rocky Mountains in the western basin contributes to streamflow in July, well after the mid April river ice breakup near Fort McMurray.

Since the goal of determining the basin average SWE was to create a basin indicator, the problems with the Thiessen polygon analysis are considered minor. No snow course data are available for the area local to Fort McMurray which rarely has snow in April. The estimation of the SWE in the mountains is poor but this area does not contribute to the streamflow until much later in the year.

The SWE for the Athabasca River basin based on the provincial snow survey sites is provided in Table A-1-2. SWE_{Mar} is the basin average SWE measured during the last week of February or the first week of March. SWE_{Apr} is the basin average SWE measured during the last week of March or the first week of April.

Table A-1-1: SWE data determined by Satellite measurement provided by Environment Canada.

	Jasper		Hinton		Windfall (east of Whitecourt)
Year	**Total Volume**	**Average SWE (mm)**	**Total Volume**	**Average SWE (mm)**	**Total Volume**
1979	1.38E+11	35.85	3.77E+11	36.56	7.01E+11
1980	1.58E+11	41.12	4.13E+11	40.01	7.01E+11
1981	1.31E+11	34.12	3.65E+11	35.39	6.75E+11
1982	1.34E+11	34.83	3.68E+11	35.69	7.15E+11
1983	1.39E+11	36.15	3.78E+11	36.65	6.89E+11
1984	1.36E+11	35.37	3.80E+11	36.87	7.30E+11
1985	1.57E+11	40.67	4.17E+11	40.41	7.60E+11
1986	1.42E+11	36.79	3.81E+11	36.91	6.97E+11
1987	1.10E+11	28.68	3.05E+11	29.61	5.73E+11
1988	1.50E+11	39.03	4.01E+11	38.82	7.12E+11
1989	1.66E+11	43.11	4.24E+11	41.12	7.24E+11
1990	1.32E+11	34.17	3.66E+11	35.44	6.99E+11
1991	1.33E+11	34.63	3.60E+11	34.91	6.60E+11
1992	1.43E+11	37.27	3.86E+11	37.44	7.22E+11
1993	1.35E+11	35.15	3.52E+11	34.11	6.11E+11
1994	1.45E+11	37.72	3.94E+11	38.22	7.50E+11
1995	1.57E+11	40.75	4.11E+11	39.87	7.08E+11
1996	1.75E+11	45.45	4.68E+11	45.36	8.48E+11
1997	1.46E+11	37.95	3.97E+11	38.45	7.45E+11
1998	1.51E+11	39.36	4.06E+11	39.37	7.49E+11
1999	1.42E+11	36.79	3.85E+11	37.32	7.14E+11
2000	1.36E+11	35.43	3.65E+11	35.33	6.69E+11
2001	1.66E+11	43.03	4.38E+11	42.45	8.01E+11
2002	1.67E+11	43.31	4.35E+11	42.20	7.68E+11

Table A-1-2: Basin Average SWE for March and April based on Thiessen Polygon Method

Year	Average SWE (mm)	
	SWE_{Mar}	SWE_{Apr}
1974	129	162
1975	66	Not available
1976	76	Not available
1977	69	67
1978	77	27
1979	90	38
1980	63	83
1981	54	11
1982	110	141
1983	39	60
1984	58	22
1985	117	89
1986	50	27
1987	56	63
1988	42	16
1989	68	83
1990	61	36
1991	73	83
1992	92	9
1993	50	20
1994	129	112
1995	58	33
1996	107	81
1997	117	128
1998	36	10
1999	108	86
2000	34	16
2001	25	4
2002	51	71
2003	77	78

A.2.0 ICE THICKNESS ON THE ATHABASCA RIVER NEAR FORT MCMURRAY

A consistent method of measurement for ice thickness near Fort McMurray at a single site on the Athabasca River does not exist in the historical record. Since the characteristics of the channel vary widely throughout the reaches surrounding the Fort McMurray area, it is inappropriate to assume that the ice characteristics for the length of the river could be "averaged" without investigating further.

A.2.1 DOCUMENTATION OF INCONSISTENCY IN ICE THICKNESS MEASUREMENT LOCATIONS

Yaremko (1974) stated the ice thickness downstream of Fort McMurray in the winter of 1974 was between 1.5 and 2.5 feet which was less than the average seasonal maximum of 3.0 feet. The "average seasonal maximum" to which Yaremko compared was from a publication titled "Selected Characteristics of Streamflow in Alberta" by Kellerhall et al. (1970). Information provided in "Selected Characteristics of Streamflow in Alberta" for ice thickness for the Athabasca River at Fort McMurray is provided in Table A2.1. The highest annual maximum is attributed to "presence of traffic crossing on the ice". This statement alone indicates that the ice thicknesses measured is likely not representative of the same process. Ice thickened artificially for an ice bridge should not be compared with naturally occurring ice from previous years.

The location of Water Survey of Canada winter measurements for the Athabasca River at the Fort McMurray gauge has changed several times in the last 40 years. If the ice cover is not formed by similar processes at all locations, a statistical average of all sites for ice thickness will not be an appropriate comparative statistic. Andres and Rickert (1984) reported that from 1958 to 1981, measurements were made downstream of Clarke Creek and in 1982, the measurements were done above Clarke Creek. Believing the measurements to be in close proximity to each other, Andres and Rickert proceeded to compare annual measured ice thicknesses to long term averages (Andres and Rickert 1984), Andres and Rickert 1985) as did previous reports (Doyle and Andres 1979). Documentation of site visits written by WSC staff during each flow measurement state that in 1972, 1973, 1979, 1982, 1986, 1987, 1988, and 1989 some winter measurements were performed upstream of MacEwan Bridge which is approximately 5 km above the gauging site.

The first recorded comment about the variation in ice thickness by location is by Andres and Rickert (1984). When comparing the measurements of ice thickness at the WSC gauging site to over a dozen measurements done near Fort McMurray by city workers, the authors noted *"...the variation in ice thickness over the winter cannot be rationally explained..."*. After ruling out frazil ice as the cause, the authors then speculated that the variations were due to either consolidations during freeze-up or insufficiently controlled measurements. Despite the spatial variations, it was concluded that the ice cover from MacEwan Bridge to the Clearwater River Confluence was thicker than that measured at the WSC gauge.

The Regional Municipality of Wood Buffalo (RMWB) has measured ice thickness at several locations both upstream and downstream of the city of Fort McMurray. The first report available in the files from Alberta Environment is in 1989 and a continuous record is available to present day.

A.2.2 ICE THICKNESS COMPARISON: WATER SURVEY GAUGE AND RMWB MEASUREMENTS

The results of this section are summarized in a paper by Mahabir et al. (2004) presented at the 2004 Canadian Society for Civil Engineering (CSCE) Conference which is included in Appendix B for information purposes.

Ice thickness measurements done by WSC in March and April showed similar characteristics to ice thicknesses measured by the regional municipality at many of the municipal measurement locations. Reaches of the river with typically thermal ice growth were correlated regardless of the agency performing the measurements. The exception to this is a site approximately five kilometres upstream of Fort McMurray below Moberly Rapids.

The following ice thickness variables were investigated for use in river ice forecasting models:

WSC_{March}	ice thickness measured at WSC gauging site in March
WSC_{April}	ice thickness measured at WSC gauging site in April
$WSC_{Average}$	average of ice thickness measurements for March and April
Moberly	ice thickness measures at Moberly Rapids in Mid-March
$WSC_{Difference}$	ice thickness difference between the April and March ice thickness estimates at the WSC gauge
$I_{Difference}$	difference between ice thickness measurements at Moberly Rapids at the WSC gauging site
I_{Ratio}	ratio of ice thickness measurements for Moberly Rapids to WSC gauging site

Measured values are reported in Table A-2-2 and calculated relationships are reported in Table A-2-3.

Table A-2-1: Ice Thickness Statistics as reported by Kellerhals et al.(1970)

Lowest Annual Maximum (m)	Average Annual Maximum (m)	Highest Annual Maximum (m)
0.46	0.91	1.68

Table A-2-2: Measured Values WSC_{March}, WSC_{April}, Moberly Rapids

	Ice Thickness Location WSC Gauge		Moberly Rapids
	WSC_{March} March	WSC_{April} April	Mid March
Year	m	m	m
1974	0.64	0.61	0.68
1975	0.73	0.61	0.75
1976	0.85	0.82	1.01
1977	0.91	0.88	1.08
1978	0.91	0.88	1.10
1979	0.85	0.88	1.06
1980	0.80	0.80	0.96
1981	0.73	0.75	0.88
1982	0.58	0.65	0.72
1983	0.54	0.54	0.55
1984	0.81	0.81	0.97
1985	0.79	0.73	0.89
1986	1.01	1.01	1.28
1987	0.78	0.78	0.92
1988	0.66	0.66	0.74
1989	0.62	0.62	0.69
1990	0.69	0.63	0.80
1991	0.77	0.77	0.83
1992	0.83	0.75	0.86
1993	0.96	0.82	1.19
1994	0.81	0.68	0.91
1995	0.83	0.85	0.95
1996	0.75	0.73	0.86
1997	0.77	0.77	0.89
1998	0.58	0.58	0.79
1999	0.81	0.81	0.71
2000	0.54	0.54	0.61
2001	0.64	0.67	0.56
2002	0.50	0.50	0.71
2003	0.72	0.78	1.09
2004	0.70	0.70	1.02

Table A-2-3: Calculated Values: $WSC_{Average}$, $WSC_{Difference}$, $I_{difference}$, I_{Ratio}.

Year	$WSC_{Average}$ Avg (Mar, Apr) m	$WSC_{difference}$ Mar-Apr Difference m	$I_{difference}$ Moberly - WSC m	I_{Ratio} Moberly/WSC m
1974	0.63	0.03	0.06	0.09
1975	0.67	0.12	0.08	0.12
1976	0.84	0.03	0.18	0.21
1977	0.88	0.03	0.20	0.23
1978	0.90	0.03	0.21	0.23
1979	0.87	-0.03	0.19	0.22
1980	0.80	0.00	0.16	0.20
1981	0.75	-0.02	0.13	0.17
1982	0.65	-0.07	0.07	0.11
1983	0.54	0.00	0.01	0.02
1984	0.81	0.00	0.16	0.20
1985	0.76	0.06	0.13	0.18
1986	1.01	0.00	0.27	0.27
1987	0.78	0.00	0.14	0.19
1988	0.66	0.00	0.08	0.12
1989	0.62	0.00	0.07	0.11
1990	0.66	0.06	0.14	0.21
1991	0.77	0.00	0.06	0.08
1992	0.79	0.08	0.07	0.09
1993	0.89	0.14	0.30	0.34
1994	0.75	0.13	0.17	0.23
1995	0.84	-0.02	0.11	0.13
1996	0.74	0.02	0.12	0.17
1997	0.63	0.00	0.27	0.42
1998	0.64	0.00	0.15	0.24
1999	0.81	0.00	-0.10	-0.12
2000	0.54	0.00	0.07	0.13
2001	0.66	-0.03	-0.10	-0.15
2002	0.50	0.00	0.21	0.42
2003	0.75	-0.06	0.34	0.46
2004	0.70	0.00	0.32	0.45

A.3.0 SOIL MOISTURE INDICATORS

Due to the spatial, temporal and depth variation in soil moisture within a basin, there are no absolute measurements for soil moisture that can provide a quantitative assessment of the potential of the soil for spring runoff. Several soil moisture indicators were investigated.

A.3.1 SUMMER PRECIPITATION

Precipitation has been often used in hydrology as an indicator of basin soil moisture conditions as there are many precipitation measurement sites throughout the Canada. Within the Alberta Provincial Water Supply forecast, precipitation during the irrigation season is used as an indicator of soil moisture conditions for areas of the province where adequate soil moisture measurements are not normally taken and in the event that soil moisture data is not available due to equipment malfunction. As an indicator of spring breakup, the previous year's precipitation would affect the soil moisture at during the following spring breakup. For example, the precipitation during the summer of 2003 would be an indicator of the soil conditions for river breakup in 2004.

Selection of sites to be used in this study was based on the availability, length and the perceived quality of the collected data records. Data from Meteorological Service of Canada (MSC) is considered to be the highest quality of data available because this is the branch of the federal government responsible for precipitation data collection in Canada. The majority of the provincial stations in the Athabasca River Basin have a shorter length of record since many sites were installed during the 1980s. Municipal and private groups were not investigated in this data collection effort because the quality of the data collection and length of record were not readily available.

Two sites for precipitation data were considered as indicators for the Athabasca River Basin. If soil moisture conditions in the immediate area of the ice jam location are an important factor, it would be reasonable to include the precipitation at Fort McMurray as an indicator. However, if the influence of soil moisture is more important in the snowmelt generation process, it would be more practical to create a soil moisture index based on a station located in the main snowmelt generation basin. For Fort McMurray, this would be the Pembina River Subbasin.

Precipitation data from Fort McMurray was evaluated by Robichaud (2003) and determined to be an important parameter in forecasting river breakup with linear models. However, Robichaud did not include any other soil moisture indicators from the rest of the basin in her analysis. Since most of the spring melt runoff is generated in the Pembina subbasin, soil moisture in this area of the basin would be of primary importance if the process of runoff generation is the key factor in for the inclusion of a soil moisture index.

Using data from the MSC gauge 3062693 YMM at the airport in Fort McMurray, Robichaud (2003) summed the daily total precipitation during from May 1st to October 15th (based on the irrigation season in Alberta) to produce an indicator of the soil moisture in the Athabasca River Basin. Data prior to 2000 in Table A3.1 is taken from the database developed by Robichaud. Data after 2000 is MSC data that has been collected MSC preliminary data and AENV real-time data.

In the Pembina River Subbasin, there are no MSC precipitation stations. However, there are several stations with varying lengths of record surrounding the river subbasin. The stations that were evaluated are listed in Table A3.2. Both Edson and Whitecourt stations are located within the Athabasca River Basin. Since Whitecourt is located close the middle of the Pembina River Basin and would is likely to provide a better indication of soil moisture for the basin than Edson which is located to the west of the subbasin.

In Table A3.1, official MSC data was available for 1972 to 1997. From 1998 to 2004, AENV preliminary reports of MSC data was used. There were few problems with missing data for the Whitecourt station as it is located at an airport and is well maintained. For the AENV preliminary data, missing data points were estimated by evaluating the surrounding stations and determining if rain occurred during the missing time frame. There were no significant gaps in the record as the missing intervals of data were in gaps of less than 24 hours. If the surrounding stations reported less than 1 mm of rain during the missing six hour time interval, it was considered that rain did not occur during the missing time period.

AENV preliminary data for 2002 to 2004 should be used with caution as it has automated data corrections for wind effects that are not part of the MSC's data quality control. While it is believed that the automated data processing provides an accurate real-time estimate of rainfall, this data may be statistically different from the official MSC data.

Table A-3-1: Total Precipitation at Fort McMurray and Whitecourt from May 1 to Oct 15.

Year	Fort McMurray YMM (mm)	Whitecourt YZU (mm)
1972	315.1	391.9
1973	520.2	524.1
1974	329.2	388.3
1975	468.2	393.6
1976	438.1	394.8
1977	280.0	558.4
1978	345.8	487.8
1979	335.2	425.2
1980	380.1	489.1
1981	234.9	321.7
1982	260.8	405.3
1983	280.5	443.0
1984	425.5	461.4
1985	262.0	479.7
1986	258.0	483.0
1987	249.9	395.4
1988	347.5	455.7
1989	382.9	631.2
1990	289.0	405.5
1991	463.2	347.0
1992	295.3	344.9
1993	299.1	365.6
1994	228.8	408.2
1995	365.0	391.1
1996	460.1	538.2
1997	378.9	349.0
1998	162.9	295.5
1999	249.4	243.8
2000	373.3	460.9
2001	302.6	Not Available
2002	362.5	97.3
2003	363.0	100.3
2004	223.5	209.4

Table A-3-2: Precipitation stations located near the Pembina River subbasin.

Station Name	MSC Number	Length of Record
Whitecourt YZU	3067372	1978-present
Whitecourt	3067370	1971-1978
Edmonton YEG	3012205	1971-present
Edmonton YXD	3012208	1971-present
Edmonton Namao	3012210	1972-1995
Edmonton Stony Plain	301222F	1971-2002
Edson A YET	3062244	1971-1998
Edson YET	3062242	1997-present

A.3.2 GROUNDWATER

Since Freeze and Cherry's popular groundwater reference book was published in 1979, the impact of groundwater in the hydrological cycle has received significant attention. It is now generally accepted in the scientific community that groundwater levels can significantly impact the volume of runoff generated on an event basis. Groundwater and soil moisture play an integrated role determining the runoff potential of a river basin.

In Alberta, "drought" monitoring wells have been established in several locations throughout the province. Although scarce in number, these wells provide information that indicates the severity of the soil moisture conditions. Effective drought monitoring wells are unconfined or water table aquifers, usually located near the ground surface. In an unconfined aquifer, the water table forms the upper boundary. Within Alberta, a shallow well with a maximum depth of less than 50 m is generally considered a good drought monitoring well (Lorberg, 2004). Unconfined aquifers are naturally influenced on a seasonal basis by the recharge (infiltration to the water table) and bank storage effects near streams (Freeze and Cherry, 1979). These influences on the groundwater table and the level of the groundwater table itself will impact the generation of streamflow.

It is hypothesized that the groundwater level may be potentially useful in forecasting river ice jams in that the level of the spring water table could represent the potential for runoff during the snow melt season and the level of the water table in fall could be an indictor of the potential freeze-up water level.

Provincial groundwater wells were considered based on length of record, ability to represent natural soil moisture conditions and geographic location. No suitable groundwater wells were located within the Athabasca River Basin. Because groundwater does not follow the same watershed boundaries as surface water, this was not considered a substantial reason to exclude groundwater data. The locations of the two wells considered are shown in Figure A-3-1.

Devon #2 (Well #159) is an Alberta Environment observation well located Northeast of Devon at LSD 8-12-51-26-W4M. Clare (1987) provides a detailed description of the well from which the following facts have been extracted. The well is completed in a shallow unconfined sand aquifer of surficial deposits (Aeolian sand). Continuous data collection began in the spring of 1965 and the data is considered not to be influenced by direct human actions such as pumping. Depending on the amount of snowmelt, precipitation, and evapotranspiration losses, the annual fluctuations in groundwater levels at this site can vary from 0.4 to 1.2 m.

Elnora #5 (Well #129) is another provincial groundwater observation well located at LSD 16-36-34- 26-W4M. This well was identified by Lorberg (2004) as a potential indicator well because of its length of record (station established in 1964) and because it was identified as a suitable provincial drought indicator well in 2002. This aquifer is a surficial aquifer primarily located in clay.

Correlation analysis was performed on the two wells. Figure A-3-2 illustrates that the wells cannot be correlated to each other. Due to data availability and time constraints, it was not feasible to investigate the existence of corresponding groundwater wells.

Due to the large volume of missing data for Well #129, it was not feasible to attempt to fill missing data by interpolation. In some instances, such as the early 1980s, years of data were missing from the record.

From 1970 to 2003, the data for Well #159 was evaluated. There were occasionally consecutive gaps in the data of over two months. For these years, data was not used in the model. Missing data for data gaps of less than two months was estimated by interpolation. On occasion, single manual readings were available to facilitate the interpolation of data.

Although water levels generally followed the theoretical hydrograph illustrated above in Figure A-3-3, there were some years where the water level trends were different. It was decided to use the water levels in March and April for evaluation in the forecasting model as these values correspond to the dates when SWE data would be available.

In addition, it was decided to include the change in water levels as the rate of groundwater recharge may be an indication of the potential volume of snowmelt. Both monthly rates (difference between Feb and Mar, difference between Mar and Apr) and seasonal rates (difference between Jan and Mar, difference between Jan and Apr) were evaluated.

Table A-3-1: Groundwater data and calculated relationships for Devon #2 (Well #159)

Year	Water Level					
	Value on 1st day of Month		Change in Water Level			
			Since Jan 1		Since Previous Month	
	March	**April**	**March**	**April**	**March**	**April**
1970	690.483	690.504	-0.09	-0.07	-0.03	0.02
1971	690.446	690.756	-0.06	0.25	-0.01	0.31
1972	690.512	690.897	-0.02	0.37	0.03	0.39
1973	690.665	690.928	-0.08	0.18	-0.03	0.26
1974	690.913	690.893	-0.05	-0.07	-0.02	-0.02
1975	691.188	691.216	-0.14	-0.11	-0.09	0.03
1976	691.195	691.367	0.09	0.26	0.12	0.17
1977	691.060	691.144	0.04	0.12	0.11	0.08
1978	690.769	691.079	-0.08	0.23	-0.03	0.31
1979	690.832	691.158	-0.23	0.10	-0.07	0.33
1980	690.810	690.943	-0.14	-0.01	-0.07	0.13
1981	691.231	691.561	-0.01	0.32	0.03	0.33
1982	691.342	691.497	0.25	0.40	0.14	0.15
1983	691.099	691.241	-0.15	0.00	-0.03	0.14
1984	691.233	691.483	-0.02	0.23	-0.02	0.25
1985	690.970	691.714	NA	NA	-0.05	0.74
1986	690.933	691.302	NA	NA	-0.02	0.37
1987	691.023	691.148	-0.13	-0.01	-0.03	0.12
1988	690.916	690.991	NA	NA	-0.06	0.07
1989	690.905	690.951	-0.19	-0.14	-0.08	0.05
1990	691.016	691.392	NA	NA	-0.07	0.38
1991	691.273	691.529	0.02	0.27	0.05	0.26
1992	691.461	691.733	0.17	0.44	0.21	0.27
1993	690.876	691.184	-0.15	0.15	-0.05	0.31
1994	690.857	691.321	-0.17	0.30	-0.05	0.46
1995	690.899	691.025	-0.16	-0.04	-0.06	0.13
1996	690.683	690.973	-0.07	0.22	-0.02	0.29
1997	691.250	691.794	-0.09	0.45	0.00	0.54
1998	691.401	691.469	-0.18	-0.11	-0.07	0.07
1999	691.216	691.489	-0.07	0.20	-0.03	0.27
2000	690.969	691.042	-0.19	-0.11	-0.07	0.07
2001	690.671	690.669	-0.13	-0.13	-0.07	0.00
2002	690.492	690.436	-0.09	-0.15	-0.04	-0.06
2003	690.201	690.272	-0.06	0.01	-0.02	0.07

NA: data is Not Available

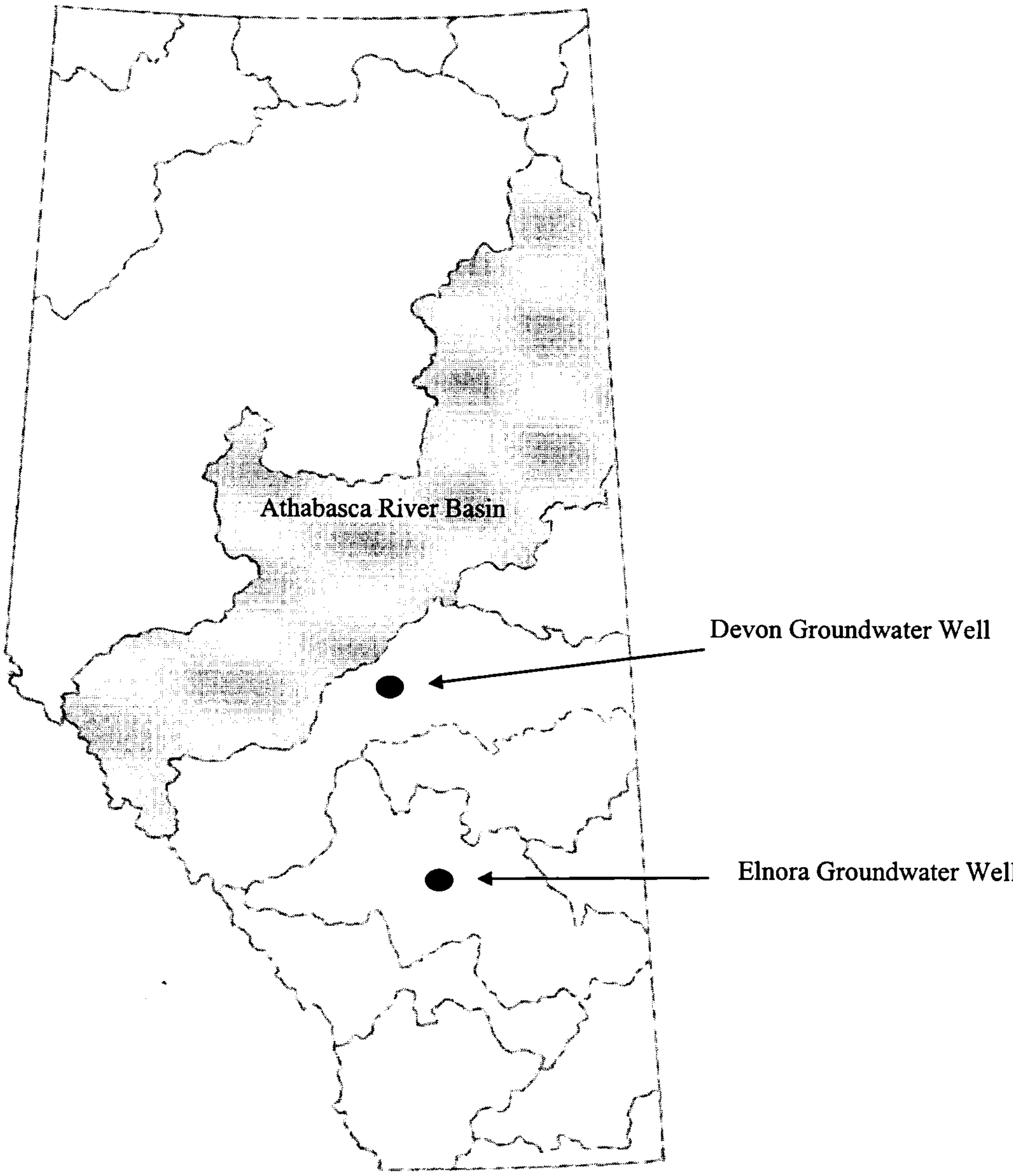

Figure A-3-1: Location of groundwater wells Devon #2 (Well #159) and Elnora #5 (Well #129) with respect to the Athabasca River Basin.

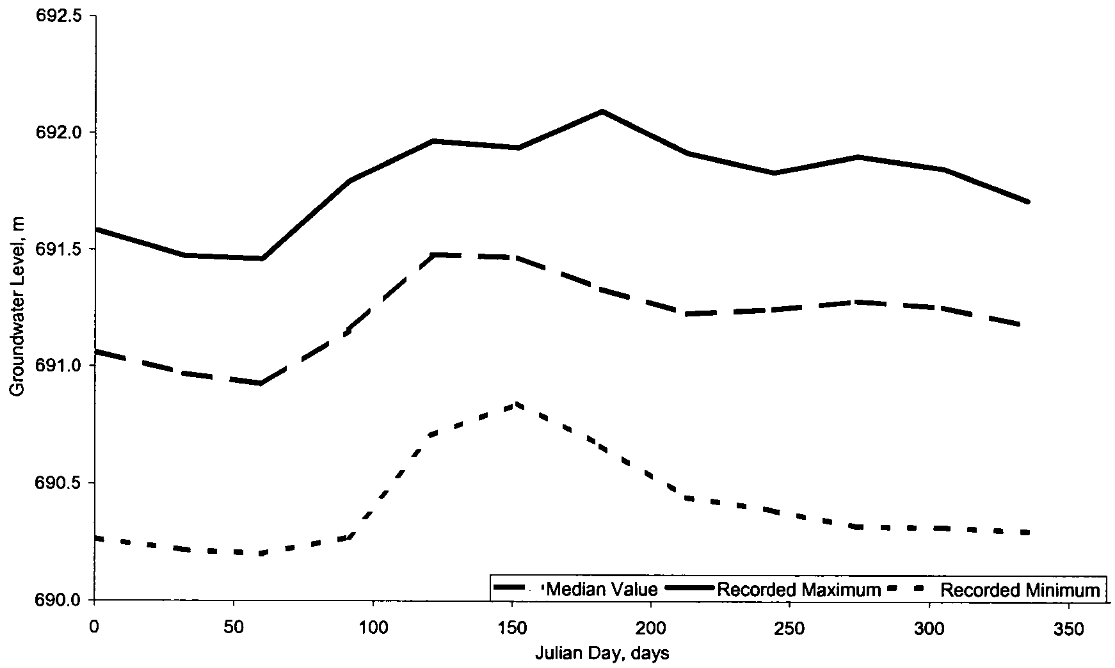

Figure A-3-2: Devon Groundwater Well #159 Hydrograph based on recorded data from 1970 to 2003.

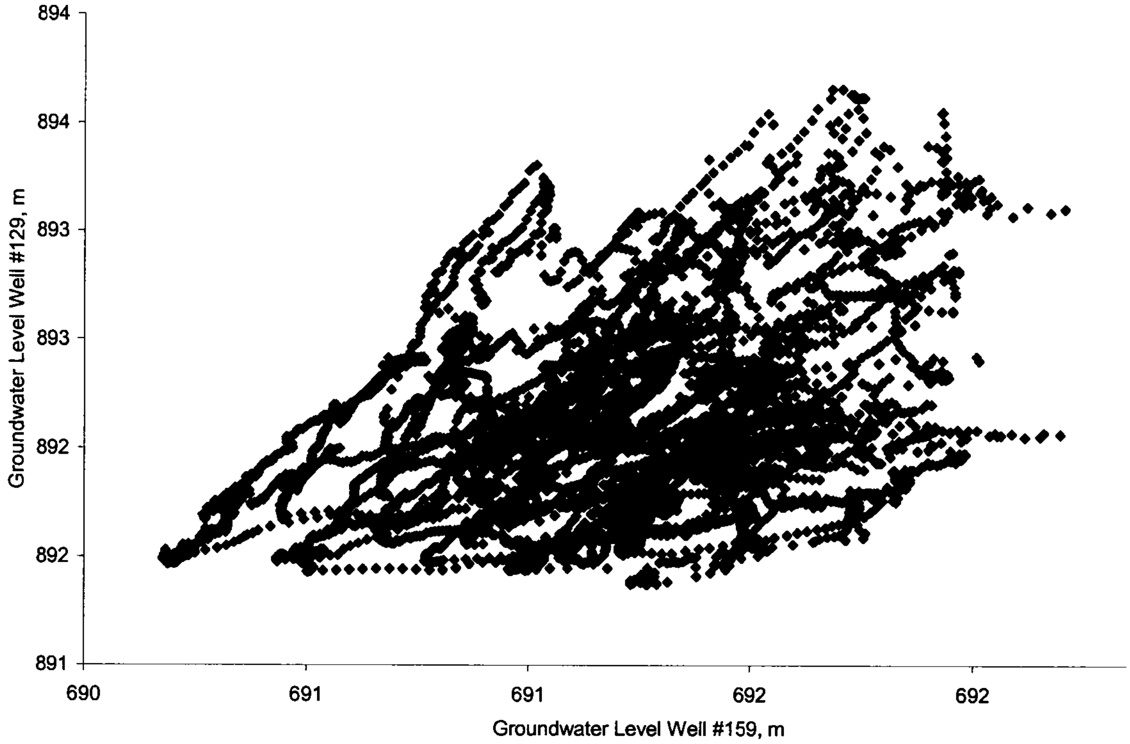

Figure A-3-3: Investigation of Relationship between Groundwater Wells #129 and #159 based on provincial data from 1970 to 2003.

A.4.0 WATER LEVELS AND RIVER FLOWS

Unlike open water conditions, water levels and river flows are not always closely correlated during the ice season. For this reason, water levels and river flows are considered separately.

Both fall and spring water levels are associated with the potential for ice jam formation. In the fall, water levels are considered before and after an ice cover forms on the river. The water level prior to freeze-up may be an indicator of the antecedent basin conditions. The water level after freeze-up plays a role in the potential flow area under the ice sheet that will be available for spring runoff. The change in water levels at a location during freeze-up is an indication of the type of freeze-up. For example, a high stage up during freeze-up could indicate a freeze-up jam has occurred (associated with thicker ice than a juxtaposed ice cover). Spring water levels prior to the spring rise could provide an indication of antecedent basin conditions. Changes in water levels months or weeks prior to river breakup are indicators of the basin response to snowmelt. Changes in water levels immediately prior to river breakup can be dramatic if ice jam are forming and releasing upstream of the site.

The maximum summer flows or late fall can be an indicator of the antecedent basin conditions related to the potential to generate spring runoff. Gerard and Stanley (1988) used the maximum water flow, Q_{fall}, during the month prior to river freeze-up as an indicator of the river freeze-up conditions. If a small storm were to locally impact the gauge during this month, the flow may not be representative of the overall basin conditions. This limitation could be overcome by using the maximum summer flow, Q_{max}, as an indicator of river basin conditions. Since there is evidence to support the selection of a summer or fall river flow, both maximum summer and fall river flows were considered.

River levels can be measured more accurately than river flows. Whereas river levels are measured directly, most streamflow or discharge measurements are determined indirectly. The river flow can be determined by measuring the characteristics of the river channel (flow width and depth) and flow (velocity). To a large degree, the accuracy of the flow measurement depends on the accuracy and consistency of the current meter used to measure the velocity of the water. Fulford (2001) tested several types of current meters and did not find a single manufacturer that produced consistently accurate meters.

A.4.1 WATER LEVEL AND RIVER FLOW DATA SELECTION

The water levels recorded as a river freezes and thaws is different each year; however, some clear patterns have emerged and been identified with physical processes. A general river breakup hydrograph is presented in Figure A-4-1.

Figure A-4-2 shows the water levels recorded during river freeze-up on the Athabasca River near Fort McMurray from October 29 to November 16, 1988. An interpretation of the water level pattern has been provided on the figure and in the following paragraph.

The water level prior to freeze-up, H_{FO}, is the water level associated with the "steady" water level prior to freeze-up. From Figure A-4-2, it can be seen that small fluctuations (in the magnitude of centimeters) occur in the water levels daily. A 7 day average was taken to calculate the value of this "steady" prefreeze-up water level. As the Athabasca River freezes downstream of the gauging site, water levels at the gauging site rise due to backwater effects. As the water level rises, the velocity is reduced. Incoming ice pans collect and the solid ice front extends back to the gauging site to form an ice cover. During freeze-up, the maximum water level, H_F, normally occurs shortly after the solid ice cover forms. A newly formed ice cover may be rough due to over turned ice pans caught in the cover. If sufficient force is applied, the ice cover may be formed by a jumble of over turned pans forming a freeze-up ice jam (also known as a hummocky ice cover). The difference between the maximum water level attained and the water level prior to ice effects, ΔH_F, represents the relative water level change during the freeze-up process. This would add emphasis to the magnitude of the water level change during freeze-up as compared to the maximum value which is partially dependent on the water level prior to freeze-up.

During the winter, water levels are relatively steady. Flows continue to slowly recede during the first few months of the year, appearing steady if viewed on a daily scale. The prebreakup elevation, H_{Winter}, has been selected as the daily average elevation on March 1 since date is likely not impacted by spring melt during any year. For north flowing rivers, spring melt begins in the headwaters prior to any significant change in the river ice conditions in reaches located significantly downstream (and north) of the headwaters. A gradual rise can be seen at the gauging station as melt water increases river flows. For the Athabasca River, the melt water from the Pembina River Basin in the headwaters of the basin must travel over hundreds of kilometres before it reaches the gauge below Fort McMurray. The dampening effects on the melt water hydrograph traveling a long distance under an ice cover result in a gradual rise in water levels. The gradual rise in stage preceding breakup, $\Delta H/\Delta t$, continues until local effects of spring runoff or ice movement become significant. The water level, H_{BO}, is the stage at which it is no longer possible to clearly identify the contribution of runoff from the upper headwaters. As melting begins in the lower basin, diurnal fluctuations in the water levels can be observed since the daily fluctuations are not masked by dampening effects. The rising water levels raise the ice cover, exerting force on the ice. As the ice begins to shift, sporadic changes in the water levels occur. This may be water level waves due to the occurrence of jam release scenarios upstream of the gauge or it could be the result of ice shifting near or over the water level sensor itself. The maximum water level, H_B, is the highest stage achieved during breakup regardless of the contributing process (runoff, ice jam, backwater, etc.) The ice sheets can become free to move by several processes. As the ice interface is removed from the water's surface, the water levels will drop due to the decrease in frictional resistance. Normally the continuing increase in melt water is not significant compared with the reduction in water levels due the removal of the ice cover. Despite the small changes in water levels due to remnant ice, the water level gauge is considered to be free of ice effects once the main river ice cover has been removed and backwater effects from downstream ice formations are no longer impacting the readings.

A.4.2. ATHABASCA RIVER

Federal Water Survey of Canada gauges are located on the following rivers:

1. the Athabasca River
    a. at the Town of Athabasca
    b. downstream of Fort McMurray
2. the Clearwater River
    a. near Draper

As of 2004, there are no provincial water level gauges on these rivers in reaches of interest. Without a reasonable length of record, it is difficult to access the value of data collected at a gauge site.

The WSC gauge at the Town of Athabasca is the closest long term upstream gauge for Fort McMurray. Historically , it has been perceived that events at this location (rate of water level rise, maximum water level obtained during breakup, etc.) have a significant impact on future events more than 300 km downstream at Fort McMurray.

The WSC gauge "Athabasca River near Fort McMurray" is located approximately 10 km downstream of Fort McMurray. Because of its downstream location, this gauge frequently does not reflect the magnitude of river breakup events in Fort McMurray. However, water level conditions that persist at a relatively steady state for several weeks, such as midwinter water levels, may be sufficiently represented with this gauge.

The Clearwater River at Draper is a WSC gauge located approximately 13.0 river km upstream of the mouth of the Snye, which is the main boat launch site in Fort McMurray. The site is located a sufficient distance from the confluence of the Athabasca River to minimize the impact of backwater effects in small to mid sized high water events. The Clearwater River rarely contributes any impact to breakup on the Athabasca River as it is generally ice covered with relatively low flows.

Water levels at the WSC gauges in the Town of Athabasca and below Fort McMurray were evaluated. Water levels along the Clearwater River have been documented for nearly three decades by manual measurements and observations. This site receives significant attention because overflow from the Clearwater River is the primary source of river breakup flooding for Fort McMurray. Typically, the water levels have been recorded at MacDonald Island at the mouth of the Clearwater Confluence. Water levels in this area are sufficiently removed from the gauging site on the Clearwater River that they will be considered a separate entity in this study.

For the Athabasca River at Fort McMurray, freeze-up data is presented in Table A.4.1 and has been taken from Robichaud (2003) for the years 1972 to 2000. These data included the values for H_O, H_F, and ΔH_F. All other values are based on hourly data obtained directly from Water Survey of Canada. For 2001 to 2004, only preliminary data was available for analysis. This means that WSC has not done a complete quality control evaluation of the data and that is subject to change at a future date of publication. Alberta Environment's real-time collection of WSC data was used for the preliminary data. Data originally disregarded by AENV quality control was re-evaluated as it was critical to visualize the freeze-up signature, not just the data deemed valid. Without knowledge of the internal data collection system within AENV, it would not be possible to view all of the data critical to this analysis.

In addition, Table A-4-1 contains the maximum flow data for both the summer (May 15 to October 31) and the maximum flow prior to freeze-up (October1 to

31). River flow trends were examined to select appropriate representation of summer and fall river flows. Figure A-4-3 compares the maximum summer flows recorded at the Town of Athabasca with the maximum summer flows recorded below Fort McMurray. Since the majority of the flow is generated by runoff in the upper and midbasins, the close correspondence between the flows recorded at the upstream site compared with the downstream site seems reasonable as little runoff would impact the river between these two sites. Late in the fall, the relationship between the two gauging sites is less apparent. As illustrated in Figure A-4-4, there is considerable less strength in the linear regression relationship. There are several possibilities for the change in the relationship. For example, small amounts of local runoff could have a larger impact during low flows. The measurement of the flow itself is less accurate during low flows and may contribute to cumulative errors.

Similar water level and flows were determined for the gauging site at the Town of Athabasca and are presented in Table A-4-2. This data was created from WSC hourly gauge data. Hourly data was analyzed and the significant variables are reported in the table.

Robichaud (2003) presented the recorded breakup water level data for the WSC gauge below Fort McMurray and provided detailed discussion on each year of data. Table A-4-3 contains data from Robichaud's database and has been updated with preliminary WSC data and Alberta Environment data.

Robichaud (2003) reported water levels at the Clearwater River Confluence as reported by several sources such as Alberta Environment, Alberta Research Council, the Municipality of Wood Buffalo, and the University of Alberta. In several instances, the water level was measured at locations in the vicinity of Fort McMurray and transposed to the confluence by questionable methods. For example, Yaremko (1978) suggest that water levels measured at the MacEwan Bridge are representative of water levels measured at the confluence less one meter. In 1979 and 1987, data was collected at both locations with a water level difference between the two sites of only 0.6 m. Friesenhan (2004) used HEC-RAS to extensively model ice jams in the vicinity of Fort McMurray. Friesenhan concluded that the effects of discharge, ice jam location, ice jam thickness and ice jam roughness are too significant to apply a general rule of thumb one metre reduction to transpose water levels from the MacEwan Bridge to the Clearwater River Confluence.

An extensive search of the provincial government records revealed additional data for river breakup at Fort McMurray. For example, water levels during the spring of 1970 rose to at least similar levels to that experienced in 1996. Although water levels were never recorded, several labelled photos were found in the provincial files. Water levels were determined from easily identifiable sites. For example, the go-cart track below MacEwan Bridge in Figure A-4-6 is remains in the same location today. The approximate date of the photos were also verified by the presence (or absence) of structures in the photos. While Doyle (1987) correctly reported the WSC gauge reading to be 238.4 m, there is no mention of the water levels at Fort McMurray.

This additional data would have a large impact on any statistical model. From 1970 to 1999 there are now six years (1970,1974,1977,1979,1996, and 1997) when water levels exceeded the emergency warning level of 246.0 m. In a small data set of 20 years, reclassification of a single year can have a large effect statistical reporting methods that are meant for large data sets. For example, the percentage of high water level years increases from 25% to 30% with the inclusion of 1970. Results from this calculation (and more complex statistics) are very sensitive to each data point since the data set is small. Often the people involved in emergency management planning are not aware of this sensitivity and may feel misled when the data interpretations, such as percentages, are changed significantly.

Published documents identified by Robichaud (2003), Alberta Environment archives, and results from Friesenhan (2004) were reviewed. Based on supporting evidence such as photos, the annual maximum water levels at the Clearwater River Confluence were determined and are listed in Table A-4-6.

The majority of the water levels modeled by Friesenhan (2004) were not significantly (more than 0.5 m) different than those reported in historical accounts. One exception is the water level for 1984 were reported by Winhold and Bothe (1993) which were originally estimated as one meter lower than the actual measurement at MacEwen Bridge. Results presented by Freisenhan (2004) suggest 243.50 m is too high and an elevation of 241.72 m is more appropriate.

Table A-4-1: Freeze-up Data for the Athabasca River at Fort McMurray.

Year	H_{Fo} (m)	H_F (m)	ΔH_F (m)	Qfall (cms)	Qmax (cms)
1972	237.71	240.15	2.44	3620	657
1973	238.22	239.52	1.30	2510	886
1974	237.83	239.16	1.33	2970	680
1975	237.71	239.10	1.38	2460	748
1976	237.63	238.80	1.17	2080	787
1977	237.82	239.09	1.26	2800	966
1978	237.94 [a]	239.20 [a]	1.26 [a]	2390	1260
1979	237.46	238.74 [a]	1.28 [a]	2900	720
1980	237.58	238.47	0.89	3930	1040
1981	237.24 [a]	237.84 [a]	0.60 [a]	1410	393
1982	237.64	238.81	1.18	3490	735
1983	237.62	238.56	0.94	2290	528
1984	238.08	239.36	1.28	1940	853
1985	237.63	238.87	1.24	1920	772
1986	237.67	239.25	1.58	4440	938
1987	237.21	238.78	1.57	2090	409
1988	237.39	239.03	1.64	2190	430
1989	237.65	238.92	1.27	2720	778
1990	237.36	238.68	1.32	3250	542
1991	237.42	238.88	1.46	2250	506
1992	237.33	238.84	1.51	1430	552
1993	237.47	239.07	1.59	1280	525
1994	237.31	238.02	0.71	2080	544
1995	237.51 [a]	239.53 [a]	2.02 [a]	3050	421
1996	-	-	-	2890	1030
1997	237.96	238.97	1.01	3900	1270
1998	237.39	238.42	1.02	1780	392
1999	237.11	238.43	1.32	2040	361
2000	237.46	238.32	0.86	1780	458
2001	237.27	238.28	1.01	2930	344
2002	237.64	244.00	6.36	1190	390
2003	237.61	239.62	2.01		
2004	237.75	239.34	1.59		

[a] WSC gauge below Fort McMurray malfunctioning, detailed explanation provided by Robichaud (2003).

Table A-4-2: Freeze-up Water Level Data for the Athabasca River at the Town of Athabasca.

Year	H_{Fo} (m)	H_F (m)	ΔH_F (m)	Qfall (cms)	Qmax (cms)
1972	no data	no data	no data	3370	544
1973	no data	no data	no data	1840	419
1974	236.05	236.30	0.25	2520	362
1975	236.13	236.27	0.14	1790	289
1976	236.17	236.30	0.13	1630	430
1977	no data	no data	no data	2340	790
1978	236.08	236.27	0.19	2290	835
1979	236.80	237.42	0.63	2230	312
1980	236.95	237.33	0.38	4190	563
1981	no data	no data	no data	1240	232
1982	236.71	237.40	0.69	3420	597
1983	236.69	237.05	0.36	1550	299
1984	237.13	237.95	0.82	1390	585
1985	no data	no data	no data	1450	556
1986	236.92	237.53	0.61	4400	750
1987	236.44	236.80	0.35	2040	273
1988	236.77	237.95	1.18	1580	274
1989	236.92	237.79	0.86	2320	477
1990	236.68	237.44	0.76	2690	332
1991	236.88	237.24	0.36	1870	291
1992	236.56	236.68	0.12	1020	321
1993	236.70	237.50	0.80	919	306
1994	236.75	237.14	0.39	1640	449
1995	236.65	237.07	0.42	2160	245
1996	237.32	237.75	0.43	2570	468
1997	237.40	237.53	0.13	2880	781
1998	236.92	236.98	0.06	1610	314
1999	236.54	237.13	0.59	2100	263
2000	236.79	236.94	0.15	1510	286
2001	236.48	237.17	0.69	2580	268
2002	236.62	237.61	0.99	1130	294

Table A-4-3: Spring Water Level Data from WSC gauge "Athabasca River below Fort McMurray" including water level prior to breakup, H_{Bo}, spring runoff water level rise, $\Delta H/\Delta t$, maximum water level during river breakup, H_B.

Year	H_{Bo}	$\Delta H/\Delta t$ (m/d)	H_B
1973	239.0	0.065	240.5
1974	239.8	0.400	241.4 [a]
1975	238.7 [a]	0.094 [a]	239.7 [a]
1976	239.0	0.131	242.4 [a b]
1977	238.9 [a]	0.123 [a]	244.2 [a b]
1978	239.0	0.037	240.6
1979	239.4	0.200	244.9 [a]
1980	238.9	0.094	240.7
1981	239.0	0.085	240.7 [a b]
1982	-	-	238.9 [a b]
1983	238.5	0.059	239.6
1984	238.4	0.029	240.9
1985	239.0	0.100	241.2 [a b]
1986	239.0	0.065	240.9
1987	239.1	0.083	240.7 [a]
1988	238.4 [a]	0.133 [a]	240.6 [a]
1989	238.2 [a]	0.022 [a]	238.2 [a]
1990	238.6 [a]	0.028 [a]	239.3 [a]
1991	238.7	0.172	240.1 [a]
1992	238.6	0.016	239.5
1993	238.5 [a]	0.032 [a]	238.5 [a]
1994	238.7	0.122	242.8
1995	238.7	0.176	239.0
1996	239.1	0.500	243.2
1997	-	-	-
1998	238.7	0.050	239.0
1999	238.0	0.045	238.5
2000	238.3	0.055	238.6
2001	-	-	-
2002	237.39	0.104	238.463
2003	237.66	0.013	244.157
2004	237.88	0.003	238.00

[a] WSC gauge below Fort McMurray malfunctioning
[b] Water level obtained from ARC

Table A-4-4: Spring Water Level Data from WSC gauge "Athabasca River at the Town of Athabasca" including water level prior to breakup, H_{Bo}, spring runoff water level rise, $\Delta H/\Delta t$, maximum water level during river breakup, H_B.

Year	Feb 1 Water level (m)	H_{Bo}	$\Delta H/\Delta t$ (m/d)	H_B
1973	no data	no data	no data	no data
1974	236.183	236.677	0.563	237.24
1975	236.186	236.194	0.659	236.853
1976	236.173	236.213	0.415	236.628
1977	236.186	236.237	0.994	237.231
1978	no data	no data	no data	no data
1979	236.904	237.657	1.019	238.676
1980	237.076	237.37	1.436	238.806
1981	no data	no data	no data	no data
1982	236.654	236.911	1.475	238.386
1983	236.786	237.008	0.602	237.61
1984	236.992	237.384	0.734	238.118
1985	237.035	237.5	2.19	239.69
1986	236.9	237.137	0.945	238.082
1987	237.182	237.299	1.73	239.029
1988	236.757	236.965	0.326	237.291
1989	236.908	237.35	1.717	239.067
1990	236.95	237.15	0.659	237.809
1991	236.974	237.808	0.731	238.539
1992	236.805	237.667	0.718	238.385
1993	236.664	237.36	0.621	237.981
1994	237.11	238.194	0.72	238.914
1995	236.814	236.999	0.512	237.511
1996	237.188	236.996	3.208	240.204
1997	237.216	236.95	2.491	239.441
1998	236.834	237.61	0.561	238.171
1999	236.774	237.26	1.106	238.366
2000	236.749	237.05	0.08	237.13
2001	236.7	236.78	2.115	238.895
2002	235.821	236.87	0.29	237.16
2003		236.89	1.28	238.17
2004		236.9	1.69	238.59

Table A-4-5: Spring Water Level Data for the Clearwater River Confluence based on recorded and modeled water levels including, maximum level during river breakup, H_B.

Year	H_B	**Source**
1972	244.3	Yaremko (1978)
1973		No data
1974	246.7	Yaremko (1974), Alberta Environment
1975		No data
1976		No data
1977	247.6	Doyle (1977)
1978	242.0	Doyle and Andres (1978)
1979	246.9	Doyle and Andres (1979)
1980	244.4	Modeled by Robichaud (2003)
1981	244.0	Alberta Environment
1982	242.2	Rickert and Quazi (1982)
1983	242.3	Andres and Rickert (1984)
1984	241.7	Modeled by Friesenhan (2004)
1985	243.5	Andres and Rickert (1985)
1986	244.0	Malcovish et. Al (1988)
1987	245.1	Winhold (1988)
1988	244.5	Rickert and Quazi (1989)
1989	243.1	Alberta Environmental Protection (1993)
1990	243.0	Alberta Environmental Protection (1993)
1991	244.6	Modeled by Robichaud (2003)
1992	241.4	Alberta Environment
1993	243.5	Modeled by Robichaud (2003)
1994	244.0	Alberta Environment
1995	244.4	Modeled by Robichaud (2003)
1996	245.9	Alberta Environment
1997	247.0	Regional Municipality of Wood Buffalo
1998	243.3	Modeled by Robichaud (2003)
1999	240.4	Robichaud (2003)
2000	240.6	Robichaud (2003)
2001	240.9	Robichaud (2003)
2002	242.0	Friesenhan (2004)
2003	241.2	Friesenhan (2004)

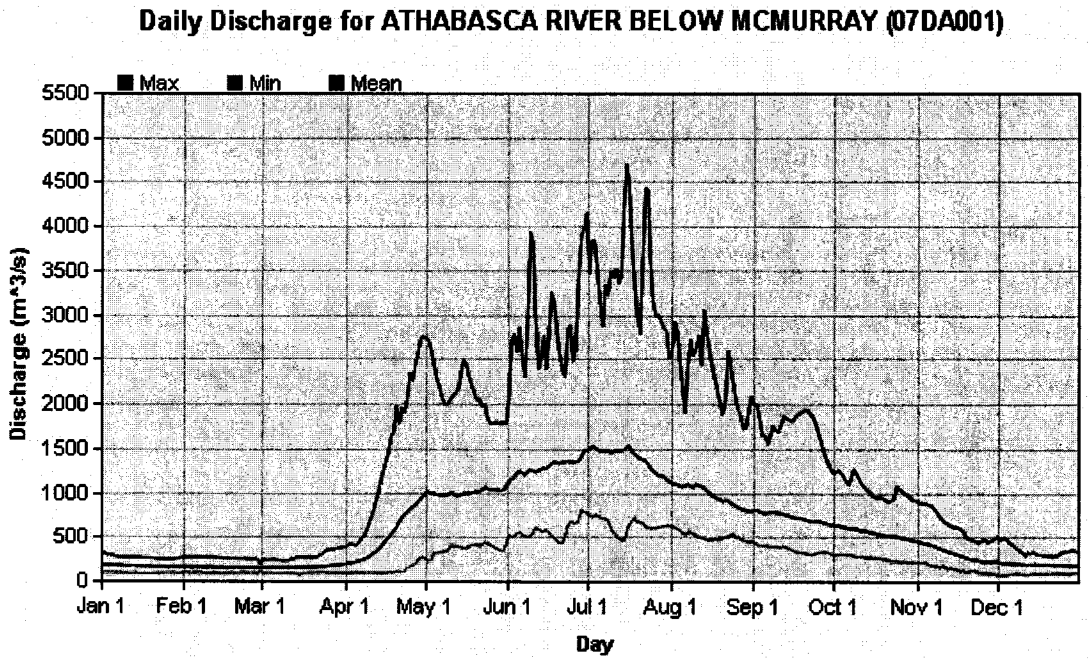

Figure A-4-1: Athabasca River at Fort McMurray: Annual Hydrograph (MSC, 2004).

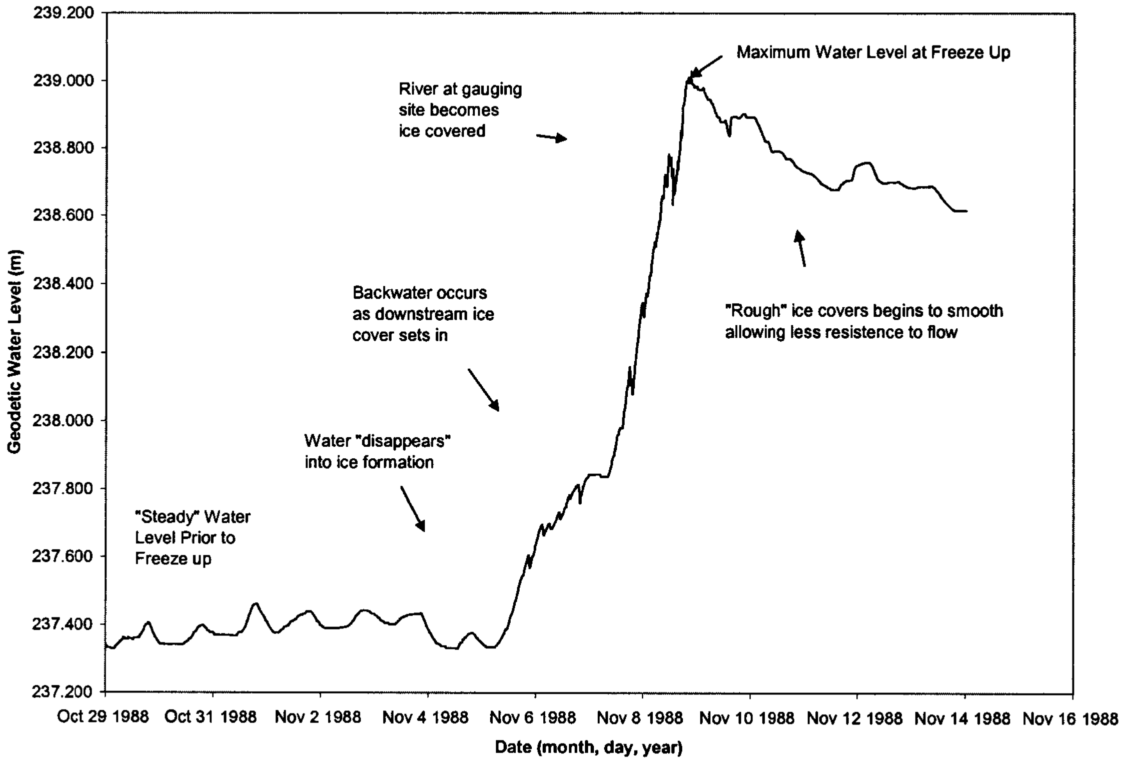

Figure A-4-2: Athabasca River at Fort McMurray: Typical Freeze-up Hydrograph.

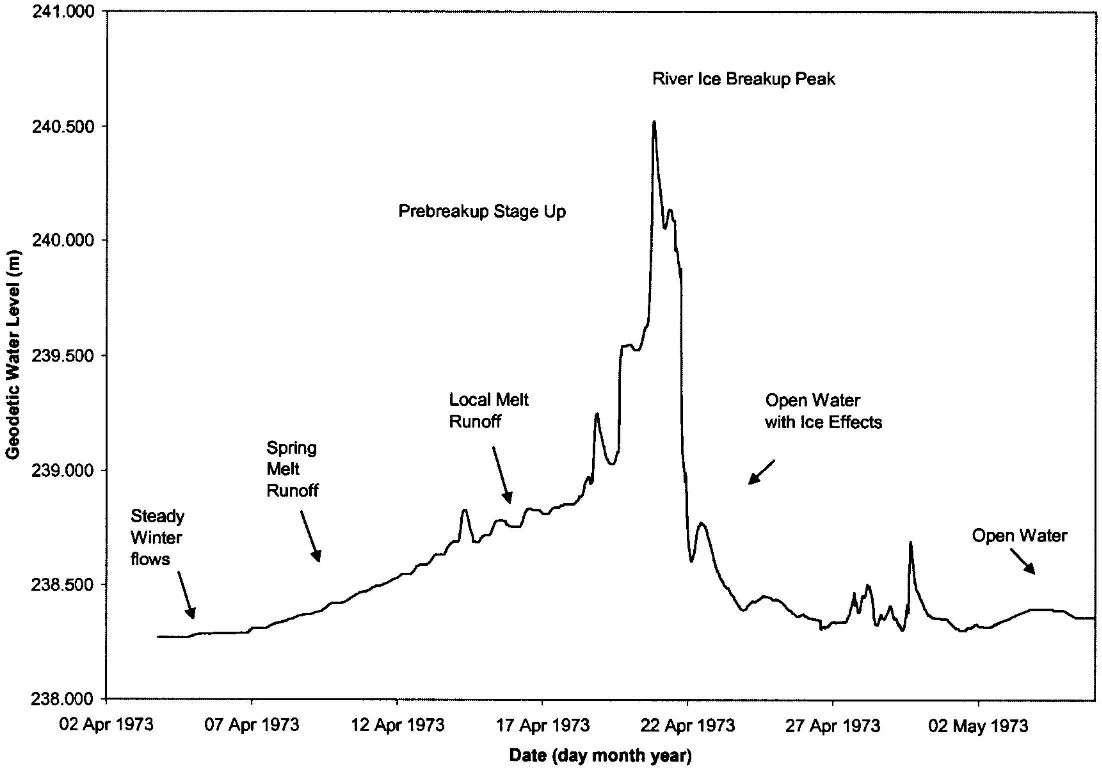

Figure A-4-3: Athabasca River at Fort McMurray: Typical Breakup Hydrograph (no ice jams).

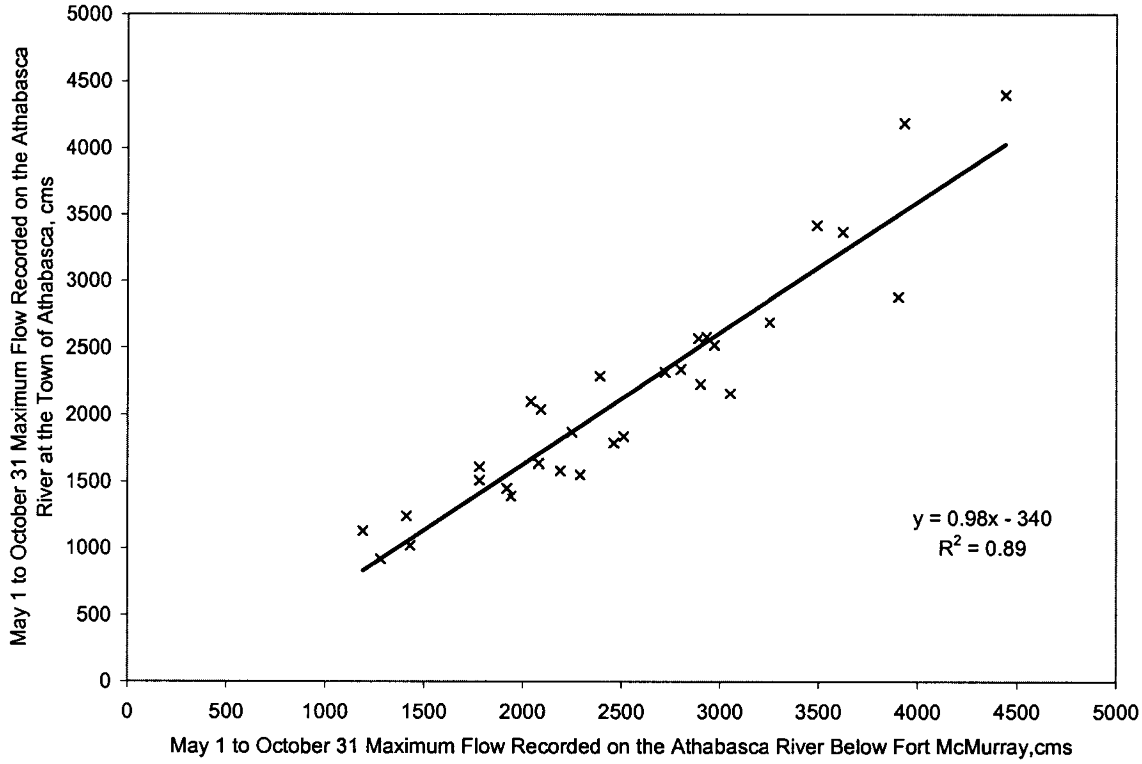

Figure A-4-4: Comparison of Peak Summer Flows Recorded for the Athabasca River Recorded at the Town of Athabasca and at Fort McMurray.

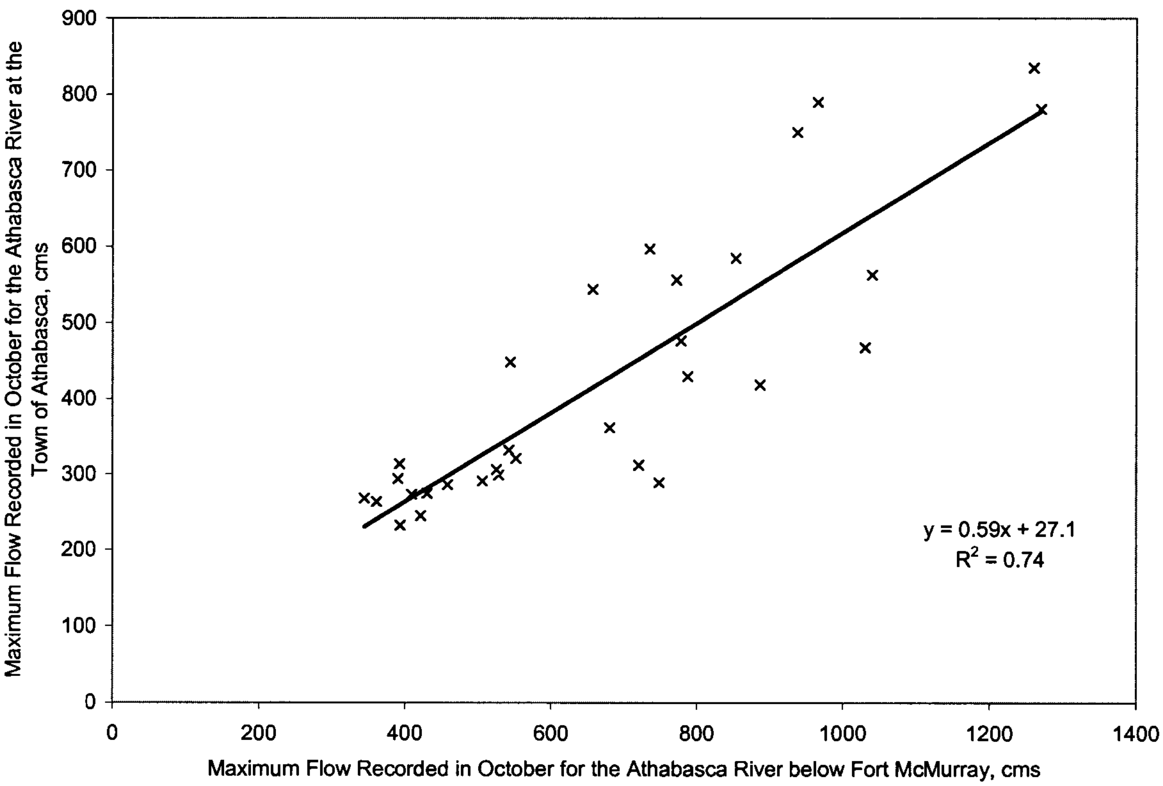

Figure A-4-5: Comparison of Peak Summer Flows Recorded for the Athabasca River Recorded at the Town of Athabasca and at Fort McMurray.

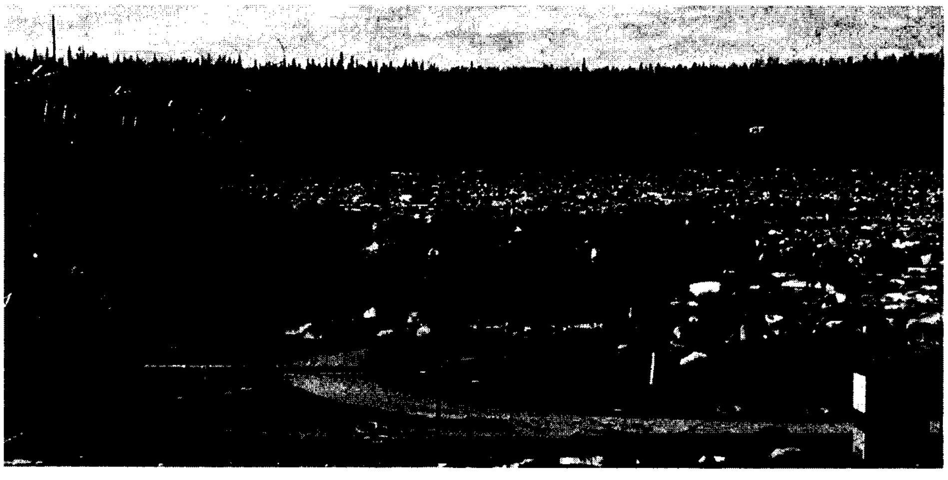

Figure A-4-6: Photo evidence of water levels during river break in 1970 (Go-Cart track just downstream of MacEwan Bridge).

A.5.0 SOLAR RADIATION

River ice processes may also be highly dependant on solar radiation. Ashton (1986) stated that solar radiation is a key element in river ice breakup. Without knowledge of the importance of this variable, river breakup can be puzzling. After observing breakup at the Paddle River near Barrhead on March 10, 1985, Andres and Rickert (Dec, 1985) reported that it was *"very difficult to explain this phenomena on the basis of the meteorological observations"* referring to the average temperatures that were well below 0°C and no significant precipitation recorded in the basin.

In 1969, Shulakovskii reported that solar radiation is independent of air temperature. This is not a universally accepted fact. Hargreaves and Samani (1982) recommended an equation to estimate solar radiation based on the product of square root of the daily average temperature, extraterrestrial radiation and an empirical coefficient. This equation cannot be used for daily average temperatures below zero due to the square root function.

Bristow and Campbell (1984) showed that minimum and maximum daily temperatures could be correlated with the amount of solar radiation received to provide a general relationship. In their relationship, warmer temperatures would be expected on days with clear skies and cooler temperatures would occur on cloudy days. This relationship is counter intuitive to the climate of Alberta where warmer days often result from a solid cloud cover which prevents the heat from a previous warm spell from radiating away from the earth. Samani (2000) states that correlations between temperatures and solar radiation will be influenced by external factors such as elevation, topography, storm patterns, and advection and proposes modifications to reduce the estimation error to 15%. Irmak et al. (2003) reported significant improvements in modeling solar radiation based on temperature if relative humidity was incorporated into the model.

The amount of solar radiation is important in the river breakup process in that it transfers heat to the ice cover, snow cover and to stretches of open water. The more intense the solar radiation during river breakup, the more energy is available to the heat transfer processes to increase the rate at which the events leading to river breakup will occur. Solar radiation on the snow pack on the land in the basin will melt the snow increasing the amount of runoff water entering river. By melting snow on the ice cover, the albedo of that particular area of the ice is significantly reduced allowing more heat to be absorbed by the ponded water on the ice cover. This results in more heat being transferred to the top of the ice cover (due to the reduction in surface albedo which results). Where there is no snow on the ice cover, the ice is directly exposed to solar radiation. As ice is removed from the river, either by thermal or dynamic means, stretches of open water are available to absorb solar radiation. Water has a much lower albedo than ice and is able to absorb relatively large quantities of heat. The heat in the water plays a significant role in reducing the volume of ice in the downstream reaches of the channel. During the 2003 River breakup in Hay River, I observed that ice jams could melt out at a visible rate due to the heat transfer from the water to the ice.

While solar radiation can be measured at a location, there are many factors that may lead to it not being representative of a larger area. The amount of incoming solar (shortwave) radiation reaching a surface is influenced by the latitude of the site, orientation and slope, distance from the sun or time of the year, time of day, atmospheric conditions (such as clouds), land cover type (forests, snow cover, etc) and reflectivity of the ice itself.

A.5.1 SOLAR RADIATION MEASUREMENT

Solar radiation is measured by pyrometer or a sunshine ball. The measurement is normally expressed in a rate of energy transferred to a surface per unit of time, such as kilojoules over a square metre per second (W/m2/s or KJ/s). Sunshine balls measure the intensity of the solar radiation by burning a hole in a strip of paper. Sunshine balls require a large commitment of manual operation time because the paper strips must be changed daily, and the burned strips manually interpreted. Pyrometers record the incoming solar radiation per area onto an electronic sensor. The sensor is surrounded by a glass or plastic shield dome to prevent dust and debris from damaging the sensor.

Although not as manually intensive as the sunshine ball, pyrometers do require much more manual maintenance than many types of environmental monitoring equipment. Without regular maintenance, it is common for a pyranometer to have errors of 10% just in instrument drift (Samani, 2000). For this reason, the Meteorological Services of Canada operates far fewer solar radiation sensors than temperatures sensors. Alberta Environment does not maintain any solar radiation data collection sites. MSC solar radiation data collection sites are shown in Figure A-5-1.

A.5.2 THEORETICAL CALCULATIONS OF SHORT-WAVE SOLAR RADIATION

The solar radiation received by a perpendicular surface at the top of the earth's atmosphere is considered a solar constant, although slight variations have been detected by satellites. The accepted value for the solar constant is 1367 W/m^2 (Kreith and Kreider, 1978). Ashton (1986) reports that the solar constant of 1353 W/m^2 which varies by 3% during the year and recommends that 1380 W/m^2 be used for winter. Kumar et al. (1997) adjust the seasonal value of the direct normal solar radiation based on Julian day as:

$$I_o = 1367\left(1 + 0.034\frac{\cos(360JD)}{365}\right) \qquad \text{(A.5.1)}$$

where:

I_o = solar constant, 1367 W/m^2

JD = Julian Day (ie: Jan 1 =1, Jan 2=2....Dec 31=365)

After the acceptance of a solar "constant", the maximum global solar radiation can be calculated based on the latitude of the site as was done by Shaw (1936). A detailed description of this process can be found in many textbooks. The summary below is edited from Ashton (1986). The first step in calculating the daily maximum solar radiation is to calculate the intensity of radiation incident on a horizontal plane above the earth's atmosphere. This is based on the solar altitude, α, which is the angle between the sun's rays and the horizon.

$$\phi_{So} = I_o \sin\alpha \qquad \text{(A.5.2)}$$

where:

Φ_{So} = intensity of radiation incident on a horizontal plane above the earth's atmosphere, W/m^2

α = angle between the sun's rays and the horizon, W/m^2

Solar altitude is a function of latitude, time of year and time of day. From basic trigonometric principals, Ashton (1986) describes solar altitude as:

$$\sin\alpha = \sin Lat \sin\delta + \cos L \cos\delta \cos H_{sun} \qquad \text{(A.5.3)}$$

where:

Lat	=	latitude (54.6° North for Fort McMurray)
δ	=	declination of the sun
H_{sun}	=	local hour-angle of the sun

Declination of the sun is the angle between the axis of the earth and the orbital plane of the earth. Declination varies during the year as follows:

$$\delta = 23.45\cos\frac{360}{365}(172 - JD) \qquad \text{(A.5.4)}$$

The local hour angle of the sun, H, accounts for the rotation of the earth about its axis. One hour equals 15 degrees.

Once the intensity of the incident radiation above the atmosphere is calculated, approximations can be made to estimate the maximum daily solar radiation that would reach the ground which is known as solar insolation. Insolation includes both the direct solar radiation that makes its way to the ground and the diffuse radiation which reaches the ground.

$$\phi_S = \phi_{So} a_t^{\ m} \tag{A.5.5}$$

where:

Φ_S	=	solar insolation
a_t	=	transmittance of the atmosphere
m	=	optical air mass

A.5.3 SOLAR RADIATION FOR THE ATHABASCA RIVER BASIN

Figure A-5-1 shows that for Fort McMurray, the nearest MSC station is Prairie River. Since Prairie River is more than 200 km north of the ice jam forecasting site and over 600 km from the midbasin area where snowmelt is generated, other data were investigated.

A.5.3.1 SOLAR RADIATION FOR THE MIDBASIN

There are two solar radiation stations located in and west of Edmonton that would best represent the midbasin solar radiation. Since the stations with solar radiation are located geographically closely together, solar radiation sites near Edmonton were used to test the correlation of solar radiation stations. If stations relatively close together could be correlated, then it would be reasonable that a single station could be used as an index as to the total solar radiation incident in the basin.

The solar radiation data is collected at the MSC site 301222F or Stony Plain. Prior to 1994, solar radiation data was collected exclusively with a pyrometer. There are frequent gaps in the data as pyrometers are subject to occasional mechanical/electrical failure and are difficult to repair. From 1993 to 2003, data was collected with both a pyrometer and a sunshine ball as hours of bright sunshine. Pyrometer and sunshine ball data are compared in terms of percentage of maximum sunshine.

The solar radiation data was converted from a total daily value in MJ/m^2 to an hourly average value in $kJ/\ m^2$. Data for the pyrometer was tabulated and a sinusoidal curve was created to express the maximum solar radiation as a function of the Julian day in relation to the winter equinox. Since the latitude for the station is a constant, an equation was developed based on the theoretical variation of the declination with the time of year. The coefficient and offset for the equation reflect the solar radiation. The net maximum daily solar radiation was determined to be:

$$S_n = 160 \cos \frac{360}{365}(172 - JD) + 210 \quad \text{(A.5.6)}$$

where:

S_n = net average hourly solar radiation flux, kJ/ m^2

Shaw (1936) calculated the energy that would have been received by direct radiation from the sun if there were no atmosphere and reported the values at weekly intervals. The values reported by Shaw have been interpolated for the Stony Plain Station which has a latitude of 53.582 °.

Missing solar radiation flux data was estimated from the sunshine data available at the same location. Gray (1970) provides a method for comparing solar radiation measured by sunshine balls and pyranometers. The total solar radiation flux is converted to a percentage of the maximum possible total solar radiation flux for the day by division. The percentage of the maximum hours of bright sunshine is calculated in a similar method. For comparison purposes, the equation relating solar insolation (as a percentage of maximum possible solar insolation) to bright sunshine (as a percentage of maximum possible hours of bright sunshine) is as follows:

$$\frac{Q_s}{Q_A} = a + b\frac{n_{sun}}{N} \qquad \text{(A.5.7)}$$

where:

Q_S	=	incoming short wave radiation, kJ/m^2
Q_A	=	solar radiation at the top of the atmosphere, kJ/m^2
n_{sun}	=	recorded hours of bright sunshine, hours
N	=	day length or maximum possible hours of bright sunshine, hours
a,b	=	coefficients

For Stony Plain, a is determined to be 0.39 and b is 0.60. Results from other studies with daily data comparisons are presented in Table A-5-1. Figure A-5-2 shows the linear relationship between the percentage maximum hours of sunshine and the percentage of the maximum solar radiation which has an r^2 value of 0.80.

Solar radiation is also measured at the Edmonton Municipal Airport (MSC site 3012208), approximately 50 km east of Stony Plain. Data was available for 1972 to 1994 in the form of hours of bright sunshine. Sufficient solar radiation data was not available at Edmonton Municipal Airport to establish a relationship between measured sunshine hours and the measured solar radiation. However, if the data collected at Edmonton Municipal Airport is representative of the solar radiation recorded at Stony Plain, the relationship between the percent of maximum sunshine and percent of maximum solar radiation should be similar to the relationship established for these two parameters at Stony Plain. The coefficients for the regression equation in Figure A-5-3 are similar to those for the Stony Plain site (Figure A-5-2). Although the r^2 value is slightly weaker (0.75 compared to 0.80), the sunshine recorded at the Edmonton Municipal Airport can be used to estimate the solar radiation over 50 km away.

Since the solar radiation data collected at the Edmonton Municipal Airport correlates with the data collected at Stony Plain, it is reasonable to consider that solar radiation recorded at Stony Plain could be an indicator for the solar radiation that would be received in the midbasin (Pembina sub basin of the Athabasca River Basin), located just over a 100 km northwest of Stony Plain. Since no solar radiation is currently collected at in the Pembina basin, it is not possible to establish a relationship between the Stony Plain station and any location within the Pembina River Basin.

While it is recognized that a better estimate of solar radiation in this area may be beneficial to forecasting river ice breakup, none are available at the time of this work. Within the Mackenzie GEWEX Study (MAGS), there is an initiative to develop an estimate of solar radiation based on satellite or other remotely sensed data which will be available to assist with future modeling.

A.5.3.2 Solar Radiation Data for Fort McMurray

In the database created for river ice breakup forecasting, Robichaud (2003) documented the data collection of solar radiation data in Fort McMurray. The record consists of data from a now discontinued MSC station, records collected by a local consulting firm and data from a site established by the University of Alberta. Robichaud (2003) examined the relationship between the recorded hours of bright sunshine and the recorded solar radiation to establish a long term record at the University of Alberta meteorological site.

The only solar radiation data currently available is from the University of Alberta meteorological station in Fort McMurray. Solar radiation data is collected every 5 minutes and the Total Solar Radiation Flux for 30 minutes is reported in kilojoules per square meter. By summation and unit conversion, the daily solar radiation can be reported as the daily total watts per square meter.

A.5.4 MODEL DATA

Three basic values of solar radiation were considered for evaluation in the river ice breakup forecasting models. The total solar radiation accumulated four days prior to breakup, S_4, including the date of breakup was identified by Robichaud (2003) as a potential indicator of the severity of river ice breakup. In this study, the total solar radiation accumulated ten days prior to river breakup, S_{10}, was included based on the reasoning that solar radiation in the vicinity of Fort McMurray could potentially influence the water temperature for a longer time period than accounted for by the S_4 variable.

The total solar radiation accumulated from the first degree day accumulation, S_d, was also used as a potential indicator of the severity of river ice breakup. Degree day were accumulated beginning with the first 5 consecutive days of above zero daily air temperatures and summed until the day of river breakup. The daily average accumulated solar radiation starting March 1 including breakup day, S_{avg}, was also considered with the time averaging used to allow the intensity of the solar radiation over a longer time period to be a factor.

Table A-5-2 contains the solar radiation data for Fort McMurray. The S_4 data reported years prior to 2000 is taken from Robichaud (2003). All data from after 2000 has been obtained from the University of Alberta meteorological station. Calculations for S_{10} and S_d were done from this data.

Table A-5-3 contains the solar radiation data for Stony Plain which is considered an indicator of the solar radiation received in the Pembina River Basin. Since flows in the Pembina River basin cannot reach Fort McMurray in four days, S_4 has not been considered for this site.

Table A-5-1: Published results for the a and b coefficients based on daily data.

Location		a	b	r^2	Reference
Canada					
	Fort Providence, NWT	0.465	0.617	0.89	Hicks et al. (1993)
	Fort McMurray, AB	0.22	0.40	0.91	Robichaud (2003)
	Southern Saskatchewan	0.25	0.60		Gray (1970)
	Southern Saskatchewan	0.34	0.52		Gray (1970)
	Guelph, ON	0.23	0.57	0.92	Selirio et al. (1970)
International					
	Virginia, United States of America	0.22	0.54		Gray (1970)
	Canberra, Australia	0.18	0.55		Gray (1970)
	United Kingdom	0.18	0.55		Gray (1970)
	Trinidad, West Indies	0.59	0.20	0.91	Smith (1959)

Table A-5-2: S_4, S_{10}, S_{avg} and S_d solar radiation data for Fort McMurray.

	Solar Radiation Flux, W/m^2			
Year	S_4	S_{10}	S_d	S_{avg}
1972	593	1521	1834	52
1973	764	1859	3581	64
1974	790	1822	2079	59
1975	605	1733	2763	61
1976	652	1909	2878	69
1977	586	1389	1420	65
1978	423	920	2598	56
1979	619	1263	1039	45
1980	477	1599	2771	65
1981	563	1341	1298	67
1982	608	1106	2313	57
1983	530	1326	730	59
1984	334	1357	2886	66
1985	606	1769	5277	63
1986	374	1540	3424	61
1987	526	1266	2070	52
1988	765	1795	1309	58
1989	691	1995	2282	62
1990	675	1467	3426	65
1991	576	1753	2535	75
1992	409	1554	2836	68
1993	317	823	3084	57
1994	761	1613	0	36
1995	656	800	1420	54
1996	717	1752	2266	74
1997	799	2374	1233	73
1998	653	1930	2890	81
1999	670	1723	3963	69
2000	Data	Not	Available	
2001	775	1699	3996	64
2002	812	1803	3476	65
2003	779	1683	5385	65

Table A-5-3: S_{10}, S_{avg} and S_d solar radiation data for Pembina River Basin as recorded at Stony Plain MSC site.

	Solar Radiation W/m^2		
Year	S_{10}	S_d	S_{avg}
1972	2231.2	2655.4	78.6
1973	2286.9	4153.3	84.6
1974	2553.4	3050.0	88.1
1975	2255.6	3669.5	79.7
1976	2447.8	3899.9	90.4
1977	2308.9	2107.1	91.6
1978	1623.2	3340.9	68.9
1979	2457.7	1796.3	71.5
1980	2199.4	4075.5	93.3
1981	2299.1	1953.0	91.7
1982	2223.8	3909.4	82.8
1983	2244.2	1296.9	77.2
1984	2216.0	4201.9	90.5
1985	2423.4	7107.9	87.1
1986	2086.6	4726.9	76.4
1987	1909.4	3295.0	77.5
1988	2605.3	1967.9	83.4
1989	2743.0	2895.1	86.7
1990	2369.3	4857.2	84.4
1991	2419.8	2974.7	92.6
1992	2345.9	3853.3	93.9
1993	1915.4	4523.8	73.9
1994	2149.2	5788.5	94.9
1995	1935.6	2560.6	71.9
1996	2929.9	3639.0	99.8
1997	2627.1	1222.3	87.2
1998	2326.4	2956.7	88.3
1999	1494.8	5415.5	92.7
2000	2182.6	6199.8	73.6
2001	2255.7	4577.3	76.8
2002	2553.2	6198.9	99.3
2003	2746.6	8952.1	105.7

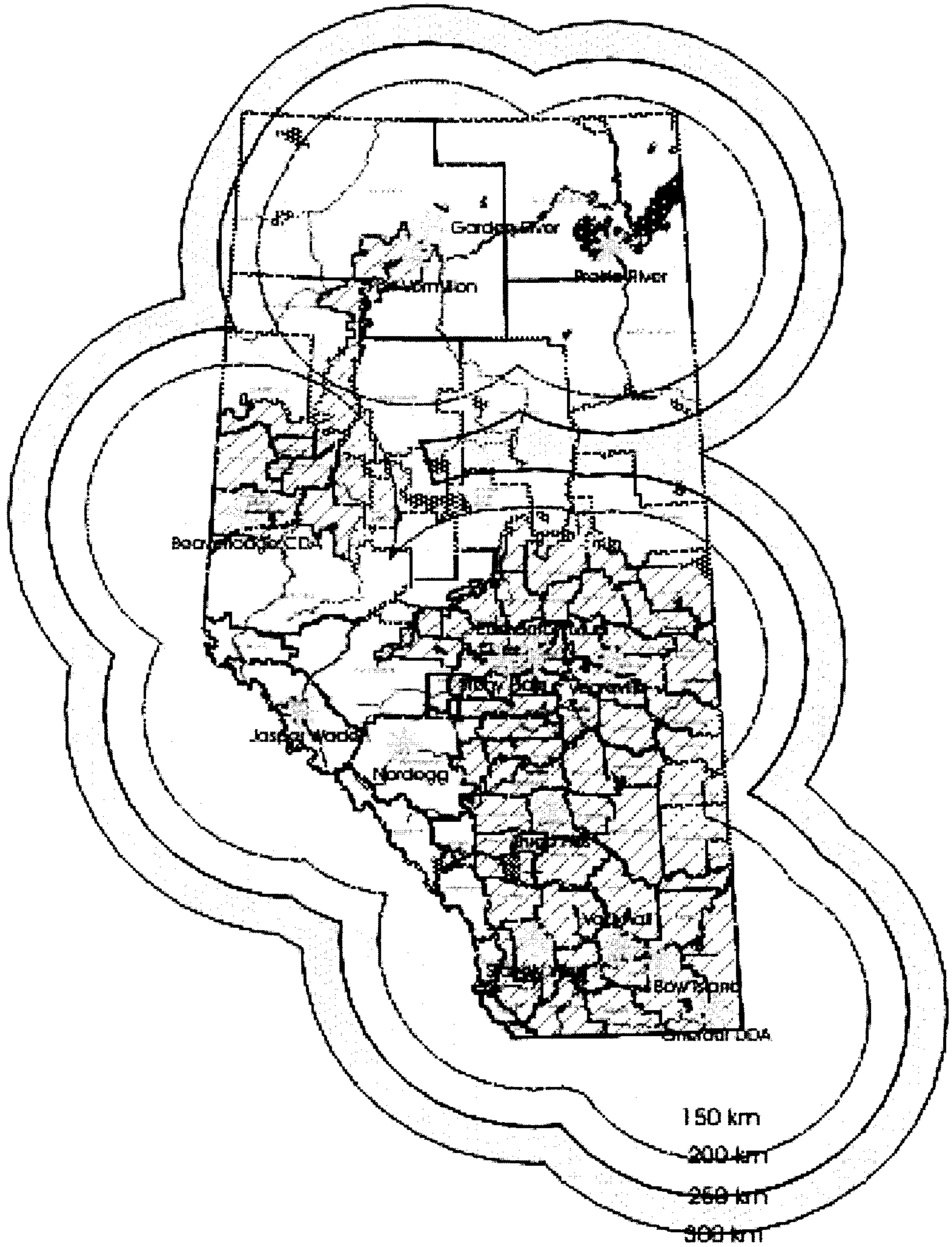

Figure A-5-1: Solar Radiation Stations and Coverage Map for Alberta provided by MSC (2004).

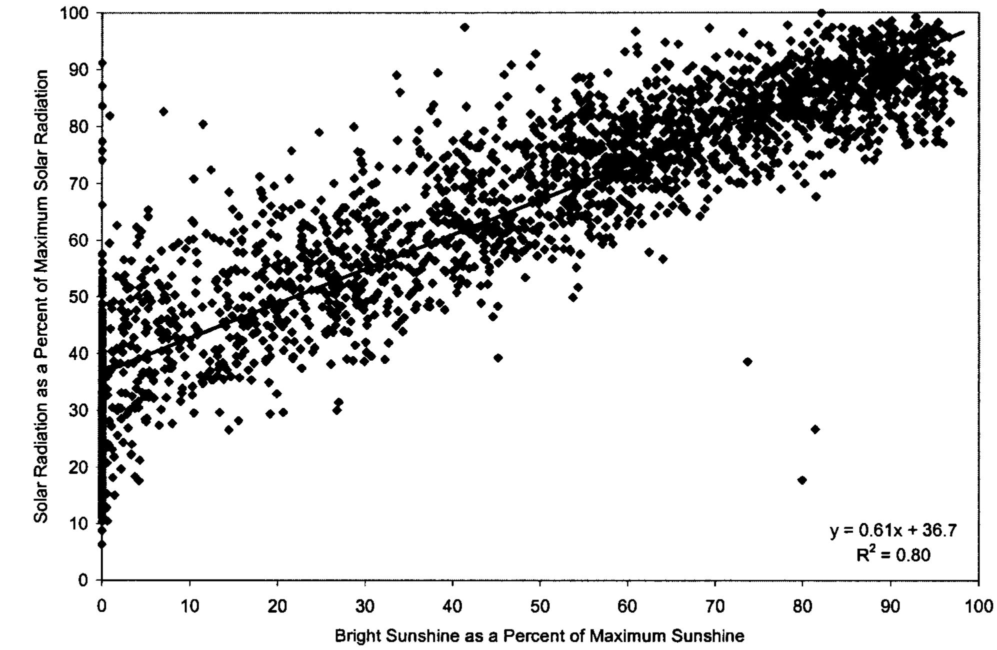

Figure A-5-2: Relationship between duration of bright sunshine and solar radiation at Stony Plain, 1993 to 2001.

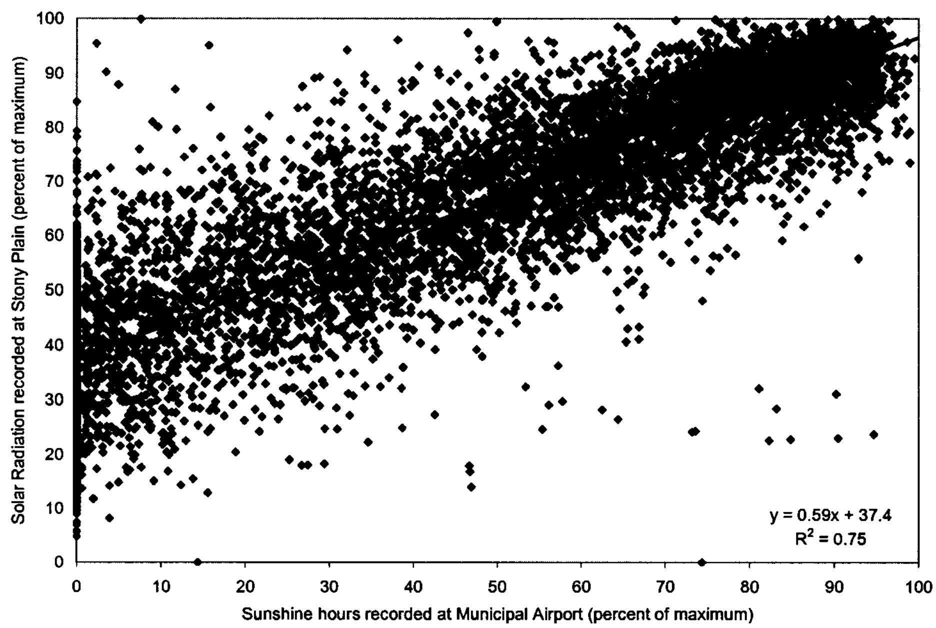

Figure A-5-3: Linear Correlation between solar radiation data collected at Edmonton Municipal Airport and Stony Plain from 1972 to 1994.

A.6.0 AIR TEMPERATURE

Air temperatures may influence river ice breakup conditions throughout the year. In the spring, air temperature has been widely identified as a significant parameter in modeling hydrologic processes. In addition, air temperature plays a role in the thermal processes which increase the water temperature. In the winter months, air temperatures are primarily responsible for the thermal ice growth, a key factor in spring river ice thickness. It was recognized half a century ago that air temperatures measured over land would differ from those measured over water (or ice) by Markham (1960). At present only air temperatures are only recorded over land in Alberta.

A.6.1 AIR TEMPERATURE IN THE ATHABASCA RIVER BASIN

Robichaud (2003) included daily air temperatures at Fort McMurray in the development of the river ice breakup database. Data was collected from the MSC station at Fort McMurray YYM. While Robichaud used data from the University of Alberta to estimate 2001 data, all the data for this study was collected from the MSC meteorological site. Data for this station has been updated to include data up to 2004 with data from AENV's collection of preliminary MSC data. This preliminary data has been verified by AENV staff at the River Forecast Center but has not undergone the rigorous evaluation that MSC staff perform prior to releasing the data for publication.

Due to the size of the Athabasca River Basin, there can be significant differences in air temperatures throughout the basin. Due to potential for significantly different meteorological conditions in the basin, a second station which is representative of the middle basin may be beneficial.

A single air temperature stations can represent a large area. Unlike some meteorological parameters such as solar radiation, air temperatures between stations in a close proximity to each other can usually be related by simple relationships, recognizing that there are always exceptions like local climatic zones such as sheltered valleys. Edmonton YXD (MSC 3012208) and Edmonton Stony Plain (MSC 301222F) stations are located geographically close together and the recorded temperatures are closely correlated as shown in Figure A-6-1.

Similar to the precipitation stations, there are no MSC air temperature sites located in the midbasin. However, several stations were located adjacent to the Athabasca River Basin and are listed in Table A-6-1. Since Whitecourt is located close the middle of the Pembina River Basin, it is likely to provide a better indication of snowmelt for the basin than Edson (located to the west of the subbasin) or Edmonton (located southeast of the Pembina River Basin). Many of the stations listed in Table A-6-1 were examined to create a continuous daily temperature. Whitecourt YZU 3067372 and Whitecourt 3067370 are essentially the same station. Whitecourt 3067370 was relocated within the airport in 1978 and the name was changed to Whitecourt YZU to reflect the international call letters of the airport. MSC did not run these stations in parallel for a year as normally occurs with any change in location that is deemed to potentially bias the data.

A regression analysis was performed against the long term MSC station Edmonton International Airport to confirm the validity of combining the stations into a single continuous record. Figure A-6-2 and Figure A-6-3 show that the slope for each regression is identical with a difference in the offset of 0.6 C. For the purposes of this study, the two Whitecourt stations can be considered the same location.

For the combined record of Whitecourt stations, there were several years that were missing data for several months. Surrounding stations were investigated to determine which station data would best correlate with the Whitecourt data. Edson A YET (MSC identification number 3062244) had the best correlation with the air temperature data from Whitecourt. This relationship is shown in Figure A-6-4. When Edson A YET was not available, Stony Plain (MSC identification number 301222F) was used to fill data following a similar technique of establishing a linear regression relationship.

To test the validity of this regression relationship, data at Edson A YET was used to forecast air temperatures at Whitecourt over a two year period when the data was available at both sites. Figure A-6-5 shows a good relationship (R^2=0.98) between the recorded air temperature at Whitecourt and the predicted air temperature estimated by using data from the Edson site.

A.6.2 DEGREE DAYS

The Degree Day approach is a highly empirical method of estimating heat transfer. The advantage to the Degree Day approach is that only air temperature is required. The method is limited in that many heat fluxes are neglected, such as solar radiation.

Degree days provide one method for accounting for temperature variations over time periods ranging from a few days to several months. A "degree day" is defined as the number of degrees a temperature varies above or below a defined value. The selected temperature data could be a daily maximum, minimum or average depending on the application (Richards, 1964). If the temperature during the day was 6 degrees different from the reference point, then six degree days would have accumulated during the day. Degree days are used extensively in many fields of natural science, for example, Richards (1964), Doug Hohnson et al. (2005), (Riseborough, 2002) and Hinkler et al. (2002). Degree day methods can be subjective in that there are no clearly defined rules for applying the analysis. While river ice textbooks (Ashton, 1986) and manuals (e.g. Beltaos et al., 1989) define degree days, they do not specifically give details about the application of the method, particularly the starting point for accumulations.

Typical snow and ice modeling relate degree days relative to 0 °C since it is the freezing/melting point for water. Air temperatures from several years can be evaluated by comparing the accumulated degree days of freeze (negative degree days) or the accumulated degree days of thaw (positive degree days). Bibello (1980), however, accumulated degree days of "thaw" above a base of -5 °C citing a potential for snowmelt at temperatures below 0 °C. With the exception stated previously, all of the papers referenced in this thesis related to snowmelt or river ice modeling made use of the average daily temperature, not daily minimum or maximum temperature values.

Despite the wide use of this type of analysis, there is no commonly agreed upon standard for the initiation of the accumulation of degree days or the average period of temperature that should be considered. Many studies use defined calendar dates (eg: Faulkner, 1999). Markham (1960) had limited success using the average monthly temperature as indicator of the accumulated degree days for fall, winter or spring. Molotch et al. (2004) used a seven day accumulation of degree days as one component for estimating the snow water equivalent and the extent of snow cover. After applying a minimum error analysis, Molotch et al. (2004) reasoned that seven days was logically appropriate for snow accumulation estimation because it would represent the short time-scale climate variability that they wanted to model. Several options were evaluated in the search for an indicator for river ice breakup forecasting.

A.6.2.1 Degree Days of Thaw

The degree days of thaw are often evaluated as an indicator of the ripening of a snowpack, the weakening of an ice cover by thermal deterioration and several other processes which may play a small role in river ice breakup such as frozen soils. Estimating the first day of melt has been identified as a crucial element in modeling river ice breakup but remains a difficult variable to quantify. There are several methods of calculating the first day of melt and many of these involve degree day analysis.

Because of the subjectivity in selecting the initiation date of the degree day calculation, both accumulated and consecutive degree days of thaw were investigated. Accumulated degree days of thaw" are a summation based on a starting date. For example, the National Weather Service Climate Prediction Center calculates degree days of thaw from July 1st to June 30th as the "heating year" (National Weather Service, 2005). Melt is often considered to have started if several positive degree days occur in a row. The exact number of days required to initiate melt is unknown. Robichaud (2003) used five consecutive positive degree days to initiate degree day accumulation.

A.6.2.1.1 Consecutive Positive Degree Days

Rather than use accumulated days, consecutive positive degree days was chosen based on the work of Robichaud (2003). For this thesis, a degree day is based on the daily average temperature in reference of zero degrees Celsius. Once a set number of consecutive positive degree days was recorded, the accumulation of positive degree days was initiated based on the first day consecutive day that began the initiation. Degree days of thaw continue to accumulate until the day of river breakup at Fort McMurray. Table A-6-2 provides an example of consecutive positive degree day accumulation for air temperature at Fort McMurray if three consecutive positive degree days were used to initiate the accumulation.

Through a sensitivity analysis, it was determined that the ideal number of consecutive days would be between three to four. The historical record at Fort McMurray was examined and it was determined that breakup can occur prior to 5 consecutive days of being recorded. Frequently in the historical record, two consecutive days can occurred in midwinter which would result in an early or false start in days of thaw accumulation. From the results of the sensitivity analysis in Figure A-6-6, it was determined that the degree days of thaw for either a 3 or 4 days would be similar. A three day consecutive positive degree day initiation was chosen because, for the purpose of developing a forecast model, a shorter initiation time is better as it allows the forecasting period to begin quicker. The Consecutive Positive Degree Days for Whitecourt and Fort McMurray are presented in Table A-6-3.

A.6.2.1.2 First Continuously Positive Degree Day

The first continuously positive degree day occurs on the day when the summation of degree days will remain positive for the remainder of the spring. This method has the advantage that it is not sensitive to the selection of a starting point. Each year has mathematically defined accumulation start date. Table A-6-4 presents the results for Fort McMurray and Whitecourt.

A.6.2.1.3 Positive Degree Days Prior to River Breakup

It is believed that conditions prior to river breakup may be significant. For 3, 5, 10, 15 and 20 days prior to river breakup, the positive degree days were accumulated for further study. Table A-6-5 and Table A-6-6 provide the accumulated degree days based on the days prior to river breakup Fort McMurray and Whitecourt respectively.

A.6.2.2 Degree Days of Freeze

The total number of negative degree days can be used as an indicator of the severity of the winter. Table A-6-7 provides the accumulated degree days of freeze for Fort McMurray and Whitecourt during the river ice season. The river ice season is considered to begin at the first observed time of backwater in the WSC records and end at spring river ice breakup.

The total negative degree days can also be calculated based on other definitions of when the calculation should begin. If degree days of freezing are accumulated over the winter to estimate the thermal ice thickness, then it would be reasonable for the starting point for the accumulation to occur in late fall or early winter when the accumulated freezing degree day curve goes from a negative to a consistently positive slope. The negative degree days during spring breakup may have an impact on the occurrence of ice jams. For each of the methods of determining the date to initiate positive degree day calculations, the corresponding negative degree day information was calculated. This consisted of the total summation negative degree days, the number of consecutive negative degree days and the total number of day negative degree days which occurred. The results of these calculations are presented in Table A-6-8 for Fort McMurray and Table A-6-9 for Whitecourt.

Table A-6-1: Air Temperature Stations near the Middle to the Athabasca River Basin.

Station Name	MSC Number	Length of Record
Whitecourt YZU	3067372	1978-present
Whitecourt	3067370	1971-1978
Edmonton YEG	3012205	1971-present
Edmonton YXD	3012208	1971-present
Edmonton Namao	3012210	1972-1995
Edmonton Stony Plain	301222F	1971-2002
Edson A YET	3062244	1971-1998
Edson YET	3062242	1997-present

Table A-6-2: Four consecutive positive degree day accumulation for air temperature at Fort McMurray in 1979.

Date month day, year	**Average Daily Temperature** °C	**Accumulated Positive Degree Days** °C	**Comments**
April 20, 1979	-0.9		
April 21, 1979	-2.3		
April 22, 1979	0.4	0.4	Accumulation Start Date: First Positive Degree Day in a series of 4 positive degree days
April 23, 1979	3.2	3.6	
April 24, 1979	1.4	5	
April 25, 1979	4.1	9.1	
April 26, 1979	5.3	14.4	
April 27, 1979	1.3	15.7	
April 28, 1979	3.7		River breakup occurred

Table A-6-3: Positive degree day accumulation based on initiation of 3 consecutive degree days of thaw for air temperature at Whitecourt and Fort McMurray from 1972 to 2002.

Year	Whitecourt Accumulated Degree Days	Fort McMurray Accumulated Degree Days
1972	83.5	40
1973	91.5	73
1974	83.8	65
1975	56.8	75
1976	116.9	103
1977	114.4	85
1978	90.4	34
1979	99.7	38
1980	75.1	83
1981	113.7	68
1982	54.7	47
1983	78.8	60
1984	135.8	96
1985	134.4	92
1986	186.1	111
1987	120.3	74
1988	180.8	69
1989	107.5	43
1990	177.9	63
1991	122.2	98
1992	163.5	92
1993	143.8	161
1994	101.2	79
1995	114.9	55
1996	86.5	33
1997	99.5	53
1998	98.6	60
1999	45.5	83
2000	174.7	103
2001	145.1	52
2002	80.1	37

Table A-6-4: Positive degree day accumulation based on First Continuously Positive Degree Day at Whitecourt and Fort McMurray from 1972 to 2002.

	accumulated degree days	
	Fort McMurray	Whitecourt
1972	6.9	42.1
1973	54.2	63.0
1974	65.3	65.8
1975	75	54.8
1976	102.6	79.8
1977	66.9	80.2
1978	9.2	67.5
1979	15.7	32.9
1980	79.2	68.4
1981	24.4	49.5
1982	49.5	54.7
1983	21.2	58.7
1984	83.6	80.2
1985	64.7	103.9
1986	43.7	70.3
1987	68.8	102.8
1988	38.9	150.4
1989	14.1	76.9
1990	34.6	81.5
1991	73	65.2
1992	34.6	148.0
1993	95.6	84.4
1994	17.2	62.2
1995	55.4	76.8
1996	27.8	56.4
1997	33.7	46.0
1998	59.5	69.9
1999	70.4	36.3
2000	47.6	90.0
2001	43.4	79.2
2002	6.0	45.0
2003	90.7	77.6
2004	72.2	124.6

Table A-6-5: Accumulation of positive degree days at Fort McMurray based on number of days prior to river breakup.

	Days Prior to Breakup Positive Degree Days				
	3	**5**	**10**	**15**	**20**
1972	7.8	7.8	15.5	17.2	17.2
1973	13.1	13.1	39.8	48.8	69.0
1974	17.3	30.2	56.3	65.3	65.9
1975	22.3	29.3	46.9	70.6	75.0
1976	32.6	47.9	87.7	100.0	103.2
1977	27.0	39.6	66.9	67.2	67.2
1978	9.2	9.2	17.1	27.8	28.8
1979	10.7	15.3	17.9	20.3	29.7
1980	24.2	37.1	52.6	74.8	82.6
1981	0.0	4.8	19.3	30.4	34.5
1982	13.5	30.7	47.0	53.7	53.7
1983	15.1	20.6	20.6	49.5	60.4
1984	12.8	19.4	49.2	72.8	80.7
1985	6.0	24.5	51.6	52.8	69.8
1986	12.4	16.0	18.6	58.8	68.4
1987	23.3	24.8	43.4	64.8	74.2
1988	23.5	32.4	38.9	51.2	54.0
1989	13.6	13.6	26.8	34.5	38.6
1990	25.2	25.9	26.6	32.0	46.5
1991	17.8	28.3	53.5	73.0	73.0
1992	15.9	15.9	27.9	40.5	44.2
1993	11.8	25.7	39.7	43.3	67.8
1994	11.8	12.4	15.5	38.5	40.4
1995	19.2	30.2	40.3	55.4	55.4
1996	6.0	6.8	25.3	32.7	32.7
1997	18.1	33.7	35.3	35.3	35.5
1998	22.3	29.2	49.2	58.8	62.0
1999	18.0	18.4	29.0	41.3	53.7
2000	32.8	44.7	47.6	47.6	49.5
2001	15.6	15.6	28.9	35.3	47.3
2002	6.0	6.0	23.5	24.3	36.5

Table A-6-6: Accumulation of positive degree days at Whitecourt based on number of days prior to river breakup.

	Days Prior to Breakup				
	Positive Degree Days				
	5.0	10.0	15.0	20.0	25.0
1972	14.3	23.9	26.5	33.0	43.8
1973	4.6	33.5	42.9	62.4	69.7
1974	34.0	55.8	64.0	72.2	73.1
1975	19.2	34.3	56.8	56.8	56.8
1976	42.8	73.8	81.7	83.4	84.5
1977	30.9	77.8	81.1	81.8	81.8
1978	8.4	24.4	42.2	49.4	60.0
1979	27.7	30.6	30.6	42.3	44.1
1980	37.4	49.7	63.1	68.4	70.6
1981	11.7	23.3	44.6	51.2	55.5
1982	32.9	45.8	52.3	56.7	56.7
1983	32.6	32.6	59.0	71.7	73.4
1984	17.2	38.7	55.6	73.5	80.2
1985	31.1	64.7	69.8	87.7	88.0
1986	13.7	17.5	57.4	69.8	88.5
1987	28.8	52.6	87.8	102.8	107.7
1988	42.2	66.8	86.2	93.9	108.1
1989	33.8	55.5	68.5	77.6	84.5
1990	36.1	47.8	55.9	77.1	101.9
1991	18.2	37.1	64.1	65.2	76.9
1992	33.7	47.1	64.8	77.2	101.6
1993	30.1	49.7	59.5	70.1	72.5
1994	15.7	23.4	54.2	60.9	63.8
1995	30.4	38.1	52.9	57.9	77.4
1996	19.9	47.3	56.4	56.4	56.4
1997	37.4	46.0	46.0	50.7	64.7
1998	27.6	52.1	61.7	68.9	73.1
1999	16.0	30.0	32.8	40.1	43.2
2000	42.0	44.8	51.6	62.1	85.0
2001	24.0	46.2	55.7	66.3	72.7
2002	6.9	26.2	30.0	54.2	54.2
2003	40.0	56.2	77.6	77.6	86.9
2004	32.8	36.3	66.2	101.0	126.6

Table A-6-7: Total accumulated degree days of freeze during the river ice season for Fort McMurray and Whitecourt.

Year	Fort McMurray Total Ice Period -ve Degree Days	Whitecourt Total Ice Period -ve Degree Days
1972		
1973	-2022	-1380
1974	-2685	-1946
1975	-1886	-1502
1976	-2022	-1421
1977	-1609	-909
1978	-2258	-1671
1979	-2663	-1852
1980	-1699	-1391
1981	-1539	-998
1982	-2588	-1890
1983	-2034	-1246
1984	-1750	-1070
1985	-2288	-1589
1986	-1879	-1256
1987	-1489	-1001
1988	-1669	-934
1989	-2157	-1431
1990	-2188	-1002
1991	-2244	-1367
1992	-1704	-994
1993	-1830	-1353
1994	-2078	-1309
1995	-1857	-1346
1996	-2511	-1869
1997	-2445	-1726
1998	-1477	-1004
1999	-1747	-1294
2000	-1664	-983
2001	-1768	-1012
2002	-2096	-1416
2003	-2023	-1165
2004	-1842	-1242

Table A-6-8: Analysis for Degree Days of Freeze based on 3 consecutive days of positive temperatures prior to breakup at Fort McMurray.

Start Date: 3 Consecutive +ve Ddays

Year	Consecutive Freeze Days	Sum D-Days of Freeze	Total D-Days of Freeze
1972	10	-101	22
1973	4	-25	9
1974	0	0	0
1975	0	0	0
1976	1	-1	1
1977	17	-195	23
1978	5	-38	10
1979	18	-225	27
1980	2	-3	2
1981	6	-76	11
1982	0	0	0
1983	5	-39	5
1984	16	-259	27
1985	4	-27	13
1986	10	-182	27
1987	3	-5	3
1988	13	-156	32
1989	4	-38	10
1990	4	-28	8
1991	37	-561	44
1992	6	-86	17
1993	24	-460	41
1994	7	-118	19
1995	0	0	0
1996	2	-5	2
1997	10	-107	16
1998	1	-1	1
1999	4	-13	6
2000	14	-248	25
2001	2	-9	4
2002	4	-33	8
2003	0	0	0
2004	6	-13	7

Table A-6-9: Analysis for Degree Days of Freeze at Whitecourt based on 3 consecutive days of positive temperatures prior to breakup at Fort McMurray.

Start Date: 3 Consecutive +ve Ddays

Year	Consecutive Freeze Days	Sum D-Days of Freeze	Total D-Days of Freeze
1972	4	-41	12
1973	13	-125	26
1974	45	-455	48
1975	1	-2	2
1976	13	-410	46
1977	14	-154	34
1978	12	-163	22
1979	14	-116	24
1980	5	-9	6
1981	7	-81	18
1982	0	0	0
1983	14	-94	20
1984	17	-375	53
1985	26	-560	55
1986	41	-654	74
1987	27	-284	43
1988	3	-30	13
1989	51	-698	57
1990	29	-651	71
1991	39	-1033	87
1992	3	-16	7
1993	19	-327	39
1994	6	-40	13
1995	16	-249	27
1996	15	-136	16
1997	21	-284	30
1998	31	-853	83
1999	5	-9	7
2000	51	-728	83
2001	23	-482	58
2002	32	-856	83
2003	6	-38	7
2004	5	-15	5

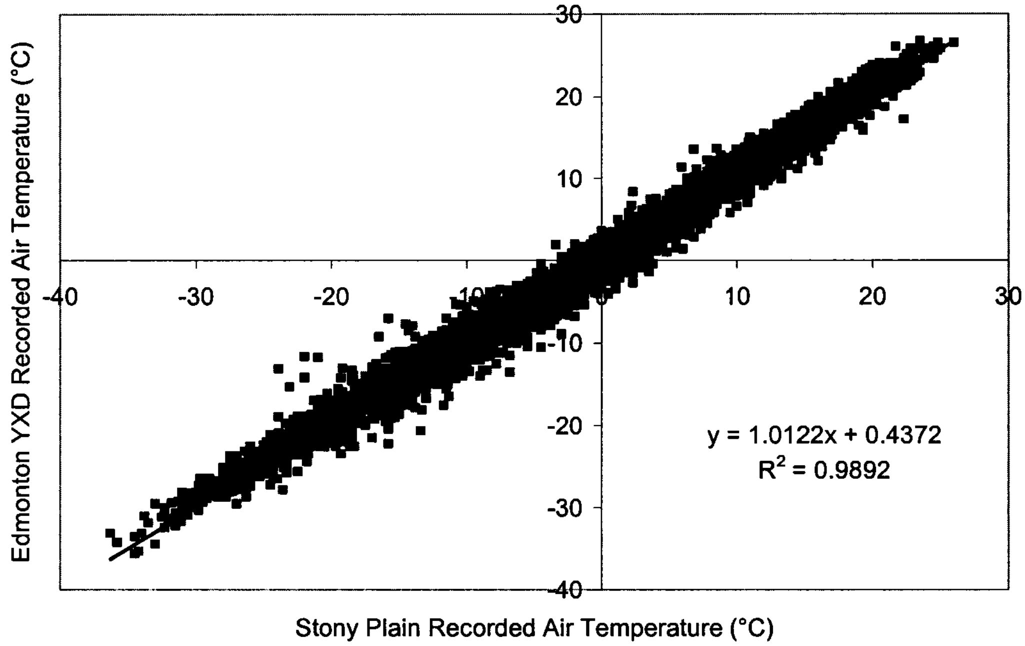

Figure A-6-1: Linear regression to establish a relationship between Edmonton YXD (MSC 3012208) and Edmonton Stony Plain (MSC 301222F) stations.

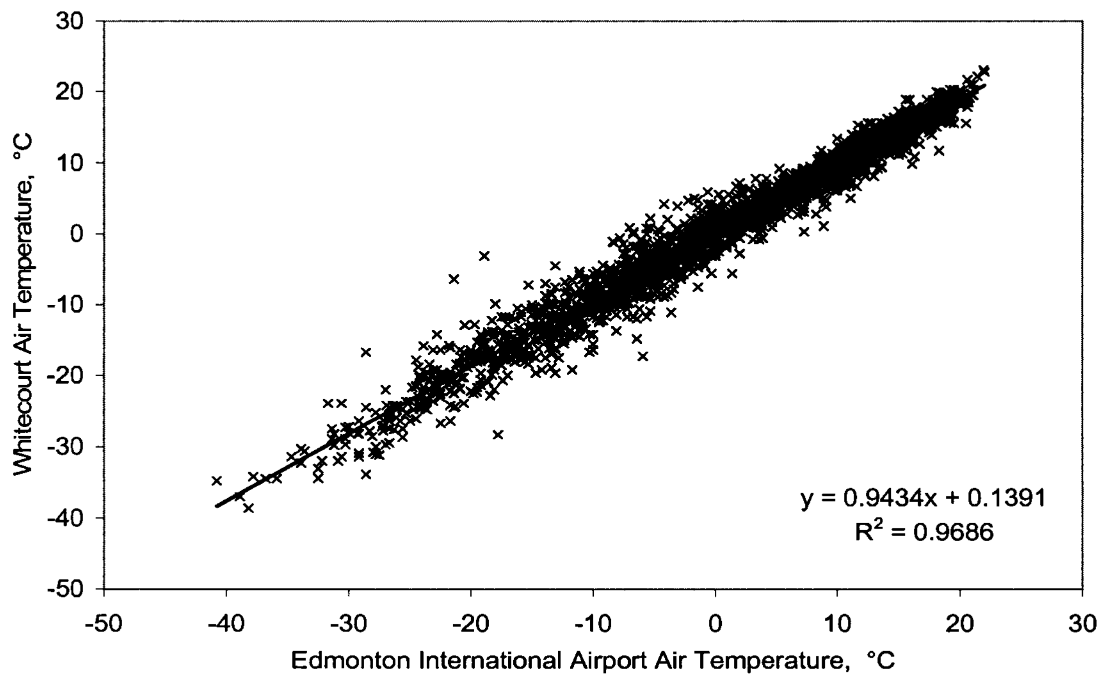

Figure A-6-2: Relationship between air temperatures at Edmonton International Airport and Whitecourt 3067370 MSC Meteorological Stations.

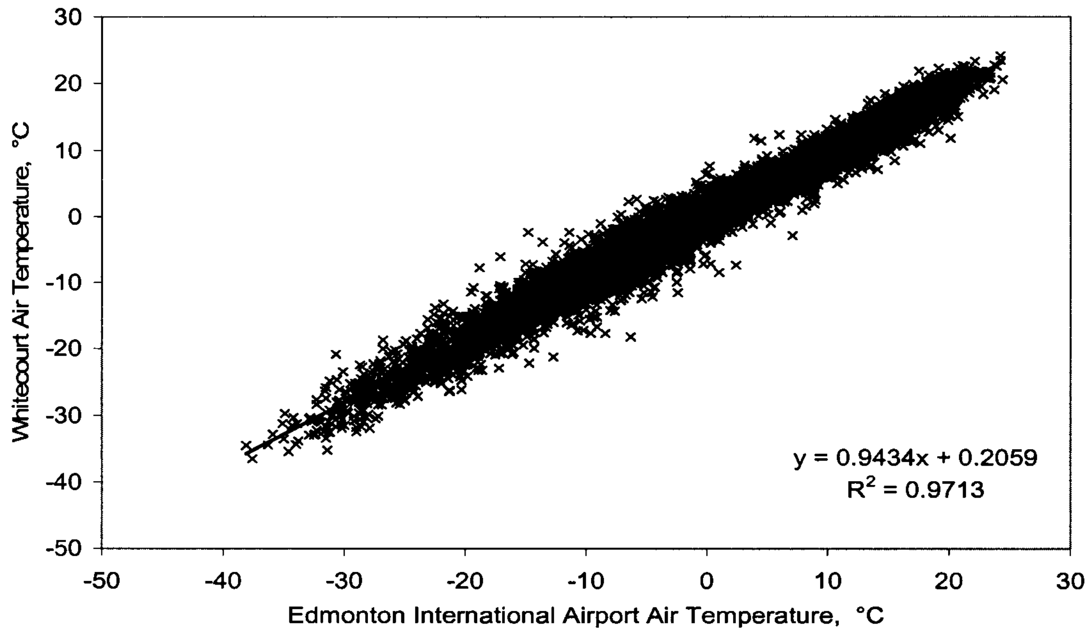

Figure A-6-3: Relationship between air temperatures at Edmonton International Airport and Whitecourt YZU 3067372 MSC Meteorological Stations.

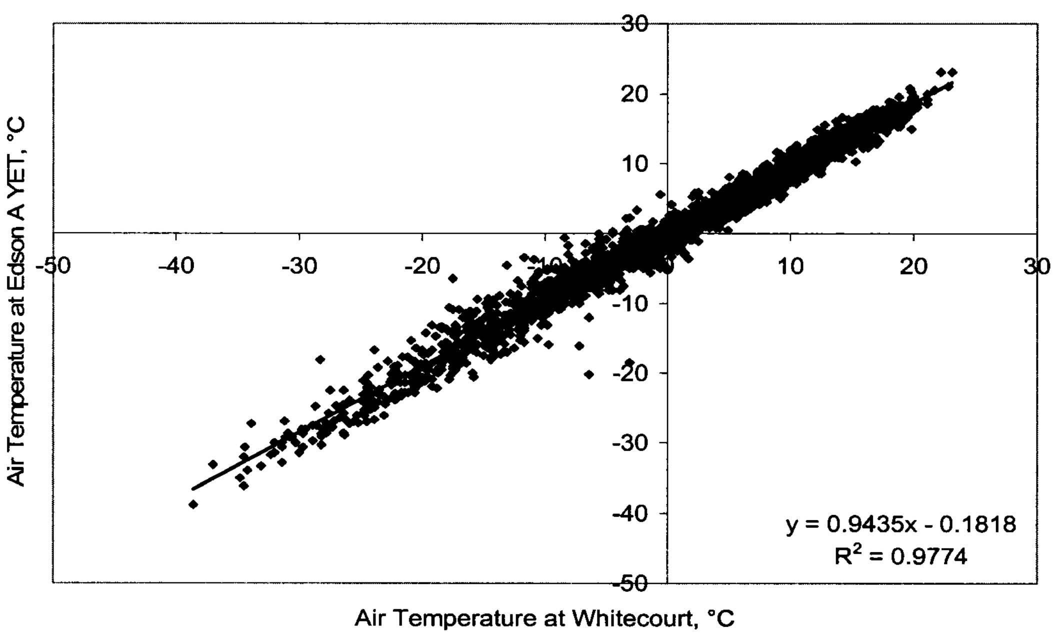

Figure A-6-4: Linear Relationship for Air Temperature between Whitecourt and Edson A YET.

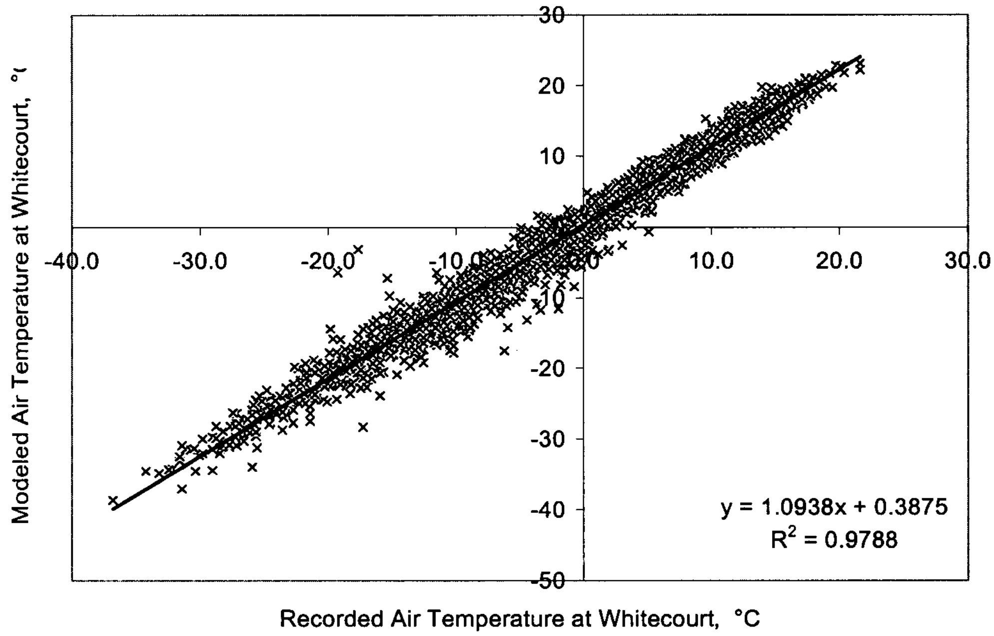

Figure A-6-5: Comparison of Recorded Air Temperature with Predicted Air Temperature at Whitecourt based on values recorded at Edson A YET.

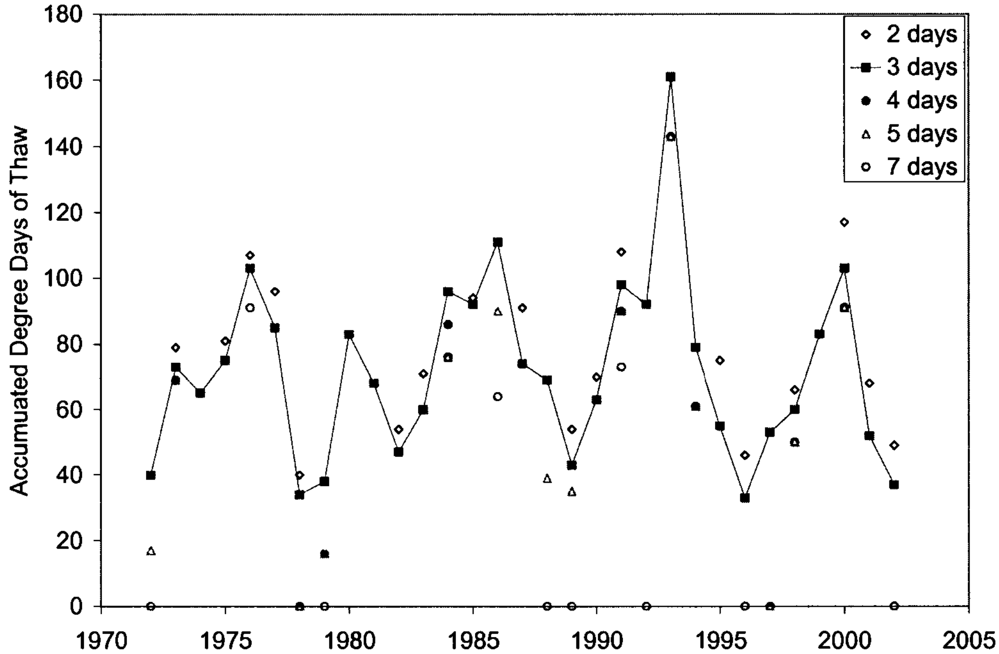

Figure A-6-6: Sensitivity Analysis for initiation of accumulation of degree days for Fort McMurray.

A.7.0 CLIMATE INDICES

The effectiveness of using sea surface temperatures (SSTs) as a index for large scale weather patterns has been brought to the forefront of the scientific community by the a number of successful applications of the El Nino/Southern Oscillation (Ramussen and Wallace, 1983). A teleconnection exists between an index and a signal when a climate signal in a particular phase shows a significant relationship to another measured pattern. For El Nino, teleconnections have been reported for several parameters including precipitation (Kahya and Dracup (1993), streamflow (Cayan et al., 1999) and temperature (Higgins et al., 2000) In addition to El Nino, there are several other researched climate patterns that have been linked to climatic patterns around the world.

While no papers have been found that directly link a climatic index to river ice breakup, there are papers that relate indexes to some of the factors that have been identified as possible key parameters for river breakup forecasting such as streamflow and snowpack accumulation. Hamlet and Lettenmaier (1999) reported opportunities to improve the predictability of runoff in some regions with advances in understanding the teleconnections of SSTs.

Maurer et al. (2004) examined the relationship of several climate indices to runoff, snow and soil moisture data for North America. The climate indices investigated were El Nino-Southern Oscillation (ENSO), the Pacific Decadal

Oscillation (PDO), Arctic Oscillation (AO), Normalized Arctic Oscillation (NAO), the North Pacific (NP) index and Atlantic multidecadal oscillation (AMO). In this paper, PDO was identified as a significant indicator for runoff for the Canadian Prairies during spring (March to May) for up to 9 months prior to spring. Other researchers have also related PDO to snow pack and stream flow patterns in western North America (Cayan 1996, Bitz and Battisti 1999, Nigam et al. 1999).

Pacific Decadal Oscillation (PDO) is a long-term ocean fluctuation of the Pacific Ocean related to the regular pattern of high and low pressure systems over the Aleutian Islands in the Pacific Ocean off the coast of Alaska. A technical description of the SST anomalies the make up the PDO is provided by Mantua et al. (1997). PDO was named in 1996 by Steven Hare while researching connections between Alaska salmon production cycles and the Pacific climate. A full warm and cold cycle of PDO occurs over 20 to 30 years.

The PDO index for this study was obtained from the web site:ftp:/ftp.atmos.washington.edu/mantua/pnw_impacts/Indices/pdo.latest during February 2005. The January annual values for PDO are provided in Table A-7-1.

Table A-7-1: Annual January Pacific Decadal Oscillation Value as reported by http://jisao.washington.edu/pdo/PDO.latest

Year	PDO Index Value
1970	0.61
1971	-1.90
1972	-1.99
1973	-0.46
1974	-1.22
1975	-0.84
1976	-1.14
1977	1.65
1978	0.34
1979	-0.58
1980	-0.11
1981	0.59
1982	0.34
1983	0.56
1984	1.50
1985	1.27
1986	1.12
1987	1.88
1988	0.93
1989	-0.95
1990	-0.30
1991	-2.02
1992	0.05
1993	0.05
1994	1.21
1995	-0.49
1996	0.59
1997	0.23
1998	0.83
1999	-0.32
2000	-2.00
2001	0.60
2002	0.27
2003	2.09
2004	0.43

URL: ftp://ftp.atmos.washington.edu/mantua/pnw_impacts/INDICES/PDO.latest

And http://jisao.washington.edu/pdo/PDO.latest

A.8.0 HEAT FLUX: A COMBINED METEOROLOGICAL PARAMETER PROCESS

There are some physical processes that are understood well enough to allow rough estimates of the process from readily available data. By incorporating a combination of two or more variables (such as temperature and solar radiation) into a single parameter (heat flux), a better understanding of the contribution of each variable can be achieved. While including each variable separately should lead to a similar analysis of significant variables, the reduction in the number of variables is often beneficial in complex analysis with limited data. In this section, well known physical processes are described that allow variables to be combined in such a way that the significant meaning of the combined parameters is increased.

A.8.1 LINEAR CUMMULATIVE HEAT TRANSFER

The state of the ice cover is very important in the river ice breakup process. If the ice cover is in the late stages of decay, the strength of the ice is reduced. Large jams are less likely to form as the ice cannot withstand the application of large forces. On the other hand, if a competent ice cover is ruptured by hydrodynamic forces, it is more likely that a large ice jam could form.

The thermodynamics of an ice covered river is a very complicated process involving interactions between the atmosphere and ground cover surfaces (land, air and water). This section presents a condensed version of heat transfer as is relevant to the type of river breakup process modeling in this thesis. Further information on the influence of heat transfer on river ice formation, and degradation can be found in Ashton (1980, 1986) or Michel (1971). The basic principals of heat transfer are well documented in many textbooks such as Black and Hartley (1991).

There are numerous simplifications that allow the heat transfer process to be practically modeled. As with any process, a simplification results in a reduction in the precision of the method. The availability of data along with the current state of parameter measurements is a limiting factor for heat transfer calculations. Hicks et al. (1995) found that linear cumulative heat transfer methods worked equally as well as full budget methods for approximating the heat transfer to an ice cover on the Mackenzie River.

A.8.1.1 ENERGY BALANCE

There are several heat components that act on a river ice cover. Since the flow in most rivers is turbulent, it is generally accepted that complete mixing occurs in any vertical column of water resulting in the same rate of cooling as the water surface (Prowse, 1996). The following description is adapted from Hicks et al.

(1997) where each component is described in greater detail. The potential heat available to contribute to melting as ice cover can be described as:

$$Q_m = Q_{si} + Q_{li} + Q_{ei} + Q_{hi} + Q_{pi} + Q_{fi} + Q_w \qquad \text{(A.8.1)}$$

Where:

Q_m = total heat available to melt the ice cover, J/s

Q_{si} = net solar radiation absorbed by the ice (or snow), J/s

Q_{li} = net long wave radiation heat exchange (between ice/snow and the atmosphere, J/s

Q_{ei} = net heat gain (or loss) due to condensation or evaporation from the

ice/snow surface, J/s

Q_{hi} = sensible heat transfer from the atmosphere to the ice/snow cover, J/s

Q_{pi} = heat transfer to ice/snow surface by precipitation, J/s

Q_{fi} = heat energy contributed to the ice cover by friction of river flows beneath the ice cover, J/s

Q_w = advected heat transfer to the ice cover by warmer river water, J/s

The net solar radiation is frequently the largest term in the equation (Prowse, 1996) when solid ice covers the river. Many components are temperature dependant, such as net long-wave radiation and sensible heat transfer from the air. Wind can also significantly impact the amount of heat transferred to the ice cover (Dingman et al. 1968).

In spring, the heat transfer from the river flow to the water can become significantly larger. Open leads and ice free areas upstream of the ice cover can act as heat sinks, absorbing energy. The water temperature may increase to the point that the heat transfer from the warmer river water becomes a major component in the energy balance. The heat transfer from the water is a function of many heat fluxes similar to the heat fluxes that act on a surface of the river ice.

Full energy budget methods account for each non negligible energy flux explicitly. It is not practical or possible to exactly determine each variable in a full energy budget. Some terms such as the net solar insolation can be measured and generalized to apply to the reach of interest. This often involves a point measurement value being applied over a large area. Other terms, such as the amount of solar radiation penetrating the ice cover, are determined empirically. Possible negligible parameters might include the heat transfer from the frictional flow of water to the ice cover.

A.8.2 LINEAR HEAT TRANSFER APPROACH

The linear heat transfer approach is a common empirical simplification of the full energy budget method. A simple linear relationship between the temperature gradient and conductive heat transfer is assumed (Andres, 1988). The advantage of this approach is that only solar radiation, air temperature, discharge and incoming water temperature are required for modeling purposes. Heat fluxes due to evaporation, condensation and long wave radiation are assumed to be incorporated adequately into the linear heat transfer coeffiecient. Equation A.8.1 is simplified to include only three parameters as follows:

$$Q_m = Q_{si} + Q_{hi} + Q_w \tag{A.8.2}$$

The heat directly advected to the ice cover by the warmer river water, Q_w, can be described as:

$$Q_w = Q_{sw} + Q_{hw} + Q_{water} \tag{A.8.3}$$

where:

Q_{sw}	=	net solar radiation incident on the open water surface, J/s
Q_{hw}	=	sensible heat exchange between the water surface and the atmosphere due to convection, J/s

Q_{water} = initial heat energy contained in the water at the upstream boundary location, J/s

The surface heat loss is approximated as a product of the water to air temperature difference and a heat transfer coefficient. Average daily temperatures can be used to estimate heat flux as:

$$\Phi_{lch} = C_w (T_a - T_{ice}) \quad \text{(A.8.4)}$$

where:

Φ_{lch} = linear cumulative heat flux, W/m^2

C_w = convective heat transfer coefficient above the water, $W/m^2/°C$

T_a = average daily temperature of the air, °C

T_{ice} = average temperature of ice, °C

At breakup, T_{ice} can be considered 0°C. This reduces the equation to:

$$\Phi_{lch} = C_w T_a \quad \text{(A.8.5)}$$

Dingman and Assur (1969) provide various methods for calculating the heat transfer coefficient. Prowse (1996) reported that typical values range from 15 to 25 $Wm^{-2}\,°C^{-1}$ but was highly variable. Andres (1984) determined a heat transfer coefficient of 15 W/m^2/°C between air and water for the Peace River in Northern Alberta. Based on the work of Williams (1965), he applied a value of 9 W/m^2/°C for the heat transfer coefficient between air and ice. From Hicks et al. (1997), an average value of 20 W/m^2/°C between the air and water and 8 W/m^2/°C between the air and ice was used for the Mackenzie River. Similar results were reported by Van Der Vinne (1995) values for a small pond in Alberta.

The main criticism of this method is that known non-linear functions are approximated as linear functions. Hicks et al. (1995,1997) demonstrated that for the purposes of ice modeling, the full energy budget can be simplified to a linear cumulative heat transfer.

A.8.2.1 Linear Cumulative Heat Transfer Calculation for Fort McMurray

Linear cumulative heat transfer was calculated as a linear cumulative heat flux combined with net daily solar radiation. A transfer coefficient of 8 W/m^2/°C was selected as the Mackenzie River (Hicks et al., 1997) was the geographically closest site reported in literature based on site data. It is recognized that this is an approximation and could result in errors. However, since it is a linear coefficient, any error would be of a constant factor, allowing the resulting value to still be meaningful as an index of heat transfer in this modeling effort.

Similar to the degree day calculations, the start date for the accumulation of heat to a river system during the spring must be selected. Since there is currently no standard for selecting a starting accumulation date for the heat transfer date relative to river ice breakup, a variety of start dates have been considered.

Table A-8-1: Accumulation of degree days of thaw starting with the first day of Continuously Positive Degree Days.

	Accumulated Heat Energy	
Year	Total Heat at Breakup W/m^2	Average Heat per day W/m^2
1972	430	143
1973	3665	183
1974	2483	207
1975	3177	199
1976	3668	204
1977	1815	202
1978	451	150
1979	1048	175
1980	3313	174
1981	2251	132
1982	2232	172
1983	2617	145
1984	3409	155
1985	5651	149
1986	3670	153
1987	2503	147
1988	1316	219
1989	2265	189
1990	3528	147
1991	2836	203
1992	1783	137
1993	3545	122
1994	1921	128
1995	1653	127
1996	2156	196
1997	1300	260
1998	2879	180
1999	4375	162
2000	381	54
2001	4307	179
2002	395	197
2003	3142	209

Table A-8-2: Accumulation of degree days of thaw starting with the 3 consecutive degree days of thaw.

	Accumulated Heat Energy	
Year	Total Heat at Breakup W/m^2	Total Heat per day W/m^2
1972	3970	97
1973	4330	167
1974	2483	207
1975	3177	199
1976	3668	204
1977	4160	101
1978	2202	100
1979	3139	77
1980	3313	174
1981	4074	127
1982	1810	201
1983	2617	145
1984	4665	91
1985	5651	149
1986	5372	105
1987	2503	147
1988	4714	92
1989	3923	171
1990	3528	147
1991	4615	69
1992	4113	108
1993	5664	72
1994	2243	56
1995	1653	127
1996	2156	196
1997	4705	152
1998	2879	180
1999	4375	162
2000	3496	66
2001	4307	179
2002	3349	176
2003	3142	176

Table A-8-3: Accumulation of degree days of thaw starting with an accumulation of 10 degree days of thaw.

	Accumulated Heat Energy	
	Total Heat at Breakup	Total Heat per day
Year	W/m^2	W/m^2
1972	3970	97
1973	3665	183
1974	2483	207
1975	3177	199
1976	3668	204
1977	4160	101
1978	1137	95
1979	1048	175
1980	3313	174
1981	4074	127
1982	1810	201
1983	4044	104
1984	3409	155
1985	5651	149
1986	5372	105
1987	2503	147
1988	2189	137
1989	2265	189
1990	3528	147
1991	3895	144
1992	4113	108
1993	5664	72
1994	2243	56
1995	1653	127
1996	2156	196
1997	1300	260
1998	2879	180
1999	4375	162
2000	3496	66
2001	4307	179
2002	3349	176
2003	5638	53

Table A-8-4: Accumulation of degree days of thaw starting with a selected number of days prior to river ice breakup.

Total Heat and Daily Average Heat Accumulated Days Prior to Breakup (W/m^2)

Year	3	Avg	5	Avg	10	Avg	15	Avg	20	Avg	25	Avg
1972	430	143	798	160	1415	142	1767	118	1972	99	2534	101
1973	677	226	899	180	1961	196	2619	175	3665	183	4191	168
1974	729	243	1250	250	2119	212	2655	177	2850	142	3042	122
1975	629	210	1031	206	1991	199	3049	203	3348	167	3727	149
1976	720	240	1231	246	2423	242	3243	216	3937	197	4020	161
1977	629	210	963	193	1855	185	2285	152	2739	137	2754	110
1978	451	150	466	93	798	80	1493	100	1907	95	2439	98
1979	482	161	906	181	1334	133	1640	109	1965	98	2132	85
1980	518	173	969	194	1800	180	2803	187	3467	173	3694	148
1981	478	159	593	119	1365	136	1953	130	2336	117	2697	108
1982	535	178	1074	215	1996	200	2329	155	2797	140	2993	120
1983	525	175	787	157	1100	110	2018	135	2928	146	3381	135
1984	392	131	664	133	1773	177	2675	178	3093	155	3567	143
1985	493	164	923	185	2004	200	2783	186	3400	170	3901	156
1986	331	110	657	131	1251	125	2293	153	2965	148	3772	151
1987	564	188	741	148	1363	136	2240	149	2655	133	2902	116
1988	756	252	1113	223	1606	161	2045	136	2523	126	3005	120
1989	575	192	978	196	1776	178	2706	180	3402	170	4046	162
1990	661	220	969	194	1614	161	2158	144	2920	146	3624	145
1991	553	184	928	186	1989	199	2895	193	3051	153	3510	140
1992	367	122	680	136	1271	127	1924	128	2394	120	2999	120
1993	317	106	671	134	1109	111	1284	86	2120	106	2894	116
1994	664	221	1041	208	1737	174	1921	128	1936	97	1972	79
1995	640	213	1007	201	1284	128	1851	123	2063	103	2428	97
1996	620	207	969	194	1942	194	2604	174	2886	144	3048	122
1997	776	259	1300	260	2376	238	2944	196	3355	168	3957	158
1998	633	211	1037	207	1904	190	2762	184	3488	174	3926	157
1999	640	213	876	175	1506	151	2400	160	3060	153	4017	161
2000	262	87	358	72	381	38	381	25	396	20	1318	53
2001	663	221	1097	219	1970	197	2846	190	3629	181	4447	178
2002	626	209	999	200	1961	196	2710	181	3506	175	3910	156
2003	840	280	1404	281	2212	221	3142	209	3647	182	4050	162

Table A-8-5: Accumulation of degree days of thaw starting March 1.

	Accumulated Heat Energy Total Heat at Breakup W/m^2	Total Heat per day W/m^2
1972	4020	77
1973	5810	121
1974	3202	65
1975	4939	90
1976	4717	110
1977	4423	101
1978	3643	74
1979	3680	63
1980	4121	92
1981	4537	113
1982	4425	79
1983	4219	88
1984	3888	97
1985	6117	127
1986	5372	110
1987	3168	69
1988	4007	87
1989	4326	83
1990	5875	118
1991	4615	107
1992	3479	105
1993	5664	116
1994	2243	55
1995	4035	78
1996	3880	84
1997	4976	100
1998	4088	105
1999	5117	116
2000	3496	66
2001	6549	119
2002	5194	88
2003	5638	108

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APPENDIX B
Evaluation of Ice Thickness as a Parameter in River Breakup Forecast Modelling

EVALUATION OF ICE THICKNESS AS A PARAMETER IN RIVER BREAK-UP FORECAST MODELLING

INTRODUCTION

Virtually all rivers in Canada are ice covered for a third to a half of the year. The transition from a stable ice covered river to an ice free flowing river is a dramatic change. River breakup can be innocuous if the ice melts in place with very little movement (described as an over mature or thermal breakup event). If the flow under an ice cover increases sufficiently while the ice is still competent, the ice cover will break into pieces (called ice floes) and will be carried downstream (this is called a premature or mechanical event). An ice jam occurs when the ice floes cause sufficient congestion so as to impede the flow of water, or if an ice run encounters sufficient competent ice to halt the movement of ice floes. In such cases, water can be forced out of the river channel, flooding areas adjacent to the river.

Rivers that flow in a northerly direction are prone to ice jams because of the nature of river breakup. The southerly reaches of the river experience warming weather before the northerly reaches. Along with ice deterioration, the upper basin may experience significant snow melt, increasing flows in the river channel. If the ice cover in the lower reaches has decayed sufficiently, so as not to impede the flow, a thermal breakup is said to have occurred. If more competent ice is encountered as the ice floes and runoff moves northwards, an ice jam may develop as melt water and ice floes become trapped behind solid ice sheets.

The Athabasca River is a northern flowing river that is subject to frequent ice jamming. Depending on the size and location of the jam, flooding can occur in the city of Fort McMurray. In 1977 and again in 1997, ice jams flooded the city with little warning. Due to the serious threat posed each spring by the river breakup process, the Athabasca River has been studied for more than 30 years by several organizations.

The collected data have been analysed in an attempt to forecast the magnitude and timing of river breakup. The first attempt to forecast river breakup was done by Andres (1988). Rather than attempt to forecast mechanical breakup events, for which there was little data in the mid eighties, Andres developed a method to forecast the development of open water, reasoning that dynamic breakup would occur once the ice was sufficiently thermally deteriorated to facilitate a mechanical deterioration of the ice cover. The practical value of this forecasting technique was limited due to the sensitivity of subjective variables required. More recently, Robichaud (2003) investigated the suitability of single variable threshold models and multiple linear regression models to forecast maximum water levels at breakup. While little success was realized with the threshold models, the multiple linear regression model showed promise for short term forecasting (one to three days lead time). Mahabir et al. (2003) extended the lead time to 1 to 2 months through the use of a fuzzy expert system.

All of the forecast models to date require ice thickness measurements as an input variable. The sensitivity of the model forecasts to this parameter prompted a comprehensive investigation into the collection and reporting of ice thickness data at this site. It was found that spatial variability had a large impact on the measurements, with two very different ice regimes existing in the vicinity of Fort McMurray. This paper reports the reanalysis of the ice thickness data collected from 1972 to 2002 , separating data for these two zone, and uses the new data to re-evaluates the breakup water level forecast models.

SITE DESCRIPTION

The Athabasca River originates in the Rocky Mountains at the Athabasca Glacier south of Jasper National Park. The river flows northeast towards the town of Athabasca where it turns sharply and flows primarily northward. Approximately 40 km upstream of Fort McMurray, the river passes through a series of rapids as it descends through an incised channel towards the city (Figure 1). Immediately downstream of the MacEwan Bridge in Fort McMurray, the channel changes dramatically. As a result of an abrupt decrease in slope, the channel widens into a large floodplain with numerous islands.

RIVER ICE FORMATION

The formation of river ice is a complex process that is dependent on the hydraulic properties of the channel and the meteorological conditions during the freeze-up period. A brief discussion of the primary processes responsible for ice formation on the Athabasca River is presented here. A more comprehensive discussion on river ice formation processes in general can be found in Ashton (1986).

Along the riverbank where the velocities are low, skim ice will form on the water surface and spread latterly across the channel. Border ice, as this formation is appropriately termed, is a primary means of ice formation on lakes or along river banks where laminar flow is present. During the winter, this ice thickens by vertical thermal growth and retains its characteristically smooth surface.

In reaches where the flow is turbulent, ice particles form on the surface where the water temperature is supercooled to sub-zero temperatures. These ice particles are quickly entrained into the turbulent flow; however, while supercooled, they are quite adhesive and thus flocculate. This rate of production of this type of ice, known as frazil ice, is dependent not only on the turbulent flow regime but also on meteorological conditions. Snowfall substantially increases frazil production by providing large quantities nucleating particles. Once frazil ice flocs reach a sufficient size, such that buoyancy overcomes fluid turbulence, the flocs rise to the surface forming frazil pans. Floating frazil pans which freeze together in an edge to edge fashion form what is termed a 'juxtaposed' ice cover. However under certain hydrometeorological conditions (extremely rapid frazil formation rates and high flow velocities) a juxtaposed ice cover can collapse, or shove, into a very thick and rough ice accumulation known as a hummocky ice cover or freeze up ice jam.

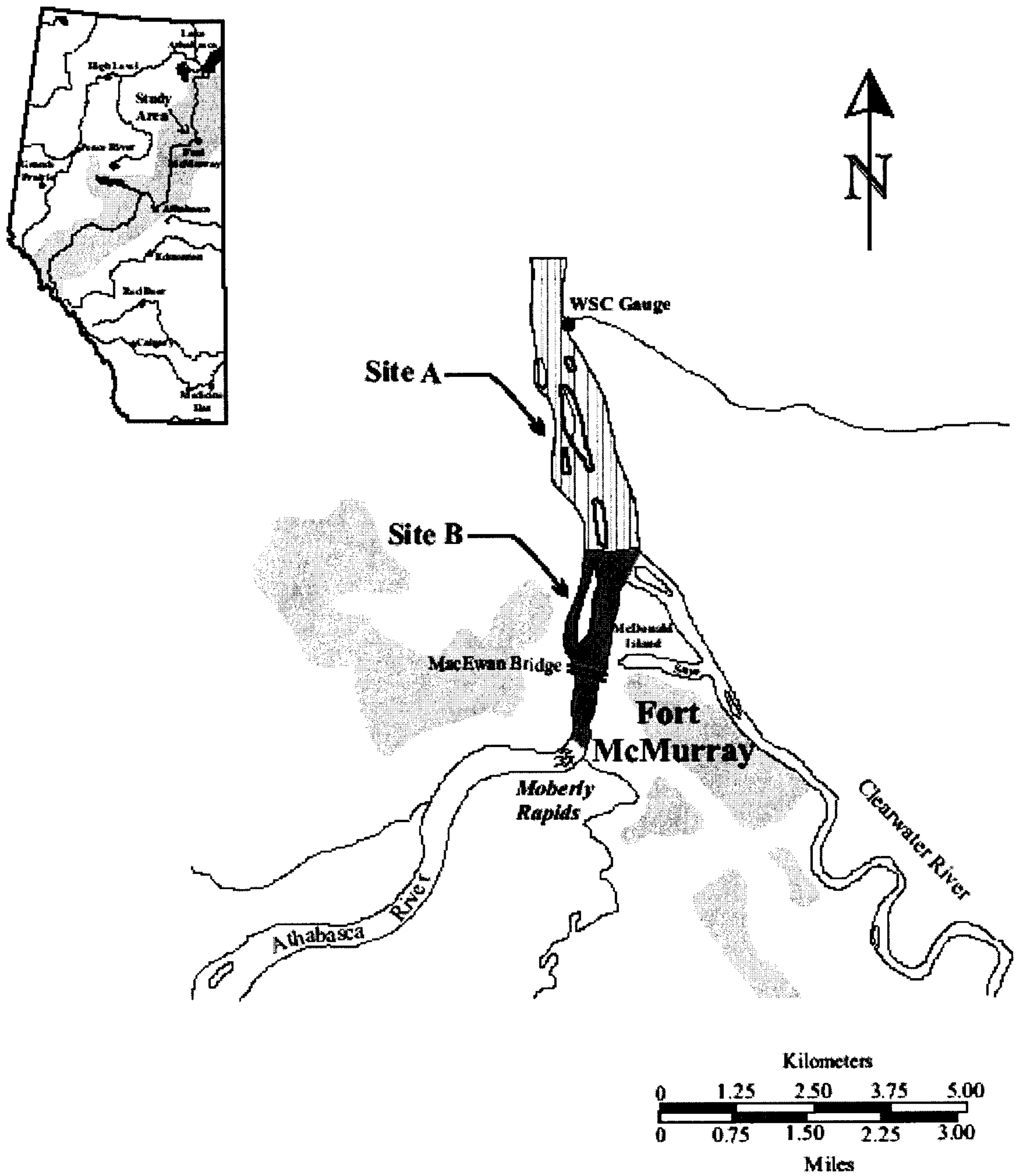

Figure 1. Athabasca River through Fort McMurray adapted from Robichaud (2003).

From historical descriptions, gauge records, and personal observations of freeze-up conditions at Fort McMurray it has been noted that hummocky ice covers occur much more frequently upstream of the Clearwater River than downstream of this confluence. This can be primarily attributed to the geomorphologic changes which occur at this point. Downstream of the Clearwater River, the Athabasca River slope decreases significantly and numerous islands and bars exist in the channel. Flows are deeper and slower, and thus a hummocky ice cover is only likely to form in rare cases where substantial quantities of frazil ice form in a very short period of time. Upstream of the Clearwater River confluence, the river slope is steep and flow velocities are faster; also the series of rapids upstream of Fort McMurray provide a substantial supply of frazil ice. Consequently hummocky ice covers commonly form in the river reach between Moberly Rapids and the Clearwater River confluence (Figure 1).

There are several publications that present ice thickness data at Fort McMurray with misleading statistics. In 1970, the ice thickness was reported to have a mean annual maximum of 0.91 m and a range between 0.46 m and 1.68 m with the latter believed to be due to traffic crossing the ice (Water Survey of Canada, 1970). Four years later, Water Survey of Canada (1974) published a more detailed account of ice thicknesses for selected rivers in Alberta. The criteria utilized by the report for selecting good winter measurement stations lead to the exclusion of the site at Fort McMurray. Andres and Rickert (1983) recognized the importance of location for ice thickness measurements and provided maps for measurements done by Water Survey of Canada and the Regional Municipality of Wood Buffalo.

The purpose of this paper is to report the findings of a through analysis of ice thickness records for Fort McMurray, and to review the current spring breakup forecasting models that are dependent on ice thickness data.

ICE THICKNESS MEASUREMENTS

Over the past three decades, two groups have systematically taken ice measurements at Fort McMurray: Water Survey of Canada and the Regional Municipality of Wood Buffalo (also know as the Town/City of Fort McMurray in early reports). Since each group has its own purpose for performing the ice thickness measurements, the methodologies for the measurements vary.

Water Survey of Canada

Water Survey of Canada (WSC) measures ice thickness as part of its routine winter flow measurement program. The measurement technique implemented by WSC consists of drilling 20 to 30 holes in the ice cover along a transect across the channel. At each hole, water velocity as well as ice thickness are measured. Allowing for shorefast ice and slush ice, a mean value of ice thickness is calculated for the channel. Since the primary purpose is for flow measurement, the location and spacing of the holes is established by flow measurement criteria.

Unlike ice thickness, the measurement of streamflow is not normally sensitive to the location of the measurement. If the measurement is done in a location other than near the gauging station, a note stating the location of the measurement is put on the file. As part of establishing a database for river breakup at Fort McMurray, Robichaud (2003) collected and summarized the measurements taken between October 1972 and May 2001. Based on written descriptions of the measurement locations, the locations of the WSC ice thickness measurements were divided into two regions. The first region, Site A (Figure 1), included measurements that were not likely influenced by freeze-up jams. These measurements were taken within 2 km upstream of the gauging site, at the gauge, and downstream of the gauge. The second region, Site B (Figure 1), included measurements that were taken more than 4 km above the gauge but below Moberly Rapids. This is the reach in which freeze up ice jams have been known to occur.

Since a flow measurement consists of only one transect, the ice thickness measurements for a particular date are available for either location Site A or Site B but not both. Frequently, all measurements for the entire year have been done at one location with no information available for the other location. Although most measurements were performed near the gauging station, there are some years where data is only available above the gauging station.

Regional Municipality of Wood Buffalo

In 1989, the Regional Municipality of Wood Buffalo (RMWB) began an annual ice thickness measurement program. The purpose of these measurements was to assess the spatial variability of the ice thickness through Fort McMurray, from Moberly Rapids to below the Clearwater River confluence. The measurement technique employed by RMWB consists of a single point measurement of ice thickness taken at specific observation sites. Although there were variations between years, about ten measurements were taken below the Clearwater River Confluence (similar location to Site A measurements) and nine were taken between the Clearwater River Confluence and Moberly Rapids (similar location to Site B measurements). Of these nine, six measurements were taken above the MacEwan Bridge and three were taken in the middle of the channel below the bridge. Additional measurement locations omitted from this study include those locations where ice growth may not be representative of either process being considered. Examples of such sites are those situated immediately adjacent to the bridge or in small channels that may contain no flow during the winter period.

In 1996, the ice thickness measurement sites were reduced in number. Measurements are no longer collected at sites downstream of the Clearwater River confluence. Four sites are measured between the Clearwater River Confluence and Moberly Rapids.

Establishing a Continuous Record

WSC has measured ice thickness in the vicinity of Fort McMurray for more than four decades. The record contains a mix of data from both sites: below the Clearwater River Confluence (Site A) and above the confluence (Site B); however, rarely are measurements for both sites available in a single year. Using a different measurement technique, the RMWB has been measuring ice thickness for fewer years, but at both Site A and Site B each year. By establishing a relationship between ice thickness data collected by WSC and RMWB, a complete record for both locations can be created. An analysis of the minimum, mean and maximum ice thickness supported that the division of sites into locations was correct and that the measurements had been performed consistently between sites. For each year, the available measurements were used to produce an average ice thickness value for each location. Linear regression was used to establish a relationship between the measurements done by WSC and the RMWB. A continuous record of ice thickness at both locations can be created by estimating the missing data from the determined relationship.

Downstream of the Clearwater River confluence (Site A), there were seven years when both WSC and RMWD measured the ice thickness. Due to the point measurement style of RMWD, it is reasonable to consider a measurement error of □ 0.10 m (based on the documented variability of ice thickness across transects involving multiple measurements). A linear regression between the two sets of data was found to estimate the data sufficiently, and is presented in Figure 2. Vertical error bars represent the reasonable error in measurement. This result demonstrates that although different methods for measuring ice thickness were used, both are accurate and can be related to each other.

Between 1989 and 2001, there was only one measurement done by WSC upstream of the gauging site (Site B). Therefore, a relationship between WSC measurements and RMWB measurements for this location could not be directly established.

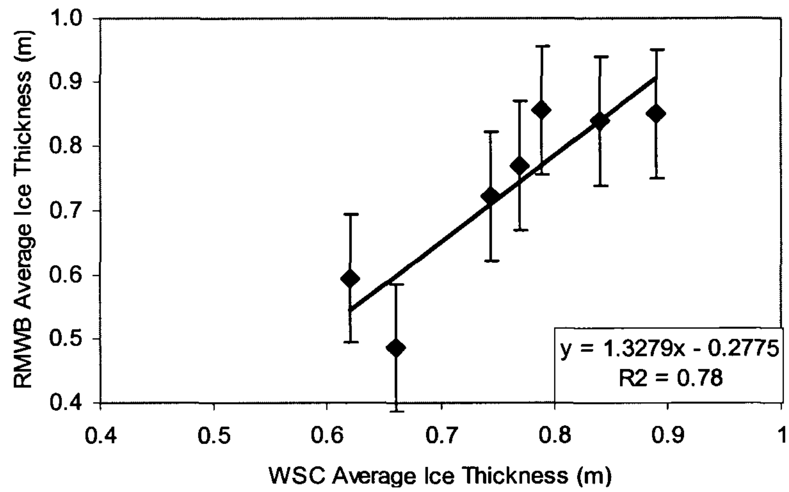

Figure 2. Ice Thickness Relationship for Site A (Downstream of Fort McMurray)

No linear relationship was found between the measurements at the WSC gauging site (Site A) and RMWB measurements through the Fort McMurray river reach (Site B) as a group. Site B measurements by RMWB were subdivided into measurement above the bridge and below the bridge. A good relationship could be established for locations above the bridge as shown in Figure 3. Note that all the points are within the measurement error bars of the regression line. No relationship was found between the WSC measurements and RMWB measurements below the bridge.

Based on this analysis, an ice thickness data set from 1973 to 2002 was created for the WSC gauging site (Site A) and Moberly Rapids above Fort McMurray (subset of Site B). A similar data set could not be generated for the reach between MacEwan Bridge and the Clearwater River Confluence. Table 1 contains the ice thickness values at both locations along with the ice thickness values used to develop the original linear regression and fuzzy expert system models. Ice thickness values for the original model are generally the last measurement done by Water Survey of Canada prior to river break-up. These values contain a combination of locations (sites A and B) as well as a wide range of dates. For years when WSC measurements were not available in late winter, point measurements from RMWB were substituted into the record.

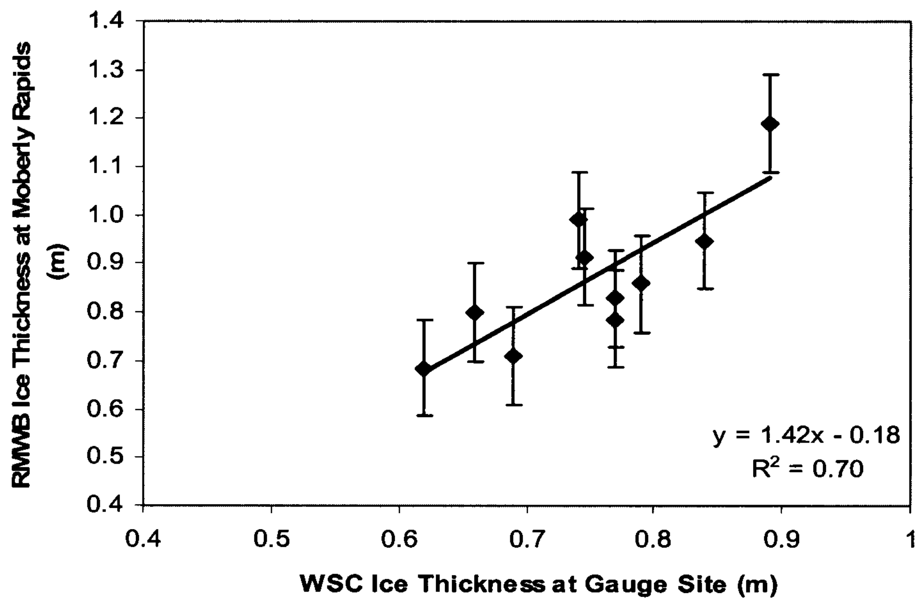

Figure 3. Ice Thickness Relationship for Site B (near Moberly Rapids) and Site A (Water Survey Gauge)

Table 1. Annual Ice Thickness Comparison

Year	Ice Thickness		
	WSC Gauging Site (m)	Moberly Rapids (m)	Initial Model Value (m)
1973	1.12	1.41	1.62
1974	0.63	0.71	0.61
1975	0.67	0.77	0.61
1976	0.84	1.01	0.82
1977	0.90	1.09	0.88
1978	0.90	1.09	0.88
1979	0.87	1.10	1.10
1980	0.80	0.96	0.69
1981	0.74	0.87	0.75
1982	0.65	0.57	0.65
1983	0.54	0.59	0.54
1984	0.81	0.97	0.81
1985	0.76	0.90	0.73
1986	1.01	1.05	1.05
1987	0.78	0.87	0.87
1988	0.66	0.63	0.66
1989	0.62	0.69	0.62
1990	0.66	0.80	0.63
1991	0.77	0.83	0.77
1992	0.79	0.86	0.75
1993	0.89	1.19	0.82
1994	0.75	0.91	0.68
1995	0.84	0.95	0.85
1996	0.74	0.99	0.73
1997	0.77	0.79	0.77
1998	0.64	0.71	0.58
1999	0.56	0.61	0.81
2000	0.52	0.56	0.68
2001	0.66	0.71	0.67
2002	0.66	0.75	1.62

Model Evaluation

Both the multiple linear regression models and the fuzzy expert system were based on a single ice thickness variable that contained a combination of data from above and below Fort McMurray. These models were re-evaluated to determine if the separated value of ice thickness would have a significant impact on the quality of results.

The maximum water level that occurs during spring break-up can be difficult to precisely measure. Ice floes and high water levels can make it dangerous to obtain a water level directly during ice jams or ice runs. After break-up, high water marks and stranded ice floes can be used to estimate the maximum water level. The accuracy associated with this type of indirect measurement is $\pm$0.5 m.

MULTIPLE LINEAR REGRESSION MODEL

The purpose of the multiple linear regression model is to provide a forecast of the maximum water level expected during river break-up. Due to its reliance on weather at the time of break-up, the forecast can be provided with a lead-time of 3 to 5 days. There are 17 years of data with which this model has been developed and verified. Robichaud (2003) describes the development process in detail. The range of potential water levels is over 8 m. Based on the original ice thickness data set and six other independent variables, the accuracy of this model is currently $\pm$1.9 m.

If the ice thickness data at the WSC gauge site are used in the model (Site A data), the accuracy is slightly

improved to $\pm$1.8 m. When the original ice thickness data are replaced with data from the Moberly Rapids reach (subset of Site B data), the accuracy is significantly improved to $\pm$1.5 m. Further accuracy could be achieved by removing two of the independent variables which become insignificant once data from Moberly Rapids is applied. Based on the remaining five variables, an accuracy of ± 1.3 m was realized.

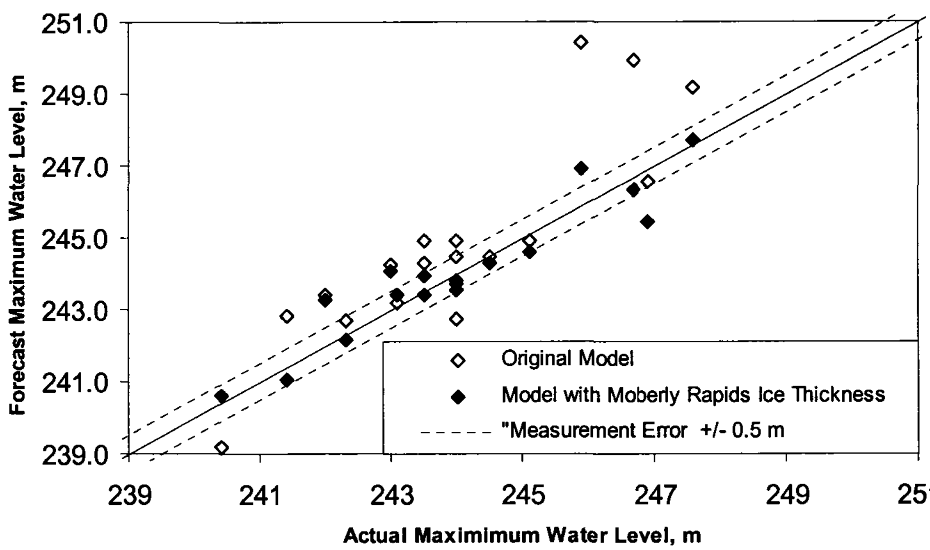

Figure 4. Multiple Linear Regression Model Comparison

FUZZY EXPERT SYSTEM

The fuzzy expert system provides a long lead (4 to 6 week advance) forecast of the risk of high water levels at break-up based on antecedent conditions. The development of this model is described by Mahabir et al. (2003). The model functions by evaluating logic based rules for three parameters (soil moisture index, basin average snow water equivalent, and ice thickness).

One of the strengths of the fuzzy modelling approach is that measurement values are converted from a single "crisp" number to a fuzzy representative set or membership function. A membership function describes the degree to which a measured value is represented by a linguistic term. For example, numerical values of ice thickness are evaluated based on the degree to which they belongs to the linguistic adjectives "thick" and "thin". The advantage of membership functions is that each data point is evaluated in relationship to a descriptive concept and in perspective to all possible values that the parameter could have. Because data sets are evaluated rather than single numbers, this type of modelling is frequently less sensitive to small changes in parameter values than other traditional approaches (Klir, 1997).

The separated ice thickness values did not have a significant impact on the long lead forecast models. In re-evaluating model performance using the revised data it was found that the potential risk of high water levels during river break-up was reclassified for only a single year. Interestingly, the numeric water level forecast for some years improved with the ice thickness values from Moberly Rapids while others appear to be more dependent on the ice thickness values from the WSC gauging site. The majority of years with high water levels were modelled more accurately with the values from Moberly Rapids. Both values may be important in determining the potential maximum high water level.

There is further potential to improve the performance of the fuzzy expert system with the separated ice thickness data. Using both values in the same model, rather than just one or the other, may be necessary to more adequately represent the processes involved. In addition, the higher annual variability of the ice thickness that occurs at Moberly Rapids increases the range of the membership function, decreasing the sensitivity of the model to error in the ice thickness measurements.

RESULTS AND CONCLUSIONS

The measurement location for ice thickness was shown to have a large influence on the measurement value for the Athabasca River near Fort McMurray. Historical values were separated by reach and a complete data record was established for two locations.

A significant improvement of ± 0.5 m was realized in the multiple linear regression model. This short term forecast could model the maximum water level of 22 break-up events with ± 1.3 m error for any year.

The risk classification results from the fuzzy expert system changed very little regardless of the type of ice thickness data used. However, results indicate that a significant difference occurs if a numeric forecast rather than a classification was the purpose of the forecast model. At this point, the accuracy of the long lead forecast model is not sufficient to produce numeric forecasts.

Studies are underway at the University of Alberta to verify the maximum water levels attained during river ice break-up using hydraulic modelling since many are currently estimated, particularly during years of ice jam occurrence. When these new data are available, a reanalysis of the current models with the ice thickness data from Moberly Rapids and from the WSC gauging station will be performed.

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APPENDIX C
Fuzzy Logic Rule Base

The rule base in the fuzzy logic model link the inputs to the output through a logical "If…Then…" statements. Input variables include (1) the number of degree days, (2) groundwater levels, (3) summer precipitation, and (4) the SWE. The water level at the time of river breakup is the output variable. A complete rule base contains all possible input combinations. Rules in this model have the following form: If the Number of Degree Days is (Low, Average, High) and the Groundwater Level is (Low, Average, High) and the summer Precipitation is (Low, Average, High) and the basin average SWE is (Low, Average, High) then the Water Level at Breakup will be (Low, Average, High). Table C-1 contains all the rules in the rule base for the fuzzy logic model based on experience with no calibration data presented to the modeler.

Table C-1: Rule base for fuzzy logic model with no points presented for calibration.

Number of Degree Days	Groundwater	Precipitation	SWE	Water Level at breakup
Low	Low	Low	Low	Low
Low	Low	Low	Average	Low
Low	Low	Low	High	Low
Low	Low	Average	Low	Low
Low	Low	Average	Average	Low
Low	Low	Average	High	Low
Low	Low	High	Low	Low
Low	Low	High	Average	Average
Low	Low	High	High	Average
Low	Low	Low	Low	Low
Low	Average	Low	Average	Low
Low	Average	Low	High	Low
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Low	Average	Average	Average	Low
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Average	Low	High	High	High
Average	Low	Low	Low	Low
Average	Average	Low	Average	Low
Average	Average	Low	High	Low
Average	Average	Average	Low	Low
Average	Average	Average	Average	Low

Average	Average	Average	High	Low
Average	Average	High	Low	Average
Average	Average	High	Average	Average
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