Assessment of Hydrological Drought in Northern Ontario
Using Standardized Streamflow Index

by

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ABSTRACT

Momentum is gaining for the use of a Standardized Streamflow Index (SSI) for the assessment of hydrological drought, which is an extension of the well-established and popularly used meteorological drought index, Standardized Precipitation Index (McKee et al, (1993). Drought characterization using SSI consists of various data treatments to transform streamflow data to standard normal Z-score values, where the mean is zero and the standard deviation is one. The underlying assumption when using Z-score in early warning systems and drought monitoring programs is that the scores associated probabilities may be represented by the normal (Gaussian) distribution. Applying data treatments that fail to achieve the conditions of normal distribution results inaccurate SSI drought assessments. There is an opportunity in Northern Ontario to conduct SSI drought assessments in early warning systems and drought monitoring programs using the abundance of long and continuous streamflow records; however, widespread applications would only be achieved if the resulting assessments are accurate, equitably and reliable. The data treatments investigated in the thesis include: Untreated and treated (i.e., Log Normal Transformation, and the Fitted Gamma Distribution).

Monthly assessments for a total of 40 rivers from across Northern Ontario with an average record length of ≈ 45 years were utilized in the analysis. Historical droughts sample periods 1976/77 and 1998 were used in evaluations as they were determined to pertain to the well-defined regional drought events with confirmation of historically significant impacts in addition to containing seasonal influences. The Log Normal Transformation followed by the Fitted Gamma Distribution exhibited the most consistency in not rejecting normality assumption of the data set when using the Shapiro Wilks and the Anderson Darling tests. These tests also

show the best performance of the Fitted Gamma Distribution for the winter season (November to May) and of the Log Normal Transformation for the summer season (June to October). Using these two data treatments for the respective seasons permitted the assumption of normality to be rejected 15.7% of the time. The use of best performing data treatments and removal of data for the month of March further reduced the assumption of normality being rejected only 12.0% of the time. In evaluating the frequency of occurrence for the severe and extreme Z-score values (-1.64 and -2.33), the Fitted Gamma Distribution followed by the Log Normal Transformation demonstrated the most acceptable scoring distribution. Untreated data performed less efficiently. All data treatments underperformed for the expected frequency at the extreme Z-score of -2.33 (i.e., the extreme drought).

The threshold level Q_{80} was determined to be the most appropriate trigger of monthly assessments for Northern Ontario because it was found to equitably delineate severe regional drought perceived by the respectively impacted sectors. The threshold level Q_{80} represents these sectors demands by identifying the point where streamflows are exceeded 80% of time. Since it is representative of the impacted sectors; it is used to assess the performance of SSI. Significant differences were recorded when comparing Q_{80} to the typical moderate drought classification with a Z-score equal to - 1. Untreated data tacitly refers to the assumption of the normal distribution of the monthly flows and correspondingly of SSI values. Thus, the analysis based on the assumption of the normality of the monthly SSI data turned out to be less reliable. All the data treatments underperformed for the expected frequency at extreme Z-score of -2.33. However, when applying Q_{80} to the theoretical equivalent Z-Score of - 0.84; identical results were achieved 76% and 66% of the time, respectively for the Log Normal Transformation and the Fitted Gamma Distribution. For the case of Q_{80}, the average difference for the drought initiation, termination, and duration were

found to range approximately 1.3 months with the Log Normal Distribution to 3.0 months for the lesser performing data treatments, such as the Untreated data.

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List of Abbreviations

AGU – American Geophysical Union
ARIDE – Assessment of the Regional Impact of Drought in Europe
CDM – Canada Drought Monitor
EC – Environment Canada
EDF – Empirical Distribution Function
FAI – Flow Anomaly Index
FDC – Flow Duration Curve
GWP – Global Water Partnership
IDMP – Integrated Drought Management Programme
IESO – Independent Electricity System Operator
IPCC – International Panel on Climate Change
KPSS - Kwiatkowski–Phillips–Schmidt–Shin
MOECC – Ontario Ministry of Environment and Climate Change
MNRF – Ontario Ministry of Natural Resources and Forestry
NOAA – National Oceanic and Atmospheric Administration
NSERC – National Sciences and Engineering Research Council
OPA – Ontario Power Authority
OLWR – Ontario Low Water Response
OMAFRA – Ontario Ministry of Agriculture, Food and Rural Affairs
PDSI – Palmer Drought Severity Index
RDI – Regional Streamflow Deficiency Index
SDI – Streamflow Drought Index
SHI – Standardized Hydrological Index
SRC – Saskatchewan Research Council
SPI – Standardized Precipitation Index
SSI – Standardized Streamflow Index
SWSI – Surface Water Supply Index
UNESCO – United Nations Educational Scientific and Cultural Organization
UNISDR – United Nations International Strategy for Disaster Reduction
USDA – United States Department of Agriculture
USGS – United States Geological Survey
WSC – Water Survey of Canada
WMO – World Meteorological Organization

CHAPTER 1: INTRODUCTION

Drought is characterized as an episode of water scarcity emanating as a direct result of less than optimal precipitation caused by various natural phenomena; the most predominant being the global climatic forcings. Drought events have a tendency to creep up unnoticed (Wheaton, 2000), and result in significant irreversible affects. The reach of drought events can cover a vast expanse, as shown in the 2012 drought event that engulfed 52% of the contiguous USA (NOAA, 2012). The growing impacts of a drought event may escalate as it draws out over numerous years such as is the case of the more recent 5-year Californian drought that ended in 2016 (USGS, 2017). This prolonged drought has resulted in extremely low reservoir and groundwater levels and restricted water use for irrigation and domestic use (Van Loon, 2015). Seven multi-billion dollar drought events have occurred (1931 to 1938; 1979; 1980; 1984; 1988, 1989; 2001 to 2002) in Canada alone (Agriculture and Agri-Food Canada, 2004). Since 1980 drought has cost Canada close to $30 Billion (Hadwen, 2009). Parts of Saskatchewan encountered extreme drought conditions in 2017 when the precipitation amount as low as 1.8 mm was recorded for the entire month of July; this amount was the second lowest when compared to 1.5 mm which had occurred in 1887 (Climenhaga, 2017). The nationwide drought event that occurred during 2001 and 2002 led to a reduction in the Canadian GDP of $5.8 billion (Wheaton et al., 2005). This loss impacted the following major sectors: agriculture, hydro-electricity, and forestry, in addition to other sectors such as recreation, health and tourism (Bonsal and Regier, 2006).

Drought indices are currently used by existing drought monitoring and early warning systems to convey the characteristics of drought in a comprehensible manner to the general public and the respective governing administrations. Indices are typically computed numerical representations of drought severity (WMO and GWP, 2016), which is used to delineate all other characteristics. Relevant characteristics of droughts over a region include duration, severity, intensity, areal extent, and frequency. The main objective of drought assessments is to bring clarity to fundamental questions such as: is drought anticipated, is it underway, how severe is it and when will it end. Standardized indices address these objectives comprehensively in a manner that also permits regional comparisons.

Standardized indices are computed by utilizing a hydro-climatic variable of interest and transforming the distribution to have a mean of zero and a standard deviation of one. Typically, a probability distribution that best fits the data is determined first so that when data is transformed would meet conditions of a normal distribution. A deficiency in precipitation is always the origin of drought, but as Van Loon and Laaha (2015) note, all drought impacts are associated with what is referred to here as agricultural drought, or hydrological drought, since both the ecosystem and society depend on catchment water storage (soil, aquifer, lakes, rivers) rather than from precipitation directly. This thesis focuses on impacted sectors of hydrological droughts, where the main alternative to the use of indices is the Threshold Method. Water managers of individual basins may utilize the threshold method as a hydrological drought tool to determine the deficit quantities of flow in relation to local demands set by a pre-defined threshold. Such threshold levels generally range from Q_{50} to Q_{95}, indicating the respective probability that streamflows are exceeded 50% to 95% of the time. These thresholds are most used to trigger responsive action during monitoring of discharge or water volumes from natural and artificial reservoirs (Van Loon, 2015). The inherent variability of low flows over time and space reduces the suitability of using the threshold method for multisite comparisons (Zaidman et al., 2001).

The Standardized Streamflow Index, SSI (Modarres, 2007 and Zaidman et al., 2001), which has the ability to provide improved multisite comparisons in the characterization of hydrological droughts, will be investigated in Northern Ontario. This, in turn, keeps with Keyantash and Dracup (2002) notion that it is advantageous for indices to focus on simple fundamental units. Early hydrological standardized drought indices (Sharma and Panu, 2010; Nalbantis and Tsakiris, 2009; Modarres, 2007; Zaidman et al., 2001), that use the same data treatment approach as the SPI of transforming data to Z-score (McKee et al., 1993), but make use of streamflow data instead of precipitation data. The streamflow data treatment exception is the Standardized Hydrological Drought Index (Sharma and Panu, 2010), which is not fitted to a probability distribution before being standardized. In investigating treatment of the SSI data, Vicente-Serrano et al. (2012) conducted a best fitting exercise for multiple probability distributions to determine the most suitable distribution for the Ebro River basin in Spain. The high degree of spatial variability in river basins is reflected in the probability distributions used to best fit monthly streamflow data (Riggs. 1973; Kroll and Vogel, 2002; Yue and Wang, 2004; Yue and Pilon, 2005; McMahon et al. 2007; Yue and Hashino 2007), making it difficult to assign one single distribution for regionally computing values of the SSI (Vincent-Serrano et al., 2012). Spatial variability in streamflow data is the result of a number of factors, including changes in topography, vegetation, and human management (Vincent Serrano et al., 2012); in addition to the spatial aggregation of flows that impact downstream statistical properties (Mudelsee, 2007).

There is an opportunity for Northern Ontario to use SSI in drought early warning systems and monitoring programs; however, for it to be accepted for widespread application drought assessments must demonstrate accuracy, consistency, and equitability. The abundance of long and continuous streamflow records throughout the region sets the foundation for these required traits, but it is the performance of the applied SSI data treatment that determines if such drought assessments are appropriate and representative of the respectively impacted sectors. Establishing an operational definition is required to identify the impacts of droughts on such sectors. Using inappropriate data treatments would result in inconsistencies and inaccuracies that could lead to oversight in drought assessments, less effective use of allocated resources, and reduced confidence in decision making abilities of governing administrations.

In general, monthly flows in northern Ontario tend to follow the gamma probability distribution (Sharma and Panu, 2008). In many environments across the world, the lognormal probability distribution has also been found a suitable distribution to fit the streamflow data (Zaidman et al., 2001). The simplest distribution is the normal one, which can be assumed to fit the data to begin with the analysis. In the present thesis, therefore all three distributions shall be attempted on the SSI data. The validity of the promising distribution would be assessed using the relevant statistical tests while involving the drought durations as observed in the historical data set. When the assumption of normal distribution has been invoked on the monthly SSI data, it is being referred to as untreated. When the gamma and lognormal probability distributions are used for the monthly flows, the SSI data are being referred to as treated.

CHAPTER 2: REVIEW OF LITERATURE

Hydrological drought is the result of hydro-meteorological interactions generated from global climatic forcings that in turn reduces precipitation and leads to water scarcity for a prolonged but defined period of time. The form of water scarcity of hydrological drought is streamflows or lake levels or storage and how they relate to their associated impacted sectors. These forms have the potential to cause significant and possible irreversible affects to the economy, society and the environment. Sectors that are impacted include agriculture, hydropower, and forestry, as well as intangibles such as recreation, health and tourism (Bonsal and Regier, 2006). Hydrological drought characteristics vary for each event, making it difficult to identify oncoming events. Panu and Sharma (2002) indicate that there still is no universal definition for the term severity. These inconsistencies result in a tendency for hydrological drought events to creep up unnoticed (Wheaton, 2000) and what is referred to as a 'creeping disaster' (Van Loon, 2015) that is well developed before it becomes noticed. Delineating the beginning and the end of a hydrological drought is difficult (Mishra and Singh, 2010), and impedes the ability of water managers to characterize hydrological drought and to determine when it will end. Lack of an established trigger to delineate drought reduces the effectiveness of adaptation and response measures developed as part of drought mitigation plans.

Planning minimizes the susceptibility of a region to drought. Drought planning consists of three main aspects; monitoring and early warning systems, risk assessment along with mitigation, and response (Wilhite and Svoboda, 2000). The slow onset of drought makes monitoring and early warning systems essential for effective drought mitigation planning (Wilhite and Svoboda, 2000). Existing drought planning programs are constantly going through process review to improve adaptability and reduce vulnerability. Bonsal et al. (2011) identified drought research needs in Canada, many of which relate directly to drought planning. In general, Bonsal et al. (2011) recommendations focus on improvements to overall understanding of drought, improved associations between the physical components of drought and how they identify with impacted sectors, variability of drought in space and time, and overall drought development characteristics. In addition, Bonsal et al. (2011) recommend linking drought impacts and potential triggers to programs and policy. Linkage of drought impacts and potential triggers require that the indicators utilized in assessments be based on the type of drought and the sectors directly affected. Only a few monitoring and early warning systems use hydrological variables (Barker et al., 2016) such as streamflow in their assessments. Barker et al. (2016) use the example that on its own, meteorological indicators should not be used to assess hydrologic drought due to the non-linear responses of terrestrial processes to climate inputs (Van Loon and Van Lanen, 2012; Van Lanen et al., 2013).

Characterization of hydrological drought and analysis are key tools in the development of drought plans. Optimization in planning is achieved when investigations focus on the nature of water shortage (Dracup et al., 1980), and can be embraced when assessments are accurate, transparent and equitable. Hydrological drought planning in Northern Ontario should focus on its predominance and therefore on susceptible water supplies, inland rivers, and lakes.

2.1 Hydrological Drought Assessment Studies – A Historical Perspective

Without an impact on humans or a human influence, hydrological drought remains a simple natural process. Hydrological drought research aims to improve economical, societal and environmental adaptability to drought and reduce vulnerability that results from some form of inadequate water supplies. In order to provide tangible evidence that such impacts are the result of hydrological droughts, a definition is necessary. Wilhite and Glantz (1985) identified over 150 hydrological drought definitions, which they categorized as being either conceptual or operational. Conceptual definitions are those stated in relative terms; a hydrological drought is a shortage of surface or subsurface water supplies (Hisdal and Tallaksen, 2000). Operational definitions identify onset, severity and termination of hydrological drought periods (Mishra and Singh, 2010). Hydrological drought perception varies by region (Smakhtin and Hughes, 2004), which may require that each region apply different operational definitions. The conceptual definition of a hydrological drought is defined as a prolonged dry period that causes below normal streamflows, lake and/or reservoir levels. The impact of this dry period makes sustainable water displacement practices unable to meet the demands of one or more reliant entities that results in economic, environmental or societal stress.

Once an Operational definition is articulated, a hydrological drought can be identified and subsequently characterized. The resulting characterization is a key factor in drought planning and drought mitigation as it provides the basis for risk assessments. Risk assessments may utilize low flow events and streamflow drought, but the two are different in analysis (Beran and Rodier, 1985). Early risk assessments for single sites were based on exceedance probabilities (Gumbel, 1958) and departures from normal conditions (Heim, 2000). The initial exceedance probabilities were based on instantaneous values (Gumbel, 1958), that neglect to identify the duration or spatial extent of a drought.

Hisdal et al. (2000) indicate that the threshold method was developed by Rice (1945), which was later summarized by Yevjevich (1967). The concept of drought as being a duration in which the water availability is less than a target threshold representing a regional demand was applied by Yevjevich (1972) to the threshold method in unison with the Theory of Runs. The result was an improved multisite comparison method for identifying the statistical properties of varying basins.

Subsequent developments focused on threshold levels based on a long term mean flow (Dracup et al., 1980; Sen, 1980; Guven, 1983; Rossi et al., 1992; Bonacci, 1993; Clausen and Pearson, 1995; Sharma, 1997; Shiau and Shen, 2001; Panu and Sharma, 2002); or a percentile level of the flow duration curve (Woo and Tarhule, 1994; Tallaksen et al., 1997; Stahl and Demuth, 1999; Hisdal et al., 2001; Hisdal and Tallaksen, 2003; Panu and Sharma; 2009). A flow duration curve identifies the exceedance probability associated with a defined streamflow, which can be used to define a threshold level. In hydrological drought assessment such a threshold level ranges from Q_{50} to Q_{95}, indicating the respective probability that streamflows are exceeded 50% to 95% of the time, respectively. These threshold levels may range depending on the associated impacted sectors, for example, reservoir operational levels and drinking water supplies (Van Loon, 2015).

Improved accuracy and precision of these techniques may be achieved by applying an appropriate probability distribution (Millan and Yevjevich, 1971; Sen, 1980; Zaidman et al., 2001; Sharma, 2000; Nalbantis and Tsakiris, 2008; Modarres, 2007; Sharma and Panu, 2010). However, a universal probability distribution is not probable due to spatial variability in a region (Riggs, 1973; Kroll and Vogel, 2002; Yue and Pilon, 2005; McMahon et al., 2007). Further, theories based on probability approaches are also used to estimate the longest hydrological drought duration and corresponding greatest severity of hydrological drought for a defined return period (Sen, 1976; Sen, 1977; Guven, 1983; Sharma; 1997, 1998, 2000; Sharma and Panu, 2008).

Improved multisite comparisons may be obtained by using the standardized severity, which requires that a series of flows be treated as stationary, with a mean of zero and a standard deviation of unity (Sharma and Panu, 2008). A meteorological index referred to as the Standardized Precipitation Index (SPI), developed by McKee et al (1993), remains one of the most well-known standardized indices. The straight forward application, availability of precipitation data, and the associated ranges of drought severity based on categories that range from moderate to severe drought, is attributed to the popularity of SPI (Van Loon, 2015).

The studies noted above are generally applicable to all regions, but all regions and dependent entities of water supplies within each of them perceive and characterize hydrological drought differently. For instance, the run of river hydropower facilities that are susceptible to immediate fluctuations of streamflows view the hydrological drought differently than large storage reservoirs because of their ability to stabilize streamflows fluctuations. Transparent and equitable assessments required in drought planning basically start with suitable definition of drought characteristics. Characterization of hydrological droughts requires objective scientific assessment (Wheaton, 2000).

2.2 Characteristics of Hydrological Droughts

A hydrological drought is defined by its component parts; initiation, termination, duration, severity, intensity and frequency. Initial evaluations of hydrological droughts used the Threshold Method in unison with the Theory of Runs (Yevjevich, 1967), where focus was on the total run of water deficits represented in terms of drought severity. The degree of deficit is determined by streamflows below a predefined threshold level, which produces a drought duration. The average streamflow deficit, in turn, produces drought intensity. How each characteristic is addressed tends to significantly influence the approach to drought assessments and the applicability of information that it generates. Figure 2.1 is a graphical representation of drought characteristics and followed by respective relevant description.

The drought severity, as depicted in Figure 2.1, is the volume of water expressed in cubic meters or as a depth over the area in mm, and it is therefore a positive entity. The drought intensity, which is the ratio of severity to duration, is also a positive entity. However, if the flow sequences are standardized or converted in to SSI, then all values below the truncation level become negative, rendering severity to be negative and correspondingly, the drought intensity to be also negative. In other words, the drought intensity turns out to be tantamount to SSI or Z-score, which has been reported as negative in the thesis.

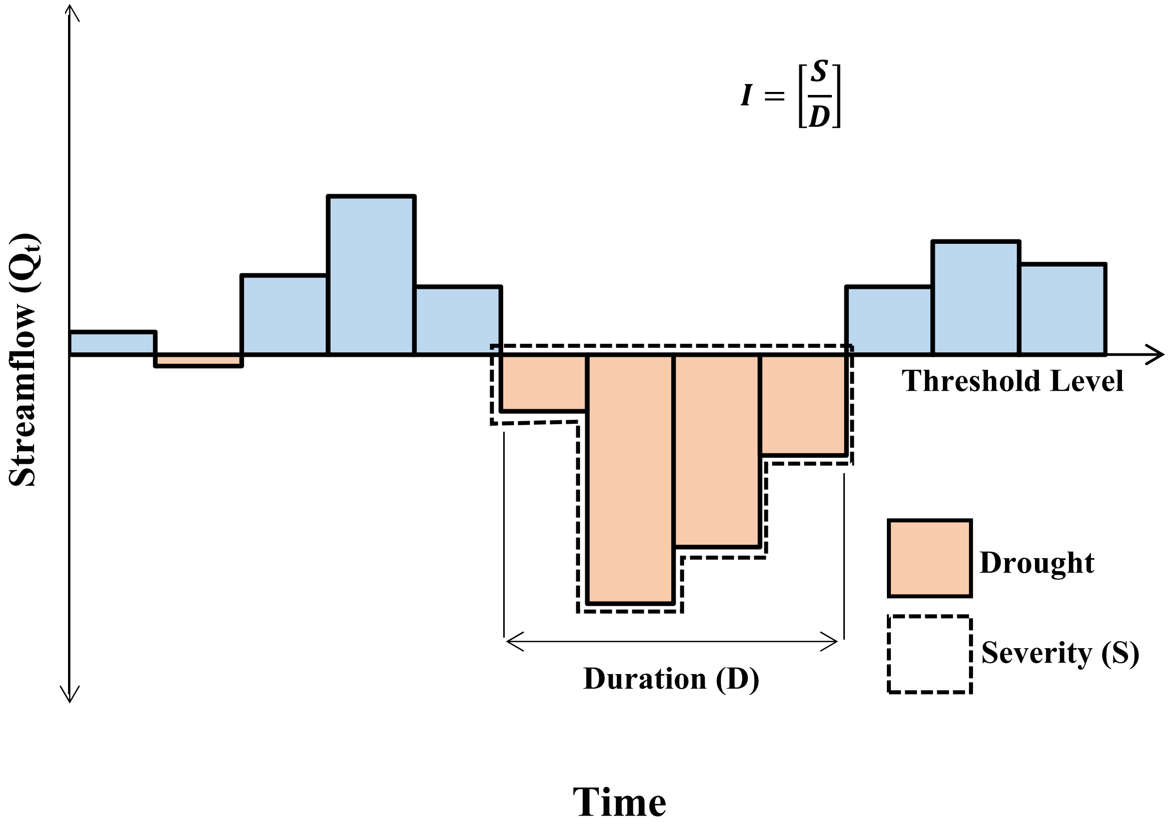


Figure 2.1: Definition Sketch of Drought Intensity (I) by its Components: Drought Severity (S), and Drought Duration (D).

2.2.1 Initiation and Termination of Hydrological Drought Events

Determination of the initiation and termination of a hydrological drought is difficult as it is surrounded with uncertainty. Decision making requires clear and consistent delineations of drought for use in assessments, which starts with an appropriate trigger. Confirming the initiation and subsequent termination of a hydrological drought is more easily justified if it can provide an illustrative picture of antecedent, existing, and predicted conditions in relation to historical context. Such an assessment procedure helps to generate better risk assessments and the corresponding optimization of water resources. Appropriate responsive action from water managers and governing administrations require confidence that a drought event has started and/or ended, and that all conditions agree with a certain level of confidence.

All conditions agree that a hydrological drought event has ended when the streamflows regeneration is in sync with water resources applications. Sharma and Panu (2008) illustrated the point of accounting for antecedent conditions in the evaluation of terminating a hydrological drought. They further observed that wet months are still susceptible to hydrological droughts, the impacts of which may be noticeable over a period of years, for example, is the case with the ongoing Californian drought (circa, 2011 through 2017).

Defining the end of a hydrological drought event and determining if successive conditions are a part of the first event or the beginnings of a new event, constitute separate entities. Scrutiny, in hindsight, will help determine if the deficit fluctuations may be considered as a single or multiple minor events to be pooled as a single hydrological drought event.

For simplicity, hydrological drought initiation and termination threshold levels are set to be typically equal to each other. However, some drought characterization methods terminate drought events when the mean or median threshold streamflow has been achieved and flows can no longer be considered in deficit conditions.

The threshold method reduces ambiguity by setting a predefined value, which once surpassed, indicates that a hydrological drought event has either started or ended. In identifying drought threshold, mean or median flows may be applied in an attempt to recognize deficits that account for seasonal norms. Mean flow is a direct measure of streamflows, a quantitative measure of water supply storage. However, the results generated by a threshold based on the mean flow may vary from the expected probability of exceedance being 50% of the time. Such a result could potentially lead to an over or under estimation of an initiation or termination of a drought. Median values, however, apply the middle most streamflow of a historical data set. From the standpoint of multi-site comparisons of hydrological drought; applying a median value for the threshold level is critical to reduce ambiguity and to increase the accuracy of comparisons. A threshold level based on the median streamflow (i.e. Q_{50}), or any other predefined flow exceedance quantile (e.g. Q_{70}, Q_{80}, Q_{90} etc.) ensures that each site will have the same number of hydrological drought days over the entire recorded period of the river (Zelenhasic and Salvai, 1987), a concept desired by water managers in making decision on a regional scale.

When selecting an initiation threshold level; it is important to know how frequently, it will be invoked (Steinmann, 2003). On one hand, the Q_{50} threshold level will result in numerous false drought alarms; while on the other hand; low flow events usually have negligible impact. Depending upon the time scale, threshold levels of Q_{70} or Q_{80} will still produce false drought alarms, however, the use of the Q_{90} or Q_{95} threshold may overlook notable drought events.

Using the central limit theorem to identify standardized drought severity will improve multi-site comparisons. The basis of using the standardized scoring in most drought assessments is that it identifies with the well understood and applied standard normal (Gaussian) distribution. Standardized drought severity requires that a sequence of flows be treated as stationary, with a mean of zero and standard deviation of unity. Deficits are made clear and more apparent using standardization, thus allowing for the selection of an appropriate deficit threshold level in specific applications and/or in specific regions (i.e. hydro power in Northern Ontario). The standardization equation given below may be used to highlight streamflow deficits.

$$z = \frac{x - \mu}{\sigma} \qquad \textbf{[2.1]}$$

Where, x is the variable of interest, μ the population mean, and the σ standard deviation of the population. The z-score determined using the above equation is the general case for annual flows. When determining z-scores on a time scale lower than annual (e.g. monthly), the population mean and standard deviation is unique to the each individual time scale increment (e.g. each individual month of the year).

Defining the threshold level of a hydrological drought event strictly based on time scale lower than annual, say monthly and/or weekly flows may overlook the significance of minor events. In practice, the selected threshold level and time scale utilized in identifying the onset and termination of a drought should be appropriate for the type of analysis.

A fixed “variable” threshold level used for hydrological drought characterization is commonly applied and usually is based on constant levels (e.g. mean annual flow). This practice may not be ideal for seasonally variable regions where water demands range significantly (Mishra and Singh, 2010). A variable threshold level (Van Loon, 2015) may be applied to account for seasonal patterns. Hisdal et al. (2000) noted that some regions encounter their lowest streamflows during the winter months, due to precipitation being stored as snow or as ice in streams. The 2014 winter drought in Scandinavia caused severe forest fires (Van Loon, 2015). For snowpack regions or heavily irrigated regions, seasonally separated hydrological drought characterization and analysis may be required (Tallaksen and Hisdal, 1997). However, with the change in climate patterns, regions that would have typically ended a winter drought due to snow melt peak may still experience that the drought continue into summer (Van Loon, 2015).

An appropriate selection of a threshold level for use in the delineation of the initiation and termination of a drought event will set the tone for its characterization, analysis and predictive features.

2.2.2 Duration of Hydrological Drought Events

In the determination of a hydrological drought event, the concept of a prolonged dry period is applied (Palmer, 1965). Tallaksen et al. (2009) in their study of hydrological drought in the United Kingdom found that hydrological drought events typically last longer around 4 to 5 months compared to the 1 to 2 months for meteorological drought events. Palmer (1965) stated that the term "prolonged" is synonymous with hydrological droughts and accounts for the long-drawn-out shortage of water which may result in destruction and devastation of human life and property. A minimum period for a hydrological drought disaster to develop requires, at least, two or three months (Palmer 1965). With the threshold method, this period may even be shorter when the hydrological drought intensity is significant or is based on demand levels.

Drought duration is represented by the run of a sequential time series of streamflows below a predefined threshold level Yevjevich (1967). Threshold levels may represent the deficits in the demands from impacted sectors like reservoir operations (Van Loon, 2015), and durations that are unable to meet those demands. It is common to encounter several minor hydrological drought events of negligible impacts, especially when using shorter time periods (or time scales) of assessment. In hindsight, pooling techniques may be applied to combine and/or to eliminate minor events.

The longest duration is an important parameter of hydrological droughts, in addition to greatest severity (Panu and Sharma, 2009). A set level of drought severity is typically used to delineate the initiation and termination of drought events, which is subsequently used to define drought characteristics.

2.2.3 Severity of Hydrological Drought Events

Hydrological drought severity (often referred to as run sum in the theory of runs), is a measurement that goes beyond an individual drought event in time and reflects consecutive streamflow deficiencies (Byun and Wilhite, 1999). Drought severity is defined by the total water deficit volume determined by deficits from a specified target threshold level. Referring to Figure 2.1, four consecutive time increments are below the targeted threshold level. The shortcomings of each time increment are described by a deficit volume. The volumes of deficits summed from all four time increments are added to determine drought severity.

Panu and Sharma (2002) note that the severity of drought is comprised of three main components; droughts duration, its probability distribution, and its auto-correlative structure. Wilhite and Glantz (1985) indicate that the geography of a region, human activities, and vegetative demands on water supplies make the determination of hydrological drought severity difficult. The severity of a hydrological drought event describes its momentum. As such, the severity analysis of hydrological droughts should be diligent and all inclusive. In general, streamflows are used to depict an accurate perception of a hydrological drought event in a basin. The function for generating values of drought severity is required to provide quantifiable estimates of streamflow deficits in the context of a historical perspective.

Ideally, a return period is determined to illustrate the severity of a hydrological drought event in a historical and comparative context. It should be kept in mind that the purpose of determining hydrological drought severity is to assess the impacted sectors reliant on the water resources. The resulting assessments of hydrological drought severity may differ for each region. As severity provides an indication of the drought momentum, the drought intensity can illustrate its scale as described in subsequent sections.

2.2.4 Intensity of Hydrological Drought Events

Drought intensity is defined as the ratio of deficit volume (drought severity) to the hydrological drought duration (Figure 2.1). It may be used to monitor whether a hydrological drought is having mild or severe impacts. The identification of intensity of hydrological drought events will largely influence the decisions to be made by water managers, along with governing administrations. The assessment of intensity of multi-year hydrological droughts should be sensitive, since the depleted water storage increases as does the vulnerability of a region. Departures below a chosen threshold level delineate a hydrological drought event, which is formed by its deficits, the duration of the run of deficits, and its corresponding drought intensity.

2.2.5 Frequency of Hydrological Drought Events

Stochastic analytical tools are often used to determine the frequency characteristics of hydrological droughts to provide historical and comparative contexts. Frequency distribution of streamflows will illustrate the probable range of flows throughout a year. The quality of data and the extent of a record period are pivotal components of frequency analysis. Measurements taken at-site for a sufficiently long period at stationary conditions would allow for nearly precise determination of a frequency distribution. A combination of shorter record periods, poorer quality data collection and anthropogenic changes to natural landscape would reduce the quality of the frequency distribution and would lead to poor decision making pertaining to the characterization and subsequent assessment of hydrological droughts.

For the characterization of hydrological droughts, percentiles and quartiles of a distribution have been used for designing infrastructure. Cumulative probabilities are often used to specify exceedance probabilities. Chung and Salas (2000) identify return periods, recurrence intervals (Kite, 1978; Loaciga and Marino, 1991), and occurrence probability (Vogel and Stedinger, 1987; Loaciga and Marino, 1991; Fernandez and Salas, 1999) that are utilized for designing flood infrastructure, which may in turn be utilized in droughts frequency analysis. In designing flood infrastructure, it is common to account for exceedance probabilities of a drought event such as 1 in 100 years to 1 in 10,000 years. Horn (1989) illustrates regional susceptibility to hydrological droughts by defining occurrence of 1 in 100 year events. However, these probabilities of exceedance and return periods are based on limited record lengths, often less than 100 years. The assumption of stochastic simulations is that they are represented by long-term trend free sample, but Millan and Yevjevich (1971) noted that when based on limited length of records the accuracy of the generated return periods is reduced. For example, using 30 years of data to determine 1 in 100 year hydrological drought would either be over or under estimated.

Conclusions based on stochastic analysis may produce conflicting results, as they relate to extreme hydrological droughts. In general, the selection of rare events is susceptible to subjectivity, if inappropriate stochastic treatment methods are applied or where assumptions are not properly translated in assessments or there are discrepancies in quality of the utilized data. An example provided by Horn (1989) indicated that when repeatedly using the same recorded length as in original data set, the simulated streamflows will have critical hydrological drought periods that tend to be longer but less severe (Askew et al., 1971). Different climatic regions have varying distributions which could impede justification of regional comparisons.

Chow (1964) proposed a method to estimate standard error of the mean annual flow as given below.

$$E_m = C_v \cdot \sqrt{N'} \qquad \textbf{[2.2]}$$

Where, E_m is the standard error of the mean annual flow, C_v is the coefficient of variation of annual flows, and N' is the minimum record length (years) for a given level of accuracy. The key concept derived from his analysis is that a coefficient of variance of 0.5 for a 25 year return period tends to generate a standard error of 10% which was found to exceed the typical margin of error value of 3% to 5%, which is usually deemed acceptable by water managers (McMahon, 2005). Having a minimum record length of 30 years results in a dataset that is statistically considered to approach a normal distribution (Brase and Brase, 2006) and thus the degree of error is minimized to an acceptable level.

Frequency analysis is the part of drought assessments as it describes the probability of how often a hydrological drought occurs. Confidence is gained by the general public and governing administrations when the characterization of frequency is accurate and equitable.

2.3 Refining Elements Used In Hydrological Drought Assessments

Characterization provides the tools to measure the physical attributes required to quantify hydrological droughts. Such applied characterization methods may be manipulated or adjusted to optimize the assessment for specific targeted impacted entities. Manipulation of these elements provides an opportunity to optimize and adapt drought characterization to the affected sectors and in turn improve assessments and/or evaluations used in drought planning.

2.3.1 Role of Time Scales in Hydrological Droughts Analysis

Drought assessments are improved when the characterizing parameters are represented at a time scale that is appropriate for the impacted sector(s). Hydroelectric such as run of the river facilities benefit from same day use and daily time scale assessments, while large reservoirs benefit from assessments on weekly or longer time scales. Time scales used for hydrological drought characterization and analyses are dependent on the essential information such as stream characteristics, time needed to collect available data, and tools available to conduct analyses. Flexibility in drought assessments has increased with the use of computers, making real time data to annual data readily available for analyses and interpretations. The cumulative deficit characteristics that define hydrological drought may range from daily to annual time intervals and require runs (drought or deficit) that are prolonged over monthly, seasonal or annual periods of time.

The use of either daily, weekly, monthly, seasonally, and annual time scales will result in differing initiation and termination points; all of which will have varying influences on droughts duration, severity, and intensity (Sharma and Panu, 2013). Byun and Wilhite (1999) indicated that there is a limited usefulness in monitoring hydrological drought when there is a greater period of time between successive steps. Early warning and drought monitoring programs represent such examples as they rely on timely and accurate assessments. Annual and semi-annual time periods may indicate regional conditions and historical behaviors of hydrological drought in a region (Panu and Sharma, 2002).

Zelenhasic and Salvai (1987) used the threshold level approach on daily recorded streamflow hydrographs. Daily flows show the behavior of short term hydrological droughts within a season or year and as such represent a useful tool for real time water management operations. Refined detail on the initiation of a hydrological drought is provided when shorter time scales are used in analysis; however, requires increasingly more demanding skill to conduct analysis appropriately. Tallaksen et al. (2004) noted that daily time resolution generates issues concerning dependency among droughts and the presence of minor droughts. Pooling procedures (Tallaksen et al., 1997; Fleig et al., 2006; Van Loon and Van Lanen, 2012) for mutually dependent droughts address such complexities by illustrating trends clearly over time.

Hydrological drought monitoring programs often incorporate monthly time steps because they are able to reveal demands for agriculture, water supply and groundwater (Panu and Sharma, 2002). However, rainfall is capable of regenerating streamflows in a matter of days, which may not be registered until the end of the month. Selection of the statistical properties used for analysis based on annual or even monthly time steps will not adequately be scaled down (Sharma and Panu, 2010).

For the analysis of hydrological droughts, the Theory of Runs has been applied to annual and multi-year time scales (Horn, 1989), as well as seasonally, monthly, weekly, and daily (Nalbantis and Tsakiris 2008; Modarres, 2007, Sharma and Panu, 2010 and 2013; Zaidman et al., 2001). The Canadian Drought Monitor (CDM) and the Ontario Low Water Response (OLWR) focus on monthly indicators that are updated weekly. Utilizing an appropriate time scale for using the threshold method is very important as it sets the boundaries of drought characterization and analysis.

2.3.2 Independent or Mutually Depended Hydrological Drought Events

Determination of the initiation and termination of a hydrological drought is often difficult to confirm with certainty. Using the Theory of Runs in unison with the threshold method, individual hydrological drought events may be delineated. If the duration and/or deficit volume between two hydrological droughts are deemed insufficient to individually separate the events, they may be combined using pooling procedures. Pooling procedures are used to better assess successive hydrological drought events that may be worse or better than what was primarily determined through initial investigations.

Fleig et al. (2006) indicated that the main pooling procedures implemented for characterizing hydrological drought using the threshold method included an inter-event criterion (time and/or volume), the moving average method, or a sequent peak algorithm.

Zelenhasic and Salvai (1987) stated that hydrological droughts are considered to be mutually dependent if the inter-event time is less than a predefined critical duration. A similar method may also be applied to an inter-event volume. Madsen and Rosbjerg (1995) suggested a combination of a hydrological droughts volume and period of time between hydrological droughts be used in determining mutual dependence. However, it may be difficult to determine and justify suitable inter-event criterion values. Tallaksen et al. (1997) indicated that the inter-event criterion method is inferior to the methods of moving average and sequent peak algorithms.

The moving average methods are versatile and may indicate dependency of certain hydrological drought events. As a part of the moving average process, the series of continuous streamflows is smoothed and minor peaks are discarded to reveal hydrological drought periods that may be pooled as a single event (Fleig et al., 2006). Moving average methods will reduce the number of minor drought events as it identifies trends in streamflows.

Vogel and Stedinger (1987) indicated that the sequent peak algorithm (SPA) is one of the most common procedures for reservoir design. The hydrological drought characteristics defined by this method are on the annual scale and comprise of deficit volumes of rare events. An advantage of the SPA is that its parameters require no initial determination. The SPA method gears towards an analysis period of less than one year and for very low thresholds (Tallaksen et al., 2004). A downside to the SPA is that it may generate many minor events (Tallaksen et al., 2004) that could result in misinterpretation. A pooled event using the SPA can be determined by the following algorithm:

$$\begin{array}{ll} w_i = (w_i - 1) + (q_0 - q_i), & \text{if positive} \\ w_i = 0.0, & \text{if negative} \end{array} \qquad \textbf{[2.3]}$$

Where, w_i is the storage required at the beginning of period i, q_0 is the desired flow into the reservoir, and q_i is the actual flow into the reservoir. The selected largest deficit volume, W_{max}, is used to set the limits for pooling an individual deficit period. Reservoir storage and depletion is represented by a continuous sequence of positive w_i. When the SPA pools two hydrological droughts, a comparison is made with the inter-event volume with both preceding and succeeding deficit volumes (Fleig et al., 2006).

Pooling techniques focus on at-site analysis of streamflows. The resulting analysis may be applied or incorporated into spatial tools to illustrate the extent of multiple streams during a hydrological drought event.

2.3.3 Spatial (Regional) Assessment Procedures for Hydrological Drought Events

Drought assessments begin with an evaluation of streamflow data collected at individual sites for regionalization towards drought planning purposes. With the collection of many at-site streamflow data points, projections may be made of the spatial extent of a hydrological drought. The resulting regionalization tools provide equitable assessments that can be used to evaluate varying regional impacts.

Selecting homogenous regions for hydrological drought characterization analysis may focus on grouping river catchments with similar hydrologic characteristics, even though they may not be contiguous. Spatial characterization is a beneficial tool in illustrating the intensity of a hydrological drought and its characterization in a historical perspective. In defining drought, Tallaksen and van Lanen (2004) deliberated on temporal and spatial aspects to account for the regional extent of the below-historical-normal conditions.

The generated frequency analysis of one or more hydro-meteorological indicator variables that are representative of regional demands may be presented by mapping tools. Mapping frequency analysis using methods such as the least squares method, and with the appropriate use of iso-lines, may generate an illustrative spatial extent of the intensity of a drought as it varies across the region. Multiple regression equations (Kumar and Panu, 1997) utilized drought parameters, geomorphology and climate for regional analysis. Kriging (Horn, 1989; Chang, 1991) is another regionalization tool. Visual interpretation is a key tool, for non-practitioner decision makers and the general public, in enhancing their comprehension of the spatial extent of hydrological droughts. Applications of spatial assessment tools are dependent on the type of analysis: regional or global.

2.3.4 Temporal and Spatial Assessment of Hydrological Drought Events

Nalbantis (2008) indicated that water managers impacted by a hydrological drought event are mainly concerned with a small number of points in space (e.g. basin outlets). This concept is appropriate for point source sites that require significant withdrawals from a stationary location (e.g. reservoirs); as such sites are mainly concerned with their immediate surroundings and existing storage supplies. Non-point water users (e.g. irrigation) would be overlooked, and yet may account for a significant amount of overall withdrawals within a region. Zaidman and Rees (2000) stated that spatial characterization of hydrological drought at a given time step generally involves the selection of a predefined region to quantify the extent of streamflow hydrological droughts. The issue with defining hydrological drought within a single region is that the spatial extent may develop over multiple river basins with varying conditions.

The causes of hydrological droughts are due to large scale spatial and temporal anomalies in the climate system (Tallaksen, 2011). The atmospheric conditions that cause regional hydrological drought may be characterized by the atypical timing of seasonal phenomena, atypical location of pressure centers, and the track of cyclones and the atypical persistence or persistent recurrence of dry weather patterns (Stahl and Hisdal, 2004). Stahl and Demuth (1999) improved the evaluation of the spatial behavior of hydrological drought by incorporating atmospheric circulation patterns. The regional extent of drought at varying temporary and spatial scales has been assessed (Panu and Sharma, 2002) using data based on defined threshold level of severity (e.g. Q_{90}) and hydrological drought frequency and intensity. Fleig et al. (2006) expanded this concept with weather types and using varying threshold levels.

The characteristics of a drought as it evolves over space and time are evaluated and portrayed by the early warning and monitoring programs.

2.4 The Development and Application of Hydrological Drought Indices

The hydrological drought assessments that make part of early warning systems and monitoring programs in North America, aim to improve economic, societal and ecological, adaptability and to reduce vulnerability through preparation and planning. Hydrological drought planning consists of three main aspects (Wilhite and Svoboda, 2000); monitoring and early warning systems, risk assessment along with mitigation, and response. A slow onset of a hydrological drought makes early warning systems and drought monitoring programs essential for the effective mitigation planning (Wilhite and Svoboda, 2000).

Assessments of hydrological drought are implemented as a part of the early warning system and monitoring program and are used by water managers, and decision and policy makers to address the stress induced by droughts. These assessments analyze various forms of water supplies with the aim of meeting consumer demands. Drought early warning systems and monitoring programs are primarily provided in Ontario by the Canadian Drought Monitor (CDM) that is operated by Agriculture and Agri-Food Canada (AAFC) along with the Ontario Low Water Response (OLWR), which is operated by the Ministry of Natural Resources and

Forestry (MNRF). Each of these programs provides their own mapped estimations of historical and current hydrological droughts.

Drought indices are currently used by the CDM and the OLWR to express drought characteristics in a comprehensible way to the general public and to be acted upon by water managers and governing administrations. Severity is the primary characteristic of interest, but assessments also convey spatial, duration, severity, intensity, and frequency characteristics as well. Indices generally provide computed numerical representations of drought severity (WMO and GWP, 2016). Indices that provide probability of occurrence, or recurrence, of varying drought severity, also provide a historical context that can be utilized by planners or decision makers (WMO and GWP, 2016). Various climatic or hydro-meteorological inputs are used by indices to generate assessment of drought. When leading up to and during a drought event, indices can help communicate the characteristics of a drought event and assists in bringing clarity to fundamental questions such as: is drought anticipated?, is it underway?, how severe is it?, and when will it end?.

Drought indices can focus on one or multiple forms of drought, all of which were based on the hydrological cycle. Panu and Crinklaw (2011) described in detail the progression of drought indices based on drought types: meteorological, agricultural, hydrological and socio-economic. Wilhite and Glantz (1985) defined forms of drought as being either, meteorological drought (precipitation), agriculture (soil moisture), and hydrological (or streamflow or groundwater). Drought characteristics may be described by indices in one of the forms of drought mentioned in the above.

Early studies of delineated hydrological drought events have primarily been based on historically observed streamflows or lake levels. These events could be associated with specific or multiple demands on a water supply system. These indices measured their duration and/or intensity (Heim, 2000). Subsequent evaluations of hydrological drought events were based on deficits and/or departures from normal (e.g. streamflows being 30% less than normal). A distinction between two separate methods for assessing hydrological droughts based on single or multiple hydro-meteorological variables was made by Palmer in 1965 (Hisdal and Tallaksen, 2000).

Using multiple hydro-meteorological variables, Palmer (1965) developed a landmark index known as the Palmer Hydrological Drought Index (PHDI) to analyze and quantify hydrological drought events. Although computationally similar to the Palmer Drought Severity Index (PDSI), the PDHI differs by having a slower response time to the onset and termination of hydrological drought events. The Surface Water Supply Index (SWSI) of Shafer and Dezman (1982) overcomes the limitations of PDHI in mountainous regions by accounting for reservoir storage as well as by replacing the streamflow variable with a snowpack variable during months of subzero temperatures in the hydrological accounting system. Tallaksen et al. (2004) refer to these types of indices as complex indices as they require a wide range of hydro-meteorological data for computations. Often one or more of the variables needs to be estimated, which potentially introduces error (Heim, 2002). In addition, both PDHI and SWSI assign weights to variables, which make multi-site comparisons inappropriate (Garen, 1993). The use of multiple variables in computations of these indices makes them less tangible to physical drought characteristics.

Current assessments of drought used in early warning systems and monitoring programs utilize either a single index/multiple indices/complex indices or a combination of these indices. A single index addresses in detail one drought variable and often one form of drought. However, this may be inappropriate for describing drought and its associated impacts as a whole. Multiple indices accounting for multiple variables encompass a more complete depiction of drought and associated impacts.

Using a single hydro-meteorological variable (i.e., streamflows), the wet and dry events are delineated by using a threshold level (e.g. median annual flow) that signifies specific demands. Frequency analysis of streamflows provides a historical perspective of hydrological drought characteristics: duration, severity (e.g. total water deficit) and intensity. The threshold method provides probabilistic characteristics of duration and severity of hydrological droughts that may be used to assist in designs and operations water management infrastructure. However, the threshold method provides limited ability for multi-site comparisons (Zaidman et al., 2001).

Zelenhasic and Salvai (1987) introduced a threshold demand level that was set to a non-exceedance probability as determined by the associated stochastic model. This provides an opportunity to compare multiple sites equitably on the basis that they would all have the same number of hydrological drought days. A limitation in terms of multisite comparisons is that different sites may still have varying drought durations and deficit volumes. Van Loon and Laaha (2015) attribute these differences primarily to catchment storage retention characteristics (e.g. geology and land use), while deficit characteristics are more influenced by moisture availability as indicated by characteristics such as mean annual precipitation. Threshold levels often exceed briefly for short periods of time during prolonged dry periods, which results in multiple minor and mutually dependent hydrological droughts (Dracup et al., 1980; Tallaksen et al., 1997; Hisdal and Tallaksen, 2000). Such factors as moving average, inter-event criterion, sequent peak algorithm and pooling methods have been investigated by Tallaksen et al., (1997) for smoothing daily streamflow time series in an effort to eliminate such minor and mutually dependent hydrological droughts. Their study demonstrated that results of the sequent peak algorithm were only consistent with the results from the inter-event criterion and the moving average when a low (Q_{70} or greater) threshold was applied. In the case of the sequent peak algorithm and also where the moving average method was used, the minor droughts were found to be reduced considerably.

Ben-Zvi (1987) defines hydrological drought as the severe shortage of natural sources of water in regards to normal conditions. Annual streamflow volume properties are described by Ben-Zvi (1987) in terms of mean and standard deviation as they fit the normal distribution. A stark shortage in water supply refers to annual volumes of streamflow that are below one standard deviation from the mean. The term severity also implies a prolonged shortage for a defined region. This follows the comment by Dracup and Keyantash (2002) that indices with dimensionless, normalized, and/or probabilistic qualities are particularly beneficial in providing multisite comparisons.

Horn (1989) used statistical parameters of streamflows over a region to identify zones that are more susceptible to extreme hydrological droughts. Using a stepwise regression analysis, Millan and Yevjevich (1971), and Horn (1989) applied the equations for determining distribution parameters for the identification of regions with a significantly large variation.

On a larger scale, Stahl and Demuth (1999); and Stahl (2001) employed their regional streamflow deficiency index (RDI) to investigate how atmospheric hydrological drought relates to variability in streamflow. A hydrological drought exists if streamflows of an individual basin are below the threshold demand level (e.g. Q_{90}). The number of basins in a hydrological drought is then related to the total number of basins of the defined homogenous region being investigated to determine the respective RDI value. If the deficit is consistent throughout the region, then the period is defined as being in drought.

Keyantash and Dracup (2002) noted that it is advantageous to base indices on simple fundamental units. Currently, the meteorological drought index that only uses the hydro-meteorological variable (i.e. precipitation), the Standardized Precipitation Index (SPI) developed by McKee (1993), has widespread applications. The drought characterization approach of the SPI is to transform precipitation data to Z-scores, where the mean is zero and the standard deviation is one. The popularity of the SPI is largely a result of its straight forward application, availability of precipitation data, and associated ranges of drought severity using categories range from moderate to severe drought (Van Loon, 2015). Drought characterization of the SPI has set thresholds to identify with increasing severity of drought. The time increments for analyzing drought: 1, 2, 3, 4, 6, 12 etc. months, for identifying drought are already predefined. As a result, each increment is referenced to intensity as the severity represented the accumulated deficits for that period of time. The corresponding evaluations are illustrated on the following Figure 2.2.

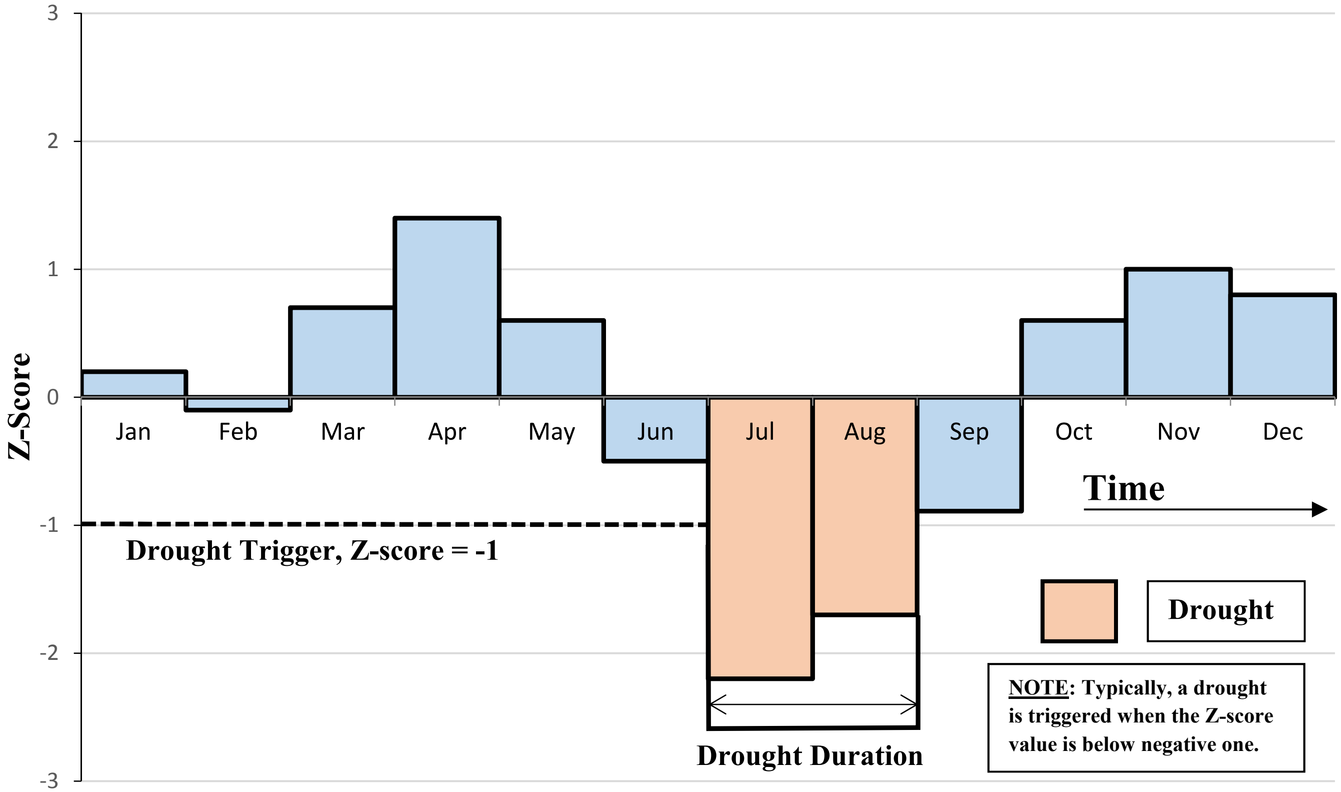


Figure 2.2: The standardized index (Z-score) used for monthly assessment of droughts.

Several studies have started to use the same approach but using the streamflow as the single hydro-meteorological variable with the intent to characterize hydrological droughts. Early studies that apply the same approach as the SPI include, the Flow Anomaly Index (Zaidman et al., 2001), Streamflow Drought Index (Nabaltis and Tsakiris, 2009), Standardized Hydrological Index (Sharma and Panu, 2010), and the Standardized Streamflow Index (Modarres, 2007). These studies apply various treatments to the data. One approach is to either fit the streamflow data to a probability distribution before transferring it to the standard normal distribution; another approach is to transform the data before transferring it to the standardized normal distribution, and the last approach is to leave the data Untreated before transferring it to the standardized normal distribution. The accuracy and appropriateness of using probabilities associated with the Z-score is dependent on how well these approaches achieve a normal distribution.

A more recent study that investigates the suitability of various streamflow data treatments was conducted by Vicente-Serrano et al. (2012). The study conducted a best fit application for multiple probability distributions to determine the most suitable probability distribution for the Ebro River basin in Spain. The results of the study show that there was a high degree of variability in probability distributions of river basins used to best fit monthly streamflow data due to spatial variability of a region (Riggs, 1973; Kroll and Vogel, 2002; Yue and Wang, 2004; Yue and Pilon, 2005; McMahon et al., 2007; Yue and Hashino, 2007). The study also noted that it was difficult to assign one single distribution to regionally compute the SSI (Vincent-Serrano et al., 2012). There were a number of factors related to spatial variability of streamflow data, among them included changes in topography, vegetation, and human management (Vincent

Serrano et al., 2012), as well as spatial aggregation of streamflows that tend to influence downstream statistical properties (Mudelsee, 2007).

The SSI is a beneficial tool for use by water managers and governing administrations to improve upon comprehension, equitability, and transparency; however, the use of unsuitable probability distributions causes inconsistencies and inaccuracies that could lead to oversight in drought assessments.

2.5 Concluding Remarks on the Adequacy of Hydrological Tools in Assessing Hydrological Droughts in Northern Ontario

Northern Ontario is a water dependent region that has become accustomed to reliable sources of water supply. This dependency makes the region susceptible to the severe economic, societal and environmental impacts due to hydrological drought. Even with the abundance of water sources in Ontario, hydrological drought still plays a notable role, for example in the burning of 635,374 ha of forested land in 2011 (Clark, 2012). The reliance on hydroelectricity amounts to 25% of total provincial demands (Ministry of Energy, 2010). Complexities arise in providing hydroelectricity during the peak demand in summer months, where low flows and drought create an uncertainty in supply (IESO, 2006). Most hydropower stations only have adequate storage for peak winter events of up to 2 hours (IESO, 2006), potentially creating a dire situation for the public. As hydropower facilities abstract as much flow legally allowed during hydrological drought events thereby, putting into stress the downstream aquatic environments which in turn impacts recreation and tourism. The $20 Billion Great Lakes boating and fishing industries were impacted by the 1998 extreme drought (NOAA, 2007). Navigation was impacted during the hydrological drought of 2001/02, where low water levels cost $11.25 million to the associated industries within the Great Lakes (Bonsal and Regier, 2006). Mainland municipal, residential, commercial and industrial sectors also continue to experience stress in their attempts to meet environmental compliance of effluent discharges. Water takings by drinking water treatment facilities feel the related problems with excessive algae and bacterial growth during hydrological drought events (Caruso, 2002). Harsh hydrological drought events have and continue to result in significant economic loss and in turn a notable societal stress. It is in this regard that drought early warning systems and drought monitoring programs constitute an integral part of the solution towards reducing associated impacts of vulnerability.

The approach used by the drought early warning systems and monitoring programs provided by the CDM, accounts for a range of variables and associated indicators to evaluate drought conditions. There is a limitation from the perspective of water manager, as most indices used by the CDM primarily target the meteorological drought. Streamflow values are incorporated in some CDM assessments of drought evaluation, but more in the form of generalized statements.

The intent of drought early warning systems and drought monitoring programs provided by the OLWR is to identify and categorize a hydrological drought into one of three progressively worse stages of water scarcity. The rating system is based on precipitation and/or streamflow deficits over a defined period of time. The OLWR is a low flow index that is limited in its ability to identify the impacts associated due to the cumulative deficit streamflows in a hydrological drought. In addition, the index inadequately relates water scarcity to user demands. During the initial 13 years of operations and leading up to year 2010, the most extreme Level III condition (i.e. streamflow less than 40% summer average) had never been declared by the Low Water Response Team or the Province (Disch, 2010). This shows the vulnerability of the drought management plan to political influence (Disch, 2010) and the subjectivity of a water manager.

Consequently, drought assessments are neither transparent nor equitable and may lack effective mechanism for implementation. The Hydrological Drought Watch Program made publicly available by Agriculture and Agri-Food Canada (AAFC) provides real time PDSI values for locations throughout Canada. The PDSI also has notable limitations (Alley, 1985; Karl and Knight, 1985) such as it particularly provides an inept assessment of cold climate regions like Northern Ontario, and in addition, the manner in which weights are assigned to variables for obtaining computational results for multi-site comparisons may also be inappropriate (Garen, 1993). Additional methods for hydrological drought assessment that are applied in Ontario are publicly inaccessible. Basic assessment tools for resource estimation include the use of mean flows, which may be used to estimate the potential generating capacity for a hydropower station (Gustard et al., 2009). Mean flows can also be used to provide an indication of deficit flows that otherwise would have been expected. Annual mean flow may provide an indication of annual variability of a stream and to illustrate the potential carry over effects (Gustard et al., 1992). The most common tool to assess hydrological drought conditions is the flow duration curve (FDC). The FDC utilizes daily or average weekly streamflows to provide a probability of exceedance of a predefined flow, which in itself fails in its entirety to identify cumulative deficits during a hydrological drought. Zelenhasic and Salvai (1987), along with Vogel and Fennessey (1994), stated that the threshold identifying hydrological drought conditions for the FDC should be the values equal to or greater than the long term median flow, thereby illustrating exceedances. In Ontario, hydropower requirements are based on winter and summer peak consumption rates with emphasis given to the latter (IESO, 2006). The FDC is used by authorities such as the MNRF to identify streamflow regions for the purpose of delineating any allowable abstractions. These abstractions account for the minimal requirements of downstream users and to ensure the preservation of downstream ecological environments. The FDC is also used for effluent discharges, including those from thermal generating stations.

Currently, an effective hydrological drought analysis tool is lacking in Northern Ontario. There is an opportunity to utilize abundance of long recorded streamflow data to assess drought across the region of Northern Ontario, and to include it in drought early warning systems and monitoring programs, such as the OLWR and CDM. Characterizing drought in the form of Standardized Streamflow Index (SSI) allows for the region of Northern Ontario to be treated equitably with transparency and accuracy.

CHAPTER 3: OBJECTIVES AND SCOPE

In view of drought impacts on major industries of Northern Ontario such as mining, logging, hydroelectric, and the abundance availability of long and continuous streamflow records; there exists an opportunity to include hydrological drought assessment through the use of drought indices as part of drought monitoring and early warning systems for the region. The main objectives of this thesis are to set the foundation for such hydrological drought assessments in Northern Ontario on a monthly time scale as follows:

1. Establish operational definitions of hydrological drought as it relates to drought impacted sectors;
2. Select threshold levels to trigger the onset and the termination of hydrological droughts that are sensitive to demands of the various impacted sectors;
3. Establish the utility of the standardized streamflow index (SSI) in successful assessment of hydrological droughts;
4. Validate the effectiveness of the SSI while involving unsuitable streamflow data treatments in providing improved understanding of implications due to hydrological droughts;
5. Quantify the implications of using unsuitable streamflow data treatments in conjunction with the defined hydrological drought characteristics used in drought assessments; and
6. Determine the best performing data treatment for SSI among the competitive data treatments [Untreated data and Treated data (Log Normal Transformation, and the Fitted Gamma Distribution)] for the assessment of hydrological droughts.

CHAPTER 4: DEVELOPMENT OF METHODOLOGY

This chapter outlines the process and rationale to achieve the objectives stated earlier in chapter 3. It starts with ensuring that data for use in computing SSI in subsequent statistical analyses be of good quality to enhance confidence in results. It then develops threshold levels that are representative of demands for analyzing droughts in various sectors of Northern Ontario. The chapter concludes with the description of processes that are applied to assess various data treatments for SSI analyses.

4.1 Assessment of the Completeness and the Quality of Streamflow Datasets

To ensure the completeness and quality of dataset, the first step was to identify missing data and, where appropriate, infill the missing data with values that do not significantly influence the underlying probability distribution of the dataset. Once the data was infilled, an assessment was conducted to ensure that the dataset meets weakly stationarity requirements to confirm that statistical assessments are conducted accurately and consistently. The methods used to provide a complete and good quality datasets are described as follows.

4.1.1 Missing Data

It was a common occurrence to observe some missing records in hydrometric (streamflow) datasets routinely maintained by Water Survey of Canada. The missing streamflow records require rectification before being used in an analysis. Tallaksen et al. (2004) noted that a small proportion of missing data may significantly reduce the meaning of summary statistics. To compensate, infilling was conducted for the missing records with the use of Linear Interpolation for short gaps of less than ten days and the Analogue River Ratio Method for longer durations.

4.1.1.1 Linear Interpolation Method

Infilling of missing records completed by the Linear Interpolation method in streamflow data was accomplished by using a straight line between the first and last known values for up to ten days. Tallaksen et al. (2004) indicate that for short gaps (i.e., a matter of few days), infilling may be conducted manually by Linear Interpolation method provided there are no apparent indications of the occurrence of a flood and or a drought event.

4.1.1.2 Analogue River Ratio Method

The Analogue River Ratio Method was applied to missing data segments that were longer than ten days and up to a year. Tallaksen et al. (2004) indicate that this is a simple approach that utilizes a nearby (analogue) gauging station to manually estimate missing flows at the target gauging station. The method implies the existence of a relationship (usually in the form of a ratio) between flows at the target station and the analogue station. This ratio was then used to infill the missing flows.

In order to infill data, the subject (i.e., target) river and the closest adjacent river(s), would ideally have a greater than 30 years of flow data, and would be used to develop a relationship (Equation 4.1) for each individual day in a given year. As a general rule, a sample size greater than 30 years was used to attain an approximation of normality (Brase and Brase, 2006). The corresponding equation is provided below.

$$X_d = \frac{\sum X_{d,y}}{\sum X_{d,y}} * Y_d \qquad \textbf{[4.1]}$$

Where, X_d represents an estimate of the missing value on a particular day and was determined from the average day ratio; the average flow ($X_{d,y}$) of the target river for day d over the average flow ($Y_{d,y}$) for the same day d of the adjacent river, was multiplied with the known flow (Y_d) of the adjacent river(s) for the same (missing) day d.

4.1.2 Weakly Stationarity Relationships

Statistical tools satisfying the assumptions of weak stationarity was used to analyze stochastic time series. The assumption of weak stationarity includes:

1. First moment, the mean, is constant in time; and
2. Second moment, the variance and auto-correlation structure, is constant in time.

The validity of the assumption of weak stationarity was tested on a time series of annual mean discharges. Since only a portion of such a time series data usually satisfy the requirements of normality, non-parametric analysis was also conducted. Rivers that failed to meet the assumption of weak stationarity were then either adjusted or discarded. A number of tests, as described in the ensuing sections, were conducted to determine whether or not the streamflow data adhered to the assumption of weak stationarity.

4.1.2.1 The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test

The KPSS (Kwiatokski et al., 1992) tests for the 'level' or rather trend-stationary time series may be established by a deterministic trend. It is particularly helpful at identifying trends as it is a test for long memory in the system (Lee and Schmidt, 1996; Donner and Barbosa, 2008).

The test assumes that time series can be broken down into sum of a deterministic trend, a random walk term, and stationary stochastic noise (Donner and Barbosa, 2008) as described below:

$$X_t = \beta t + r_t + v_t \quad \textbf{[4.2]}$$

$$r_t = r_{t-1} + \varepsilon_t \quad \textbf{[4.3]}$$

$$v_t \sim N(0, {\sigma^2}_v) \quad \textbf{[4.4]}$$

$$\varepsilon_t \sim N(0, {\sigma^2}_\varepsilon) \quad \textbf{[4.5]}$$

Where, the series X_t is described by a deterministic trend, r_t is the random walk component, and ν_t is the stationary stochastic noise (error) term. Random walk is a naturally observed behavior where successive steps of a random sample tend to follow the same path briefly. The null hypothesis for the KPSS test is that an observable series is stationary around a deterministic trend, which would indicate that there is constant variance in error (i.e. random walk). The critical values for p-values at a significance level of 0.1 are 0.347 and 0.119 respectively for a level time series and a series involving trend. If the test scores were greater than these values, then either the streamflow data was determined to be uneven and /or had a trend. R Statistical Software package was utilized to conduct computations.

4.1.2.2 Run Test

In 1940, Wald-Wolfowitz attempted to identify patterns in a time series for trends and in doing so created the Run Test. This test analyzes the string of positive or negative runs, and determines if trends exist. For example: "+ + + - - + + + + - - - + + " consists of five runs, three in the positive direction and two in the negative direction. The Run Test determines if these runs were part of a trend. The null hypothesis is that the sequence of a time series is produced in a randomly drawn fashion from the same distribution. The corresponding description of the Run Test is outlined below:

$$N = \sum_{j} j^2 n_j \qquad \textbf{[4.6]}$$

Where, N is the test statistic, j is the length of the run, n_j is the number of runs of length j. A significance level of 5% was applied with n/2 degrees of freedom. If the test statistic was greater than the critical values then the null hypnoses of a trend free series was rejected.

4.1.2.3 Wilcoxon Signed Rank Test

The Wilcoxon Signed Rank test is intended to be a non-parametric equivalent to the Student's t-test. The null hypothesis for this test states that the median for a distribution of sample is equal to a pre-defined target value. In other words, the median difference is zero. This test was used to determine if the medians and variances of the streamflow data were constant in time. R Statistical package was utilized to conduct computations.

The use of foregoing tests warrants that datasets are of good quality for assessing drought characteristics and computations of SSI to imbue confidence in the analysis and ultimately, to determine the efficacy of SSI in appraising drought conditions in Northern Ontario.

4.2 Operational Definition of a Hydrological Drought and Development of Threshold Levels Representative of Demands in Northern Ontario

A conceptual definition of a hydrological drought is defined as a prolonged dry period that causes below normal streamflows, lake and/or reservoir levels that make sustainable water displacement practices unable to meet the demands of one or more reliant entities. Such a dry period results in economic, environmental or societal stress. Further, this definition lacks the specifics required to quantify the impacts of hydrological droughts. However, numerically identifying demand characteristics make the definition operational, and in so doing validate its application in early warning systems and drought monitoring programs. Keeping with the prominently applied time scales used by drought planning tools (the OLWR and the CDM), monthly streamflow assessments were used. The remaining characteristics required for the definition to be operational are the onset and the termination, which are delineated by drought severity.

A majority of thresholds used for identifying the onset of a drought event are arbitrary because they lack specific impacts in key economic sectors (Wilhite and Svoboda, 2000). Through the use of selected sample periods of historical drought events as described in subsequent chapter 5, the influence of drought and its impacts on Northern Ontario were accounted for in the development of a drought trigger. The use of selected sample periods in drought assessments were validated by exhibiting that they represent regional events of significant social, economic and environmental impacts. A drought trigger, appropriate for the region, requires that most sites simultaneously record significant drought events. The numbers of sites that record drought during the selected sample periods have been used in evaluations.

In developing a threshold level to ascertain the occurrence of a drought event, the concept developed by Palmer (1965) was used where a drought is considered to be a prolonged dry period. An assessment was conducted in an attempt to judge the ability of each threshold level to trigger a drought event that was prolonged over time, and at the same time does not generate too many false (i.e. minor) events that had negligible impacts. Further, Svoboda et al. (2002) note that even after the cause of a drought event (e.g. anomalous atmospheric circulation pattern) has ended, the resulting characteristics of the drought event can still result in an area experiencing the lingering hydrological impacts for months and even years thereafter. Persistent behaviour in streamflow data was noted by Hurst (1951), who realized that rivers can display statistical dependencies over time. The persistent or lingering effects of a drought were measured by recording the duration that begins at the time a drought event was triggered to the point where streamflows exceeded the median flow (i.e. Q_{50}). A measure of persistence was also estimated based on the probability that the trigger would result in a more severe event.

4.3 Computations of SSI

The three different SSI dataset treatments of the monthly streamflows proposed for investigations include: Untreated and treated (i.e., Log Normal Transformation, and the Fitted Gamma Distribution).

4.3.1 Untreated Datasets

The concept of SSI to use the Untreated streamflow data originates from Sharma and Panu (2010) and their proposed Standardized Hydrological Index (SHI). The intended application of the SHI is for water storage infrastructure. This index is used to define and model hydrological drought, with a particular focus on two of the most important drought characteristics, longest duration and largest intensity. The SHI does not make an attempt to achieve conditions of a normal distribution, but rather to maintain the non-normal nature of the streamflow data (Sharma and Panu, 2012).

Since the SHI has beneficial applications in modeling and predicting hydrological drought characteristics, it was deemed pertinent to assess the implications of applying Untreated streamflow data analogous to SHI in computing values of SSI. It also makes this index the simplest for application among others that were being investigated. The application of SSI here proceeds under the assumption that the data is normally distributed.

4.3.2 Fitted Distributions

Early hydrological drought indices used an approach similar to SPI (Mckee et al., 1993) on the streamflow data (Nalbantis and Tsakiris, 2009; Shukla and Wood, 2008; Modarres, 2007; Zaidman et al., 2001). Invariably, Standardized Streamflow Indices (SSI) do apply fitted probability distributions to the observed streamflow data. The fitted probability distributions investigated here are the Log Normal Transformation and the Fitted Gamma Distribution.

4.3.2.1 Log Normal Transformation

Fitting the log-normal distribution to streamflows is a common practice in hydrology (USDA, 2007), and several studies have established its efficacy in SSI application (Svensson et al., 2017; Vincente-Serrano et al., 2012; Nalbantis and Tsakiris, 2009; Zaidman et al., 2001). The initial SSI application used by Zaidman et al. (2001) focuses on daily time steps in their analyses of spatial and temporal development of streamflow droughts. They identify that the daily subseries of streamflow generally adheres to a log normal distribution. Using the Flow Anomaly Index, they provide a method of computing SSI. They accomplished this task by conducting a log normal transformation of the streamflow dataset towards achieving normalization.

The approximation involving the log-normal distribution is considered to be positively skewed and non-negative. The simplistic nature of the log-normal distribution is a beneficial factor, as it only requires the following natural logarithmic transformation.

$$Y = \ln(x) \qquad for\ x > 0 \tag{4.7}$$

The form of SSI computations utilized by Zaidman et al. (2001) for only transforming the dataset but not fitting the transformed dataset to a distribution was also followed in this thesis. The benefits of using the streamflow data in this form was to keep computational efforts simple and efficient.

4.3.2.2 Fitted Gamma Distribution

The SPI was initially derived from fitting the Gamma Distribution. The successful application of fitting the Gamma Distribution in hydrological drought and SSI assessments are well documented (Svensson et al., 2017; Van Loon, 2015; Vincente-Serrano et al., 2012; Sharma and Panu, 2010). In computations of SSI using the Fitted Gamma Distribution, the monthly streamflow dataset at each individual site determined the best fit parameters for use in site specific probability distributions. The probability density function of the Gamma distribution is defined as follows:

$$g(x) = \frac{1}{\beta^{\alpha}\,\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} \qquad \textbf{[4.8]}$$

Where, α > 0 is the shape parameter, and β > 0 is the scale parameter, for streamflow value x > 0, and the gamma function Γ(α). The fitting of the Gamma probability density function to the frequency distribution of streamflows requires the estimation of appropriate distribution parameters such as α and β using the maximum likelihood approximation techniques (Thom, 1958).

$$\hat{\alpha} = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right) \qquad \textbf{[4.9]}$$

$$\hat{\beta} = \frac{\bar{x}}{\hat{\alpha}} \qquad \textbf{[4.10]}$$

$$A = ln(\bar{x}) - \frac{\sum ln(x)}{n} \qquad \textbf{[4.11]}$$

Where, the cumulative probability G(x) for an observed streamflow data for a given month and time scale can be expressed as follows:

$$G(x) = \frac{1}{\hat{\beta}^{\hat{\alpha}}\,\Gamma(\hat{\alpha})} \int_0^x x^{\hat{\alpha}-1} e^{-x/\hat{\beta}} dx \qquad \textbf{[4.12]}$$

With the use of the following expression for t:

$$t = \frac{x}{\hat{\beta}}$$ **[4.13]**

One obtains the incomplete gamma function as follows.

$$G(x) = \frac{1}{\Gamma(\breve{\alpha})}\int_{0}^{x} t^{\breve{\alpha}-1} e^{-1} dt$$

[4.14]

The Gamma probability density function is undefined when x = 0, where q = P(x = 0) and P(x = 0) is the probability of zero (Null) flow values. Since, there is a potential that the streamflows may contain zero values, the cumulative probability H(x) may be defined as:

$$H(x) = q + (1 - q)G(x)$$ **[4.15]**

Approximation techniques permit the computations to be completed using standard spreadsheet software.

4.3.3 Standardization and Z-Score

Improved multisite comparisons may be obtained by using the standardized severity (Sharma and Panu, 2009). Standardization identifies atypical flows in both wet and dry conditions. Early warning and drought monitoring systems may utilize the standard normal Z-score of SSI (which is analogous to SPI (McKee et al., 1993)), to describe drought characteristics in an understandable, transparent, and equitable manner for water managers and governing administrations, who routinely utilize this information to make decisions.

4.3.3.1 Standardization and the Standard Normal Distribution

Once, the appropriate initiation and corresponding termination points of a drought event have been identified; these can be used to assess the ability of respective SSI data treatments in the accurate determination of drought characteristics. For drought characterization, the SSI utilizes the standard score (Z-score) formula as follows.

$$Z_{m,y} = \frac{x_{m,y} - \bar{x}_m}{s_m} \qquad \textbf{[4.16]}$$

Where, $Z_{m,y}$ is the standard score for month m on year y, $x_{m,y}$ is the streamflow for month m on year y, $\bar{x}_m$ is the sample mean streamflow for month m, s is the sample standard deviation for month m, and m is the respective monthly time increment (January, February etc.).

Typically, the Z-score is used to compare a sample in the form of a standard normal deviate, where data is attributed to have a normal distribution, with mean of zero and standard deviation of unity. Standard score (Z) may be defined without the assumptions of normality, however, applications of the standard scores in early warning and drought monitoring systems relies considerably on the accuracy of probability estimates.

Evaluations of the Untreated and treated Log Normal Transformation data treatments were based on the application of standardization using the above equation (4.16). It should be noted that a log normal transformation was conducted prior to standardization for that treatment. The fitted Gamma Distribution treatment used approximation techniques to obtain Z-scores, as described in the following Section 4.3.4. The Z-scores enable results of the SSI into a probable scenario format that allows for regional comparisons. Table 4.1 displays the categories of drought and the associated normal probability density function as presented by Lloyd Hughes and Saunders (2002). It should be noted that the MNRF provides a similar table, but identifies Z-scores between -0.99 and +0.99 as being near normal conditions.

4.3.4 Polynomial Approximation for the Fitted Gamma Distribution

The procedure for obtaining Z-score of the fitted distributions can be complex. The initial application of the SPI (McKee et al., 1993) involved the transformation of cumulative probability using equal probability method, to obtain a standard normal distribution. This transformation is time consuming and not practical for dealing with the analysis of several large datasets (Lloyd Hughes and Saunders, 2002). A more easily computed alternative to determine the Z-score is to conduct polynomial approximations as outlined by Abramowitz and Stegun (1965), which converts the cumulative probability to the standard normal random variable, Z as follows:

$$Z_p = -t + \frac{c_o + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t + d_3 t^3} \qquad \text{for } 0 < \mathrm{H(x)} \leq 0.5 \qquad \textbf{[4.17]}$$

$$Z_p = t - \frac{c_o + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t + d_3 t^3} \qquad \text{for } 0.5 < \mathrm{H(x)} < 1.0 \qquad \textbf{[4.18]}$$

$$t = \sqrt{\ln\left(\frac{1}{\mathrm{H(x)}^2}\right)} \qquad \text{for } 0 < \mathrm{H(x)} \leq 0.5 \qquad \textbf{[4.19]}$$

$$t = \sqrt{\ln\left(\frac{1}{1 - \mathrm{H(x)}^2}\right)} \qquad \text{for } 0.5 < \mathrm{H(x)} \leq 1.0 \qquad \textbf{[4.20]}$$

Where, $c_o = 2.515517$, $c_1 = 0.802853$, $c_2 = 0.010328$, and

$d_1 = 1.432788$, $d_2 = 0.189269$, $d_3 = 0.001308$.

H(x) is representative of the cumulative probability for the Fitted Gamma Distribution. These approximations were used for the Gamma distributions to estimate the Z-score.

Table 4.1: **Drought classifications in terms of the Standard Normal Score** (**Z-score**).

State	Classification	Criterion	Cumulative Probability (%)
0	Non-drought	Z-Score ≥ 0.0	50.0
1	Mild-drought	-0.99 ≤ Z-Score ≤ 0.0	34.1
2	Moderate-drought	-1.49 ≤ Z-Score ≤ -1.0	9.2
3	Severe Drought	-1.99 ≤ Z-Score ≤ -1.5	4.4
4	Extreme Drought	Z-Score ≤ -2.0	2.3

4.4 SSI Scoring and the Standard Normal Distribution

The initial step to evaluate the appropriateness of various SSI data treatments was to determine how well the treatments identify with the standard normal (Gaussian) distribution. Since monthly streamflow data conveys drought characteristics in monthly increments, it was deemed appropriate to evaluate streamflow data treatments for each of individual months in the year. Similar to Svensson et al. (2017), a goodness-of-fit test was applied to the transformed indices to test for departures from normality, where the mean should be zero and standard deviation should be one. The Shapiro-Wilk test and the Anderson-Darling test were applied to test for normality. These tests were conducted for each month in all rivers and for each case of the data treatment. As a result of these tests the influence of seasonality was also examined.

These two tests were selected based on the findings of Razali and Wah (2011), who reported that the Shapiro Wilk test followed by the Anderson Darling test provide the most consistently accurate testing for normality. The Kolmogorov-Smirnov test (Siegal and Castelan, 1988) was not applied due to its poor performance for normality testing (Vicente-Serrano et al., 2012) for applications in monthly streamflow data.

4.4.1 Shapiro-Wilk Test

The Shapiro-Wilk test (Shapiro and Wilk, 1965; 1972) is a goodness-of-fit test for the normal (Gaussian) distribution. The null hypothesis for the test is that a random sample is from a normal distribution function with unknown mean and variance, while the alternative hypothesis states that the random sample is not from a normal distribution function. The Shapiro-Wilk statistic is expressed as follows:

$$W = \frac{\left[\sum_{i=1}^{k} a_i (x_{n-i+1} - x_i)\right]^2}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \qquad \textbf{[4.21]}$$

Where, the coefficients for the critical values of the sampling distribution W and the resulting confidence level may be retrieved from their corresponding tables (Conover, 1980). This test statistic is computationally exhaustive.

The R-Statistical Software was utilized to conduct computations. If the p value generated by the test was greater than 0.05, then the data was considered not to come from a normally distributed population and therefore fails to reject the alternative hypothesis. A 95% confidence level was applied to all Shapiro-Wilk Normality tests.

4.4.2 The Anderson Darling Test

Stephens (1979) notes that the Anderson Darling test is an effective Empirical Distribution Function (EDF) test, because of the importance this test gives to tails of the distribution being evaluated. Based on the data set, the cumulative distribution function (CDF) of the normal distribution was compared to the estimated EDF and evaluated to determine the discrepancy between the EDF and the given distribution function. The Anderson Darling test is considered a quadratic class of the EDF statistics. Computational formula of the Anderson Darling test (Stephens, 1979) is expressed as follows:

$$A^2 = -\left\{\sum_{i=1}^{n} (2i - 1)[\ln z_i + ln(1 - z_{n+1-i})]\right\}\frac{1}{n} - n \qquad \textbf{[4.22]}$$

Where, $z_i = F(x_i)$, i =1, 2, …, n. The R-Statistical Software utilizing the Nortest (2015) was used to conduct the Anderson Darling test. The test statistic ‘A’ was used to compute the probability that the sample could have come from a normal distribution. If the p value generated by the test was greater than 0.05, then the conclusion was that the data fails to reject the alternative hypothesis; that the data has not come from normally distributed population. A 95% confidence level was applied to all Anderson Darling Normality tests.

4.5 Impact of Data Treatments On Drought Characteristics

The assumption utilized in evaluations was that the threshold level appropriate for triggering a drought event (Q_{TL}) was sensitive to the impacted sectors of Northern Ontario, maintains the natural traits of the streamflow data being assessed, and in turn improves consistency by recording equal number of drought days. These traits improve multisite comparisons and when used in an index format, improve comprehension of results. The characteristics of drought determined using the Q_{TL} were used in investigations as part of the SSI data treatments in evaluating the ability of each of the data treatments to accurately determine all drought characteristics.

4.5.1 Initiation, Termination, and Duration of Drought Events

The initial evaluation was used to determine the drought characteristics for each the SSI data treatment option: Untreated and treated i.e., Log Normal Transformation, and the Fitted Gamma Distribution. Evaluation of drought on the monthly time scale is typically triggered at the Moderate drought category, with a standard score of one. However, the selected threshold level recommended to trigger drought in Northern Ontario, Q_{TL}, has a probability that was not representative by a standard score of one (or $Z= -1$). The theoretical Z-score representative of the threshold level Q_{TL} was determined and represented as Z_{TL}. The analysis compares the differences in drought characterization, including initiation, termination, and duration, by using a Z-score of Z_{TL} versus Z-score of $Z= -1$. Drought characteristics determined for each of the SSI data treatment was based on investigations into the selected sample periods representing significant drought on a regional scale in Northern Ontario.

As pointed out earlier in the text, it should be noted that drought intensity is equivalent to Z-score, evaluated as a negative entity. However, for modelling purposes, it is taken as positive entity (Sharma and Panu, 2010) or the absolute value of Z. Likewise, for modelling purposes, the drought severity in the standardized domain is taken as positive entity or the absolute value of S. In this thesis, both these parameters viz. intensity and severity have been reported in the standardized domain so are negative in terms of their values.

4.5.2 Drought Intensity of Hydrological Drought Events

The threshold method refers to the drought severity as being the accumulated deficits for the entire drought duration, while drought intensity is the ratio of the drought severity over drought duration. In the computation of the SSI, each Z-score was representative of the intensity of that time increment (i.e. monthly). In applications, the SSI typically addresses to the frequency of drought events by investigating multiple varying durations: 1, 2, 3, 6, 12 month(s) or even specified seasons. This permits evaluation of a drought event relative to its probability of occurrence.

As monthly assessments are commonly conducted in drought monitoring and planning, an investigation was made into the determination of the average SSI drought intensities, using Z-scores in a manner similar to drought severity in the threshold method. The relevance of using this technique was based on a comment made by the IPCC (2012), that some climate extremes are the result of accumulation of weather or climate events that become extreme only by their ultimate accumulation. The IPCC (2012) further observed that weather or climate events, even if not extreme in a statistical sense, can still have a significant impact, by crossing a critical threshold in a social, ecology or physical system. Average drought intensity using the values of Z-score for the SSI was computed as follows.

$$Average\ Drought\ Intensity = \sum \frac{Z\ Score}{n} \qquad [4.23]$$

Using six sites of the same drought duration that had occurred during the historically significant drought events, average drought intensities were computed and assessed for their statistical reliability and overall suitability.

4.5.3 Values Representing Severe and Extreme Hydrological Drought Events

Responsive and adaptive measures used to reduce risk, include short- and long-term actions, programs and policies that are implemented during and in advance of drought (Wilhite, 2000). Drought plans with adaptive and response measures are typically and fully employed upon the onset of severe and subsequently extreme drought conditions. The IPCC (2012) definition of extreme events is a climate variable that is below a defined threshold value near the lower 'tails' in the range of observed values of the variable (IPCC, 2012). This definition further indicates that climate extremes can be quantified either by relating to the probability of recurrence or by using a specific threshold that may relate to a particular impact. This description aligns itself with the Van Loon (2015) notion that threshold levels are typically used to trigger responsive action.

In conducting drought assessments, difficulties and potential inaccuracies may arise with the use of severe and extreme values. Such inaccuracies, in part, are a result of using extrapolations that go beyond the observed sample set. However, the distribution fitting that might be used to estimate such samples may involve inaccuracies due to the size of sample set (Tallaksen et al., 2004). The following issues are associated related to the estimating tails of unknown distributions, knowing that there are only a few observations in the tail of the distribution. In such cases, the estimates required are generally the smallest values, and that the probability distribution can introduce significant bias in estimating tail probabilities (Coles, 2001).

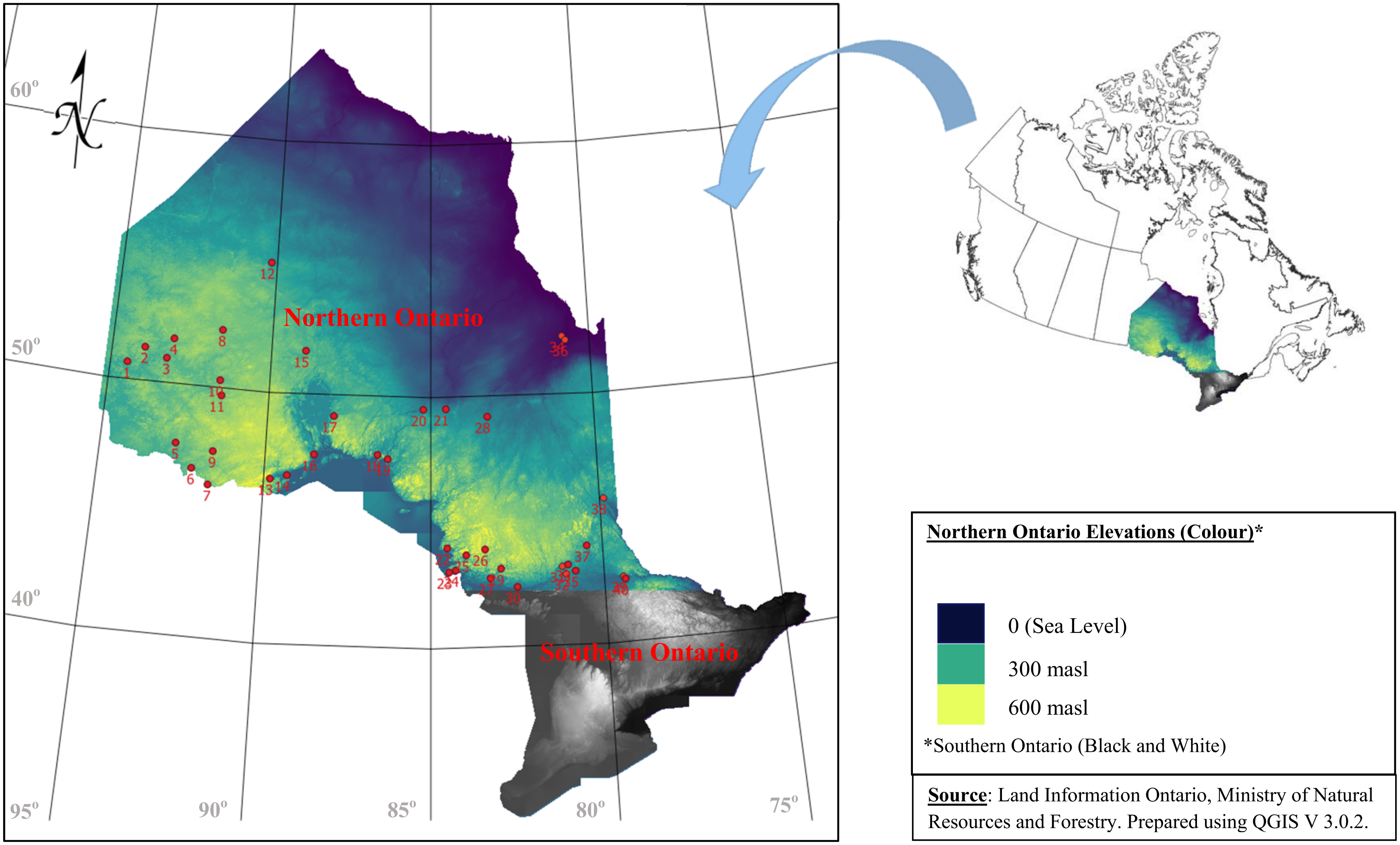
Applications of the SSI for the use of drought monitoring in this thesis assumes adherence to the standard normal distribution and associated probabilities. It is pivotal that drought assessments accurately reflect severe and extreme drought conditions that were being observed. In an attempt to gauge these accuracies, Z = -1.64 and Z = -2.33, are investigated for the distribution of severe and extreme events as they respectively relate to 95th and 99th exceedance percentiles. A Z-score of -1.64 is representative of a 1 in 20 year event, and fits with the severe drought classification. A Z-score of -2.33 is representative of a 1 in a 100 year event and fits with the extreme drought classification. Similar values of Z-score have been utilized by Vicente-Serrano et al. (2012) in their observations of extreme values.

CHAPTER 5: STUDY AREA AND STREAMFLOW DATASET

In the sections to follow, the study area used in evaluations of each drought index is outlined for its hydrological traits. The study area and relevant monthly time series datasets corresponding to various hydrometric stations that are distributed throughout the study area are described.

5.1 Study Area

Northern Ontario is roughly located at the center of the North American continent. The study area has a latitude that ranges from 46^{o}15’ to 52^o 34’ North and a longitude that ranges from 79^o 23’ to 94^o 27’ West (Figure 5.1). For brevity, it may be defined by three watersheds; the Hudson Bay Basin to the north, Nelson River Basin to the west and the Great Lakes – St Lawrence Basin to the south. The two defining climatological regions are the humid continental southern region bordering Lake Superior and the northern sub-arctic region. Frost conditions and the associated precipitation storage as snowpack are encountered for approximately half the year, with annual precipitation ranging from 700 mm at Moosonee to 970 mm at North Bay. The physiographic characteristics of Northern Ontario are for the most part boreal forest that overlay the Canadian Shield with only a thin layer of soil. The northern section recedes into the Hudson Bay Lowlands that consist mainly of wetlands. The region contains an abundance of long, continuous and well spread out streamflow records, suitable to accurately and with confidence be used in early warning systems and drought monitoring programs.



Source: Land Information Ontario, Ministry of Natural Resources and Forestry. Prepared using QGIS V 3.0.2.

Figure 5.1: Topographic map of Ontario illustrating the locations of hydrometric stations used in analysis.

5.2. Streamflow Dataset

The streamflow records for Northern Ontario were abstracted from the HYDAT (Hydrologic Data), a streamflow data resource maintained by the Water Survey of Canada. A total of 160 rivers were analyzed for completeness and statistical validity. Only 40 rivers were found to be suitable for use in the SSI analysis; the characteristics of selected rivers (or basins) are outlined in Table 5.1. The 40 rivers presented in this table contain 1781 years of recorded streamflow, with an average duration of 45 years for any river in the dataset. Brase and Brase (2006) indicate that a general rule to attain an approximation of normality is to have a sample size of 30. The minimum record length in the data set used for analysis turn out to be 27 years. Catchments sizes range from 37 to 13,400 km^2 with an average size of 2,973 km^2.

In the dataset, it should be noted that four rivers (identified by the numbers 13, 20, 28, and 30 in Table 5.1) have streamflows that are considered to be regulated by the Water Survey of Canada. However, further investigations involving aerial photographic and GIS based analyses using Land Information Ontario flow control assets database indicated that control structures on these four rivers exist downstream of the hydrometric stations.

Table 5.1: Basic hydrological catchment characteristics of the selected hydrometric stations within the study area.

No.	Identifier	Hydrometric Station	Length (Years)	Start/End Year	Area (km^2)	Latitude/ Longitude	No.	Identifier	Hydrometric Station	Length (Years)	Start/End Year	Area (km^2)	Latitude/ Longitude
1	05QE009	Sturgeon River at outlet of Salvesen Lake	42	1961/2003	1530	50°21'N 94°27'W	21	04JD005	Pagwachuan River at Highway 11	43	1973/2009	2020	49°45'N 85°13'W
2	05QE012	Long-Legged River below Long-Legged Lake	30	1980/2009	548	50°40’N 93°58'W	22	04JC002	Nagagami River at Highway 11	60	1950/2009	2410	49°46'N 84°32'W
3	05QE008	Cedar River below Wabaskang Lake	37	1972/2008	1690	50°30'N 93°15'W	23	02BF001	Batchawana River near Batchawana	37	1968/2004	1190	47°0'N 84°30'W
4	05QC003	Troutlake River above Big Falls	38	1970/2007	2370	50°54'N 93°5'W	24	02BF004	Big Carp River near Sault St. Marie	30	1980/2009	52	46°30'N 84°27'W
5	05PB014	Turtle River near Mine Centre	85	1925/2009	5880	48°51'N 92°43'W	25	02CA002	Root River at Sault St. Marie	39	1971/2009	108	46°33'N 84°16'W
6	05PA006	Namakan River at Outlet of Lac La Croix	76	1934/2009	13400	48°22'N 92°10’W	26	02BF002	Goulais River near Searchmont	42	1968/2009	1160	46°51'N 83°58'W
7	05PA012	Basswood River Near Winton	80	1930/2009	4510	48°4'N 91°39'W	27	02CB003	Aubinadong River by Sesabic Creek	30	1980/2009	1440	46°58'N 83°25'W
8	04GA002	Cat River below Wesley Lake	41	1971/2006	5390	51°10'N 91°35'W	28	02CC005	Little White River near Bellingham	57	1954/2010	1960	46°23'N 83°16'W
9	05PB018	Atikokan River near Atikokan	27	1983/2009	332	48°45'N 91°35'W	29	04LJ001	Missinaibi River at Mattice	84	1926/2009	8940	49°36'N 83°16'W
10	05QA004	Sturgeon River at McDougall Mills	44	1962/2003	4450	50°10'N 91°32’W	30	02CD001	Serpent River at Highway 17	68	1943/2010	9300	46°12'N 82°30'W
11	05QA002	English River at Umfreville	83	1927/2009	6230	49°52'N 91°27'W	31	02CF007	Whitson River at Chelmsford	49	1961/2009	272	46°34'N 81°11'W
12	04DA001	Pipestone River at Karl Lake	44	1966/2009	5960	52°34'N 90°11'W	32	02CF012	Junction Creek below Kelly Lake	33	1977/2009	207	46°25'N 81°5'W
13	02CC010	Little White River Below Boland	30	1981/2010	1190	46°12'N 82°58'W	33	02CF008	Whitson River at Val Caron	35	1975/2009	179	46°36'N 81°1'W
14	02AB008	Neebing River at Thunder Bay	46	1954/1999	187	48°23'N 89°18'W	34	04KA001	Kwataboahegan River at the mouth	39	1969/2007	4250	51°9'N 80°51'W
15	04GB004	Ogoki River above Whiteclay Lake	38	1972/2009	11200	50°52'N 88°55'W	35	02DB007	Coniston Creek by Wanapitei River	29	1981/2009	59	46°28'N 80°49'W
16	02AC001	Wolf River at Highway 17	40	1972/2009	736	48°49'N 88°32'W	36	04MF001	North French River near the Mouth	43	1967/2009	6680	51°4'N 80°45'W
17	02AD010	Blackwater River at Beardmore	38	1972/2009	250	49°35'N 87°57'W	37	02DC012	Sturgeon River at Upper Goose Falls	26	1986/2009	1200	46°58'N 80°27'W
18	02BA003	Little Pic River near Coldwell	39	1971/2009	1320	48°50'N 86°36'W	38	02JC008	Blanche River above Englehart	37	1973/2009	1780	47°53'N 79°52'W
19	02BB003	Pic River near Marathon	41	1970/2009	4270	48°46'N 86°17'W	39	02DD014	Chippewa Creek at North Bay	35	1975/2009	37.3	46°18'N 79°26'W
20	02BC004	White River below White Lake	29	1980/2008	4170	48°39'N 85°44'W	40	02DD013	La Vase River at North bay	37	1975/2009	70.4	46°15'N 79°23'W

*Start and end years are after conducting data cleaning exercises as outlined in the following sections.

CHAPTER 6: PRELIMINARY DATA ANALYSES AND APPLICATIONS

This chapter begins with a description of the process adopted to ensure the completeness and good quality of the data set. The preliminary analyses used to refine the methodology are then presented. Using the developed dataset, this chapter concludes with demonstration through applications of the refined methodology.

6.1 Complete and Good Quality Dataset

Collecting streamflow data in the natural world over a period of decades often results in missing values. The selected 40 rivers including 13 rivers containing missing data presented in Table 5.1 were used for various drought analyses. The rivers with missing records are identified in Table 5.1 by serial numbers: 1, 5, 8, 9, 13, 15, 16, 17, 28, 32, 33, 34, and 38. In total, the missing records ranged from 0.1% to 3.8% with an average value of 1.6% across the dataset. Infilling of missing records of durations less than 10 days utilized the method of linear interpolation as described in Section 4.1.1.1. Longer durations of missing records utilized the Analogue River Ratio Method as described in Section 4.1.1.2. The Figure 6.1 demonstrates the Analogue River Ratio Method for the Kwataboahegan River, which contained 42 daily missing values during the months of October and November in 1971. Average ratio was computed between the nearby larger French River and the subject Kwataboahegan River for each day of the year. The missing flows for this river were then computed based on this ratio and the flows recorded for the nearby French River. Such an operation only accounted for approximately 1.0% and 2.5 % respectively of the recoded data for the months of October and November. The infilled records by the Analogue River Ratio Method are deemed acceptable since the values appear to be within the suitable range of what was anticipated to be encountered and in term of its size not being significant enough to negatively impact the underlying probability distribution. Figure 6.1 shows that the peaks of the French River for this time period appear to occur only about two days later than the peaks for the Kwataboahegan River. The general shape of streamflow hydrographs for both rivers is relatively similar leading up to and after the portion of the hydrograph where records were missing.

6.2 Weakly Stationarity

The KPSS test, Run test, and Wilcoxon Signed Rank test were applied to annual mean discharges to test the assumptions of weak stationarity as discussed earlier in section 4.1.2. The complete datasets of 5 rivers (as noted by serial number 1, 8, 10, 14 and 23) in Table 5.1 were identified to have failed one or both assumptions of weak stationarity. Records from datasets of each river were deleted until conditions for the weak stationarity were achieved.

6.3 Preliminary Analysis for the Identification and Selection of Sample Periods

A validated dataset enables the selection of sample drought periods to be used in analysis. In determining a best sample period for use in the analysis, investigations for identifying recorded impacts and basic explorations as described earlier (Chapter 1 and Section 2.5), were conducted. A list of eight drought periods (1931/32, 1936/37, 1963/64, 1976/77, 1980, 1988, 1998, and 2001) were further reviewed. A preliminary analysis was conducted using a threshold level of Q_{70}, to identify the longest duration and the greatest severity drought event corresponding to the eight drought periods. These two characteristics are ranked for each of the 40 rivers, as summarized in the Table 6.1.

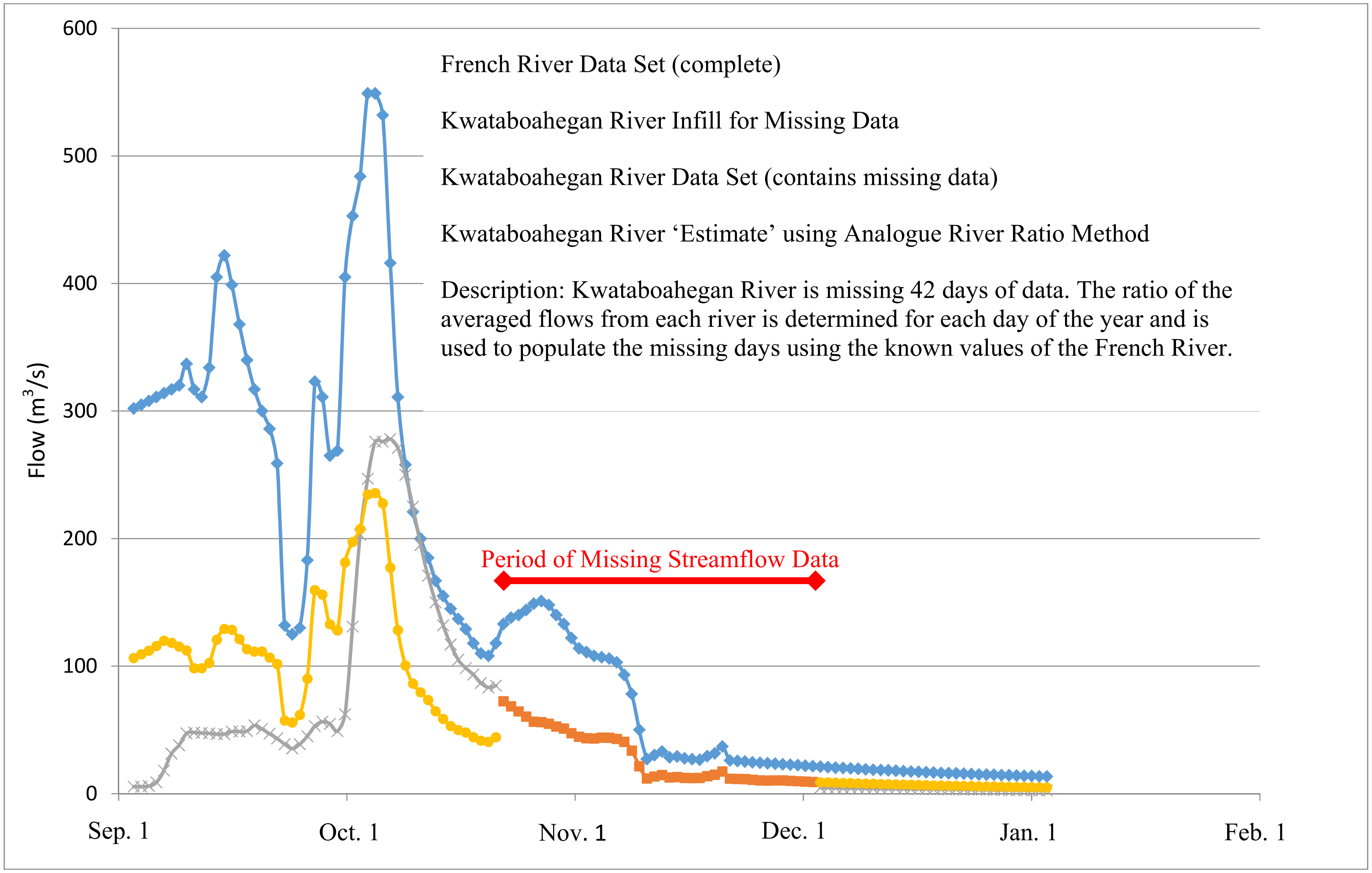


Figure 6.1: Example of the Analogue River Ratio Method for the Kwataboahegan River in 1971.

Drought periods before 1970 were eliminated due to lack of available records. Two drought events, 1976/77 and 1998, stood out for demonstrating regionally recorded impacts and containing a sufficient number of well spread out sites to represent the region of Northern Ontario. The 1976/77 and the 1998 drought events were respectively contained in streamflow records for 32 and 40 catchments.

Summer and winter were, two prevalent hydrological seasons, in Northern Ontario and should be considered in evaluations of hydrological droughts. Approximately half of the year drought relief from precipitation may not be available due to it being retained as snow pack. The selected two Sample Periods permit such evaluations of seasonality effects. This is a result of the 1976/77 drought period, consistently, recording droughts in the winter months, while the 1998 drought period consistently recording droughts for the summer months.

The ability to examine the influence of seasonality is particularly important for assessments to be conducted on more frequent time increments; such as on a monthly basis. Each one of the Sample Period is briefly described, in an effort to develop an appreciation in terms of socioeconomic effects and the spatial extent of the drought during the selected Sample Periods.

Table 6.1: **Preliminary analysis of the longest duration and greatest severity of drought based on the threshold level of Q_{70} for all 40 rivers.**

	Average Rank of the Longest Duration								Average Rank of the Greatest Severity							
Year	**1931/32**	**1936/37**	**1963/64**	**1976/77**	**1980**	**1987/88**	**1998**	**2001/02**	**1931/32**	**1936/37**	**1963/64**	**1976/77**	**1980**	**1987/88**	**1998**	**2001/02**
Mean	2.5	3.2	4.4	1.9	4.1	2.9	2.4	3.7	2.8	5.2	5.5	2.3	4.3	2.1	2.3	4.3

Note: All 40 rivers rank each drought event from 1 to 7 for longest duration and greatest severity based on a threshold level of Q_{70}. Where, a rank of 1 is the longest duration or greatest severity, and a rank of 7 is the shortest duration or least severity.

Extent of the 1976/77 drought event reached the Great Lakes region, across the Prairies and western United States and into southern British Colombia (GLC, 1990). Stocks (1979) along with Gabriel and Kreutzwiser (1993) indicate that 1976 summer forest fires resulting from drought were extensive; Heinselman (1996) even states that the fires severity and regional extent were amongst the worst on record and very well compare to those droughts observed in 1936. The cost for the 11 to 12 months (from the drought onset midsummer) of 1976 to May of 1977 was approximately $ 43 million in 1977 dollars (or $ 175 million in 2018 dollars) to Manitoba Hydro (Standing Committee on Public Utilities and Natural Resources, June 1978). Wilhite (1997) also noted that drought in 1976 and 1977 spread over several pockets throughout the United States and Canada, including Minnesota, Wisconsin, in addition to Alberta, Saskatchewan. Later on, he attributed the Canadian regions moisture conditions to be characterized by below-normal snowpack, low soil moisture reserves, and reduced streamflow and ground-water reserves. Ecological study by Hess and Hanks (1979) included the drought event, while MCWG (2012) identified the impacts to aquatic ecosystems for Ontario and Minnesota.

The most severe month observed for the Canadian Prairies was March 1977 (Khandekar, 2004). Rosenberg (1980) identified September 1, 1976, as the critical point for the drought event, noting prolonged precipitation deficiencies lasting till April 30, 1977. The study by Stocks (1979) is the only one that focuses on drought in Northern Ontario. All other studies include Northern Ontario as part of a greater study (Wheaton et al., 2005; McKay et al., 1989). Stocks (1979) noted that the development of a drought event in relation to monthly precipitation and further indicated that the severe event started in May 1976 and lasted until April 1977.

The 1998 drought event has also been analyzed in this thesis. Klaassen (2002), Bonsal and Regier (2007), and Disch (2010) have discussed this drought period and its impacts on

Manitoba, Ontario and Southern Ontario. Environment Canada identified that a nationwide average temperature of 2.5 degrees warmer than normal started in December 1997 and lasted till November 1998. Nelson (2009) noted that during this Sample Period; the forest fires extended to Quetico Provincial Park and Northern Ontario. The year 1998 also encountered the sixth driest year on record and the previous lowest levels in Lake Superior occurred 73 years ago in 1925 (Environment and Climate Change Canada, 2017). NOAA (2007) noted that amongst the impacted sectors that low lake levels hindered the $20 Billion boating and fishing industries on the Great Lakes.

6.4 Preliminary Analyses on the Determination of Threshold Trigger

In determining an appropriate threshold level to trigger the onset of a drought, threshold levels of Q_{50}, Q_{70}, Q_{80}, Q_{90}, Q_{95}, and Q_{98}, were initially assessed. Using the two significant drought events on record, and also identified in Table 6.1; the each threshold was investigated to verify if they had captured the regional events. Table 6.2 shows the percentage of sites that recorded droughts using the corresponding threshold levels. It is important that a drought trigger is representative of the region, and in doing so records simultaneously drought for all sites. Based on results (Table 6.2), it is apparent that Q_{95} and Q_{98} are not suitable drought triggers for monthly assessments because of being too severe and consequently would overlook drought conditions on a regional scale.

Table 6.2: Percentage of sites that recorded drought at a respective threshold level.

Threshold Level of Exceedance	**1976/77**	**1998**
Values < Q_{98}	42%	23%
Values < Q_{95}	74%	75%
Values < Q_{90}	93%	90%
Values < Q_{80}	100%	98%
Values < Q_{70}	100%	100%

6.5 Measurements of Persistence used in the Selection of a Drought Trigger

Persistence traits and general drought characteristics are investigated for the threshold levels Q_{70}, Q_{80}, and Q_{90}, for the four rivers, namely: English River, Missinaibi River, Turtle River and Whitson River at Chelmsford. Spatially, these four river basins are spread far apart across the entire Northern Ontario region (Figure 5.1 and Table 5.1). Long and continuous streamflow records, appropriate for in-depth investigations, exist for these rivers. The persistent or lingering effects of a drought were measured by recording the duration from the time a drought event was triggered to the point where streamflows exceed the median flow (i.e. Q_{50}). A measure of persistence was also estimated based on the probability that the trigger will result in a more severe event. As drought events developed, observations were made on the general drought characteristics using the threshold levels Q_{70}, Q_{80}, and Q_{90}, and including the perception concerning initiation, termination and duration.

Once the quantitative assessments were completed, a qualitative review was conducted to incorporate the findings of assessments and to further confirm the appropriateness of each potential threshold level used as drought trigger. Qualitative assessment includes the considerations of applications by water managers, governing administrations and the formats of current drought assessment programs used in Northern Ontario and Canada.

6.6 Applications of the Methodology on Monthly Streamflow Datasets

The SSI values were computed for all data treatments: Untreated and treated (i.e., Log Normal Transformation, and the Fitted Gamma Distribution); at all sites throughout the study area. As expected, all treatments vary slightly in their assessments of hydrological drought using monthly SSI. Graphical representation of each SSI data treatment conducted for the English River is depicted in Figure 6.2.

Though each data treatment looks similar, upon further inspection, slight differences in characterizations become apparent. The Untreated SSI contains the largest number of extreme positive values (≥ Z= +2.0). The Log Normal Transformation and Fitted Gamma Distribution contain the largest number of extreme negative values (≤ Z= -2.0). It is also apparent from Figure 6.2 that the Log Normal Transformation and the Fitted Gamma Distribution are more likely to achieve conditions of a normal distribution. This conjecture is based on the appearance the time series not being biased in extreme values in either the positive or negative direction.

The Log Normal Transformation appears to have the greatest monthly intensity recorded for the 1998 drought event. For the 1976/77 drought event, it appears that the Fitted Gamma Distribution and the Log Normal Transformation indicate slightly more severe conditions than the Untreated data.

Figure 6.2 also affirms the existence of persistence in that when dry conditions occur, they tend to persist longer. In addition, when severe to extreme drought conditions are recorded, dry conditions appear to last longer in duration.

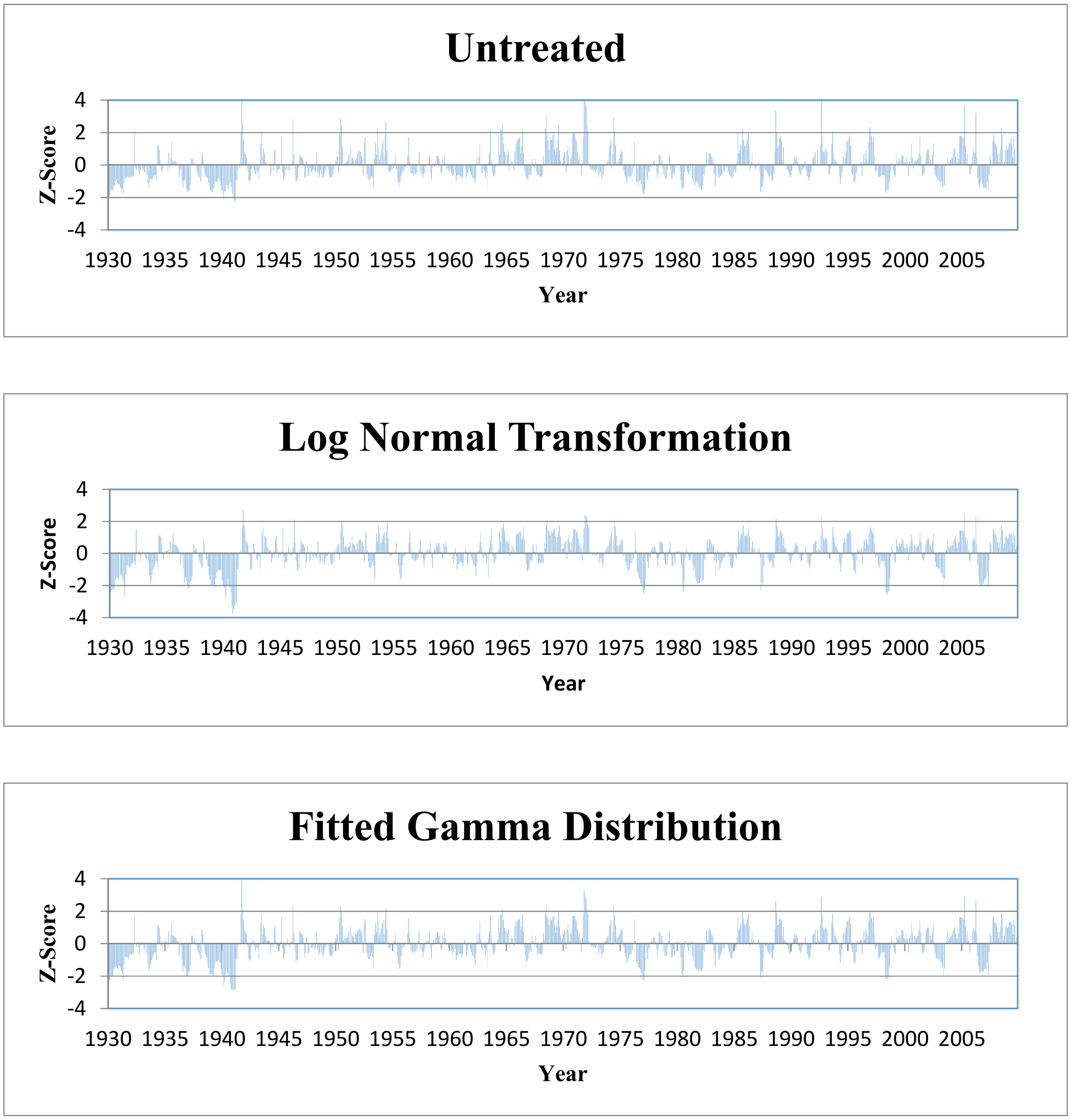


Figure 6.2: Application of all SSI data treatments using the English River.

6.7 Assessments of Normality Test on SSI Data Treatments

Assessments of drought conditions that use SSI data treatments rely on accurate determinations of standard normal distribution (Z-scores). The Shapiro Wilks test and the Anderson Darling test were used to estimate the consistency and accuracy of each SSI data treatment at achieving the conditions of a normal distribution. Table 6.3 summarizes the test results of the monthly normality tests conducted for the English River. The Fitted Gamma Distribution clearly performs best at achieving conditions of a normal distribution for this river. Untreated data performs worst, while the Log Normal Transformation achieves conditions of a normal distribution slightly more than half the time. The results also indicate that certain data treatments may perform better for different months.

This table also provides insights into the normality tests themselves. When examining results of the Untreated data, the Shapiro Wilks test shows that the months of January failed to achieve conditions of a normal distribution while the Anderson Darling test did not. Further, the Shapiro Wilks test for the English River results in more failures than the Anderson Darling test. These results are likely due to the influence of how each test is computed and the effects a particular test has on the resulting assessment. For example, it is plausible due to the fact that the Anderson Darling test gives more weight to tails of the distribution (Stephens, 1979; Farrel and Steward, 2006; Razali and Wah, 2011) or that the Shapiro Wilks test was initially intended for smaller samples to enable it to perform better and likely to reject more the null hypothesis that the sample comes from a normal distribution.

Table 6.3: A Summary of Failed Normality Tests for the English River.

Type of Test	Month	Untreated	Log Normal Transformation	Fitted Gamma Distribution
Anderson Darling Test	January	-	Fail	-
	February	-	Fail	-
	March	-	Fail	-
	April	Fail	-	-
	May	-	Fail	-
	June	Fail	-	-
	July	Fail	-	-
	August	Fail	-	-
	September	Fail	-	-
	October	Fail	-	-
	November	Fail	-	-
	December	Fail	Fail	-
Shaprio Wilks Test	January	Fail	Fail	-
	February	-	Fail	-
	March	-	Fail	-
	April	Fail	-	-
	May	-	Fail	-
	June	Fail	-	-
	July	Fail	-	-
	August	Fail	-	-
	September	Fail	-	-
	October	Fail	-	-
	November	Fail	Fail	-
	December	Fail	Fail	-
Summary	**Number of Failed Sites**	**17**	**11**	**0**

6.8 Assessments of Severe and Extreme Conditions on SSI Data Treatments

Applications of SSI data treatments in drought monitoring and early warning systems rely more often on assessments of severe and extreme value drought conditions as these are used to trigger an action. The selected scores (Z= -1.64 and Z= -2.33) were used to estimate accuracy of the severe and extreme drought conditions. For such conditions, the following table demonstrates the frequency distribution of Z-scores for the English River.

Table 6.4 shows that none of the data treatments performed perfectly in identifying appropriate frequency distribution of Z-scores. The Fitted Gamma Distribution performed best at achieving the expected frequency of 5.0% and 1.0% with the observed Z-scores less than Z= -1.64 and Z= -2.33, respectively. It should be noted that the Table 6.4 represents a single sample that has been used in illustrations in the form of Boxplots (Figures 7.5 and 7.6).

Table 6.4: Observed recurrence frequency of severe and extreme values for the English River.

Data Treatment	**Observed Values Less Than Z = - 1.64**	**Observed Values Less Than Z = - 2.33**
Untreated	1.7%	0.2%
Log Normal Transformation	7.3%	1.7%
Fitted Gamma Distribution	6.4%	0.8%

* The expected frequency distribution for Z-score values less than -1.64 is 5.0%

* The expected frequency distribution for Z-score values less than -2.33 is 1.0%

6.9 Drought Characterizations

Use of the SSI Data Treatments leading up to this point is to identify an appropriate drought trigger for Northern Ontario, and to estimate the accuracy and consistency of drought intensity. The threshold level is used as a standard to delineate drought initiation and termination. Delineation of the initiation and termination of droughts using the threshold levels representative of Northern Ontario provides the grounds to evaluate the accuracy and consistency of SSI intensity estimates.

The investigation started with the determination of drought characterization during the selected sample periods for all rivers using the untreated monthly streamflow data. This threshold level was recorded for each month using a flow duration curve (FDC). The flow duration curves were utilized to delineate a flow representing a defined threshold demand level. The steps included the following considerations:

1. Generate a list of flows for a predefined period (i.e. Streamflows for the month of August in the English River).
2. Sort the flows from highest to lowest.
3. Assign a ranking value (M), where the highest flow value is assigned the rank of (1) and the lowest flow value is the rank of (n).
4. Determine the exceedance probability (P) as: $(Q) \geq 100\ \frac{M}{n+1}$.
5. Generate the return period (T_r) as: $T_r = \frac{1}{P(Q)}$.
6. Graph the flows in relation to probability of exceedance (%).

The selected exceedance probability representing a water demand is used to determine the corresponding flow by using the flow duration curve as illustrated in Figure 6.3. This curve illustrates when the flow has exceeded 80% of the time (Q_{80}), the resulting FDC may be used to graphically determine the corresponding flow. In this case, Q_{80} corresponds to 31.4 m^3/s flow value, which is based on historical streamflow values for the month of August in the case of English River.

Once an appropriate flow representing the threshold level as the drought trigger is established for each month of the year, the initiation and termination dates were then determined for each of the two selected drought periods. These date along with the corresponding drought durations were recorded for analysis.

The corresponding results from $Z= -1$, $Z= -0.84$, and Q_{80}, for initiation and termination dates, along with drought durations, were directly compared. In order to evaluate the impacts on severity and intensity; the Q_{80} initiation and termination dates are then applied to the predetermined monthly record of the SSI treated data sets. The Figure 6.4 shows how each drought characteristic is determined corresponding to drought trigger of Q_{80}, $Z= -1$, and $Z= -0.84$.

Applying the methodology described in Figure 6.4 enables the determination of drought characteristics for each SSI data treatment and respective threshold level representing demands for Northern Ontario. Tables 6.5 and 6.6 summarize the results of applications of the methodology for the English River.

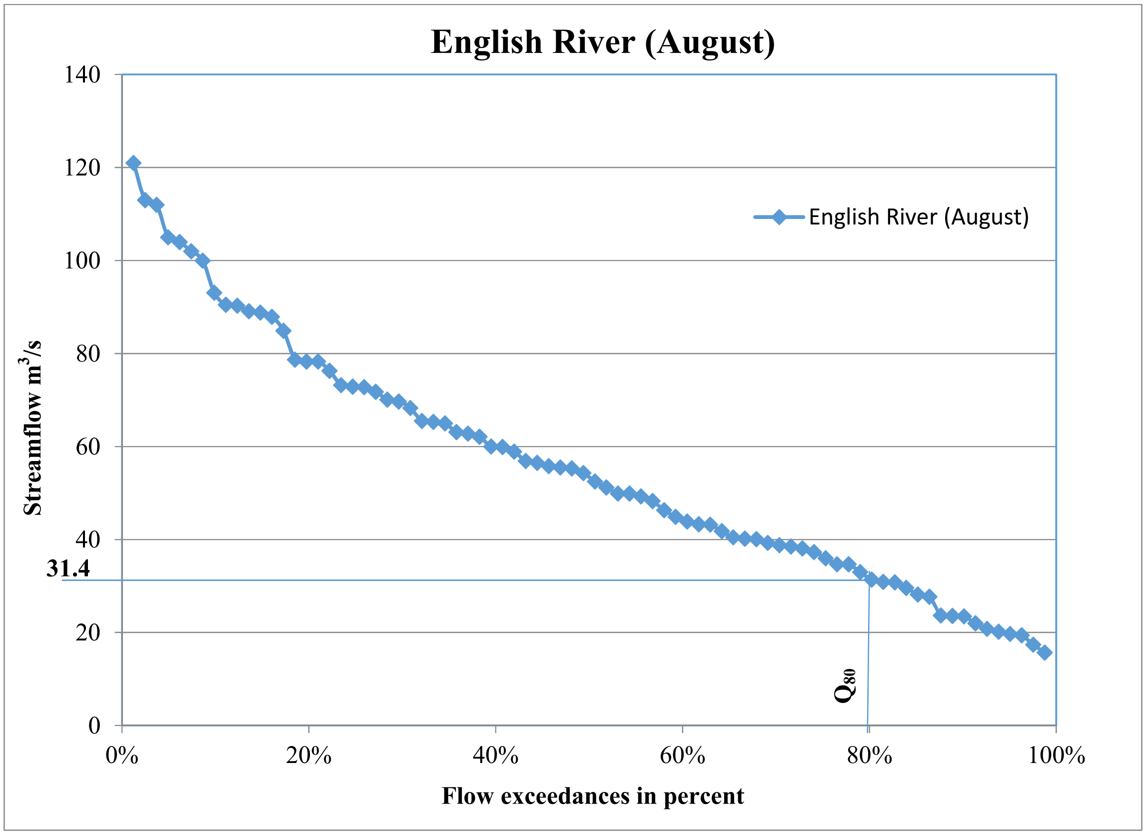


Figure 6.3: Determination of the Threshold level (Q_{80}) using the flow duration curve for the month of August.

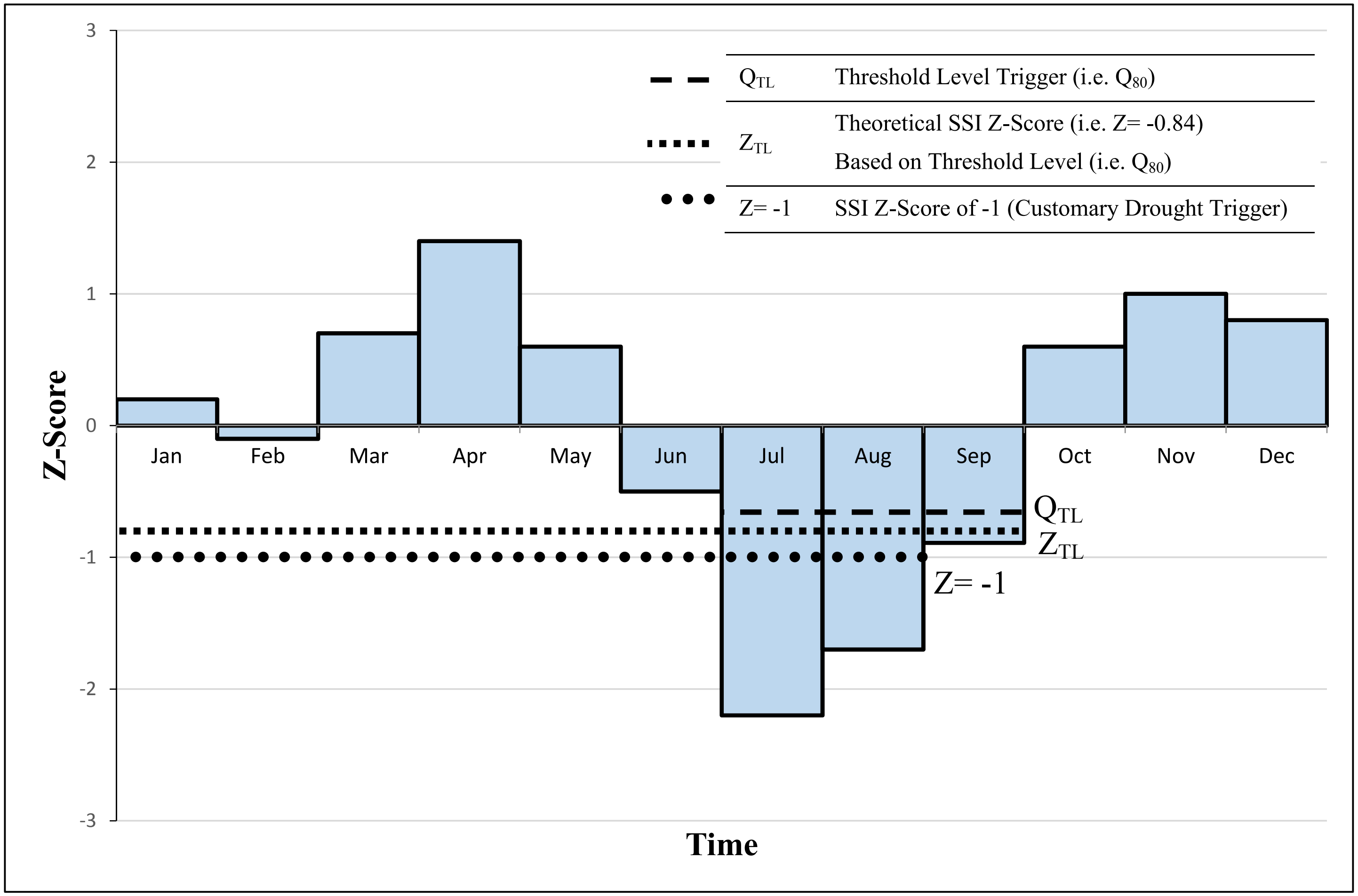


Figure 6.4: Conceptual Z-Scores of SSI data treatments in comparison to the selected threshold levels appropriate for Northern Ontario.

Table 6.5: Threshold level Q_{80} and SSI data treatment characteristics for the English River (the case of 1976/77 drought event).

Data Treatment & Threshold Level	Onset	Termination	Duration (Months)	Sum of Intensity Scores	Averaged Intensity score
Threshold Level Q_{80}	1 June 1976	30 March 1977	10	*N/A	*N/A
Untreated Z-score -0.84	1 June 1976	30 March 1977	10	-13.1	-1.31
Log Normal Transformation Z-score -0.84	1 June 1976	30 March 1977	10	-18.1	-1.81
Fitted Gamma Distribution Z-score -0.84	1 June 1976	30 March 1977	10	-16.9	-1.69

Note: N/A stands for not applicable.

Table 6.6: Threshold level Q_{80} and SSI data treatment characteristics for the English River (the case of 1998 drought event).

Data Treatment & Threshold Level	Onset	Termination	Duration (Months)	Sum of Intensity Scores	Averaged Intensity
Threshold Level Q_{80}	1 April 1998	30 Sept 1998	6	*N/A	*N/A
Untreated, Z-score -0.84	1 May 1998	30 Sept 1998	5	-7.37	-1.47
Log Normal Transformation Z-score -0.84	1 April 1998	30 Sept 1998	6	-12.2	-2.03
Fitted Gamma Distribution Z-score -0.84	1 April 1998	30 Sept 1998	6	-10.9	-1.82

Note: N/A stands for not applicable.

Tables 6.5 and 6.6 show that all data treatments accurately represent the demands of English River with threshold level of Q_{80} for the 1976/77 and 1998 drought events. The exception is the Untreated treatment that has a delayed onset of drought for the 1998 event by one month. These tables also show the variance in intensity estimates, as the average intensities for the 1976/77 drought event ranges from -1.31 to -1.81, while the average intensities for the 1998 drought event ranges from -1.47 to -2.03. The range in the 1998 drought event is significant for drought monitoring and early warning systems, as -1.47 represents moderate drought and -2.03 represents extreme drought, as classified in Table 4.1 (section 4.4.1).

CHAPTER 7: RESULTS AND DISCUSSION

This Chapter presents and discusses the results of statistical evaluations of the SSI data treatments using complete and quality streamflow dataset of catchments in Northern Ontario (as described earlier in Chapter 5). The Chapter begins with the process for selecting a sample period and the implications of using the selected sample periods for analysis, and further examines the appropriateness of the selected threshold levels to trigger drought in Northern Ontario. This analysis is appraised while focusing on the ability of various SSI data treatments to satisfy that conditions of the assumption of a normal distribution have been attained, and the influence of the respective data treatments in assessing drought characterization involving extreme values has been examined.

7.1 Threshold Representative of Hydrological Droughts in Northern Ontario

The reasons for selecting 1976/77 and 1998 as sample periods for drought assessments were described earlier in Section 6.3. The Sample Periods are confirmed by all sites investigated across the region of Northern Ontario as being drought events of significant impacts. This opens the process for determining a threshold level representative as well as equitable for the entire region.

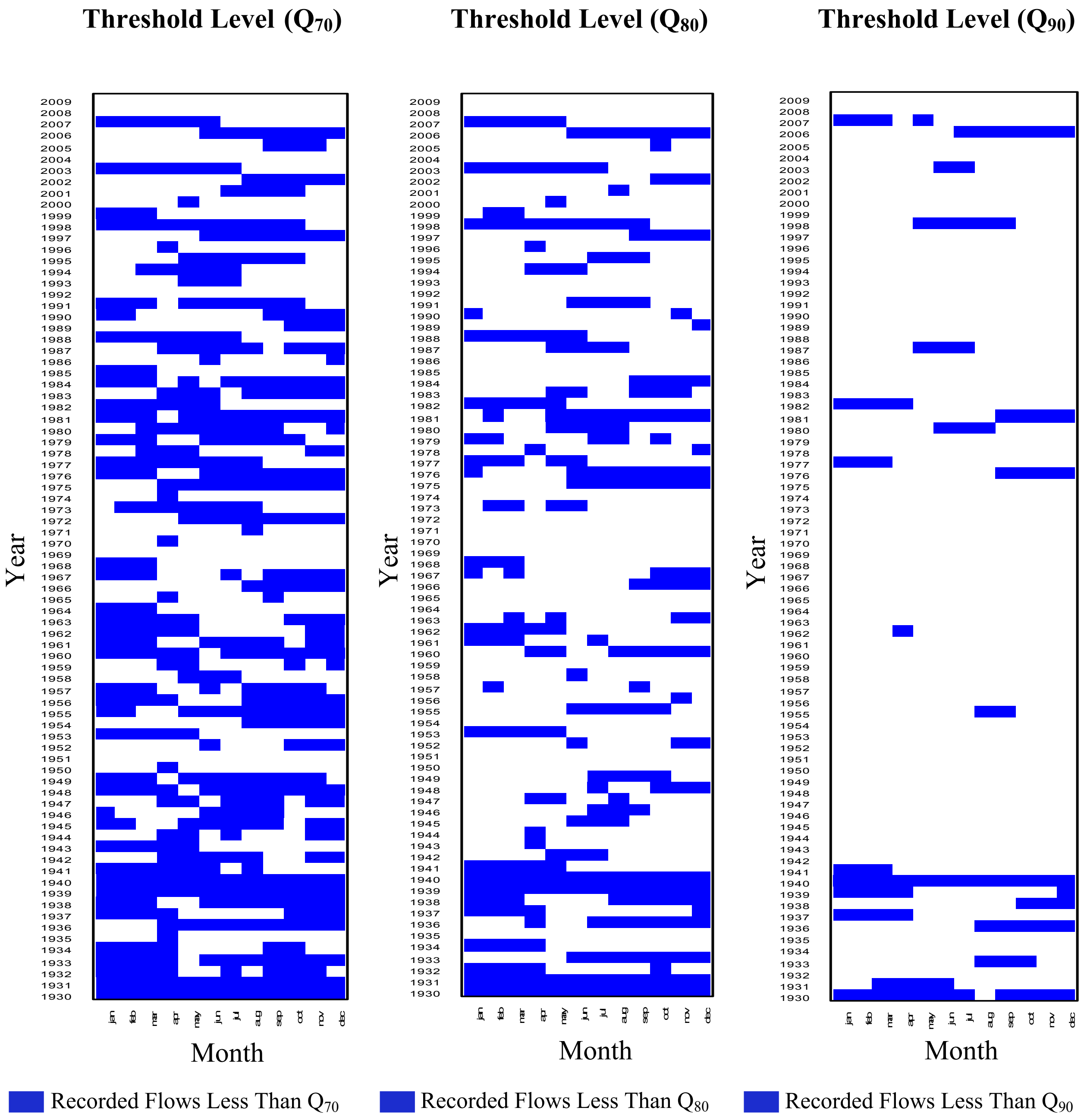
The first assessment used in the determination of an appropriate threshold level to trigger a hydrological drought in Northern Ontario pertains to the investigation of sites to assess if there is an increase in missed drought events as the threshold level increases. Using selected threshold levels Q_{70}, Q_{80}, and Q_{90}, the number of missed drought events for all rivers with recorded flows conforming to the 1976/77 and 1998 drought events are identified in Table 7.1.

It is apparent from Table 7.1 that an increase in the threshold level causes an increase in the number of missed drought events in the selected Sample Periods. It is further observed that the likelihood of threshold level (Q_{70}) to miss a drought event is minimal as it records drought events at all sites for both sample periods (1976/77 and 1998). Furthermore, it is apparent that the threshold level (Q_{80}) approaches a limit where drought events (< 2.5%) have been missed. The threshold level (Q_{90}) exhibits a significant departure because 13% and 8% droughts events respectively are missed during the sample periods (1976/77 and 1998).

Table 7.1: Ability of threshold levels to identify historical significant regional drought.

Trigger Level	Number of Sites that Historically Recorded Flows for the Specified Drought Events		Number of Sites that Failed to Record Drought for the Specified Drought Events	
	Drought Event 1976/77	**Drought Event** 1998	**Drought Event** 1976/77	**Drought Event** 1998
Q_{70}	32	40	0	0
Q_{80}	32	40	0	1
Q_{90}	32	40	**4**	**3**

Applying a threshold level that fails to identify a significant regional drought may misrepresent unfairly all impacted sectors, which may also be the case for Q_{90}. The use of the threshold level of Q_{90} identifies effectively the peak and core of severe conditions. Figures 7.1 through 7.4 allude to this fact while examining the Sample Periods (1976/77 and 1998) containing Q_{90} values with the exception of Turtle River for the 1976/77 event. A much closer review in case of the English River, Missinaibi River and the Whitson River at Chelmsford for the 1976/77 drought event, one can observe that the duration of the events get shorter. Such an interpretation is feasible from the delayed onset and earlier termination for all rivers. The Missinaibi River for the 1976/77 exhibits that the more severe is the threshold level, the more minor events occurring immediately prior to the core Q_{90} event are removed. These figures also show that the prolonged impacts of a drought event from the beginning to the end are ineffectively represented by Q_{90}. This point is elaborated through these figures by displaying that Q_{80} and even more so the Q_{70}, are better able to encapsulate the onset and termination of the drought process, particularly for drought events that reach a significant event such as the threshold level of Q_{90}. In the same manner, the lesser is the threshold level, the more blurred and respectively difficult it is to delineate significant drought events.


Threshold Level (Q_{70})

Threshold Level (Q_{80})

Threshold Level (Q_{90})

Figure 7.1: Threshold levels deficits captured in monthly time series of the English River.

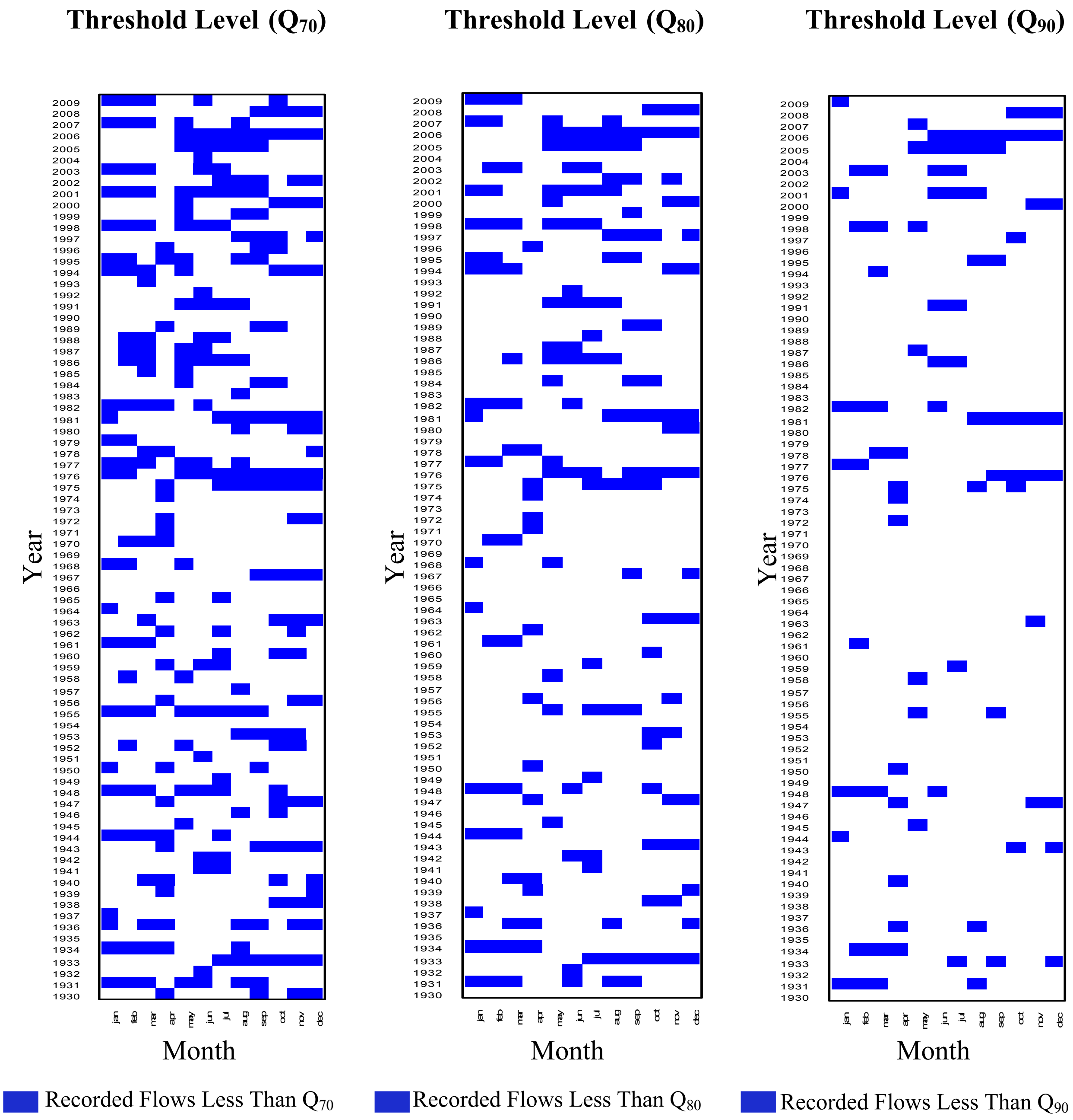


Figure 7.2: Threshold levels deficits captured in monthly time series of the Missinaibi River.

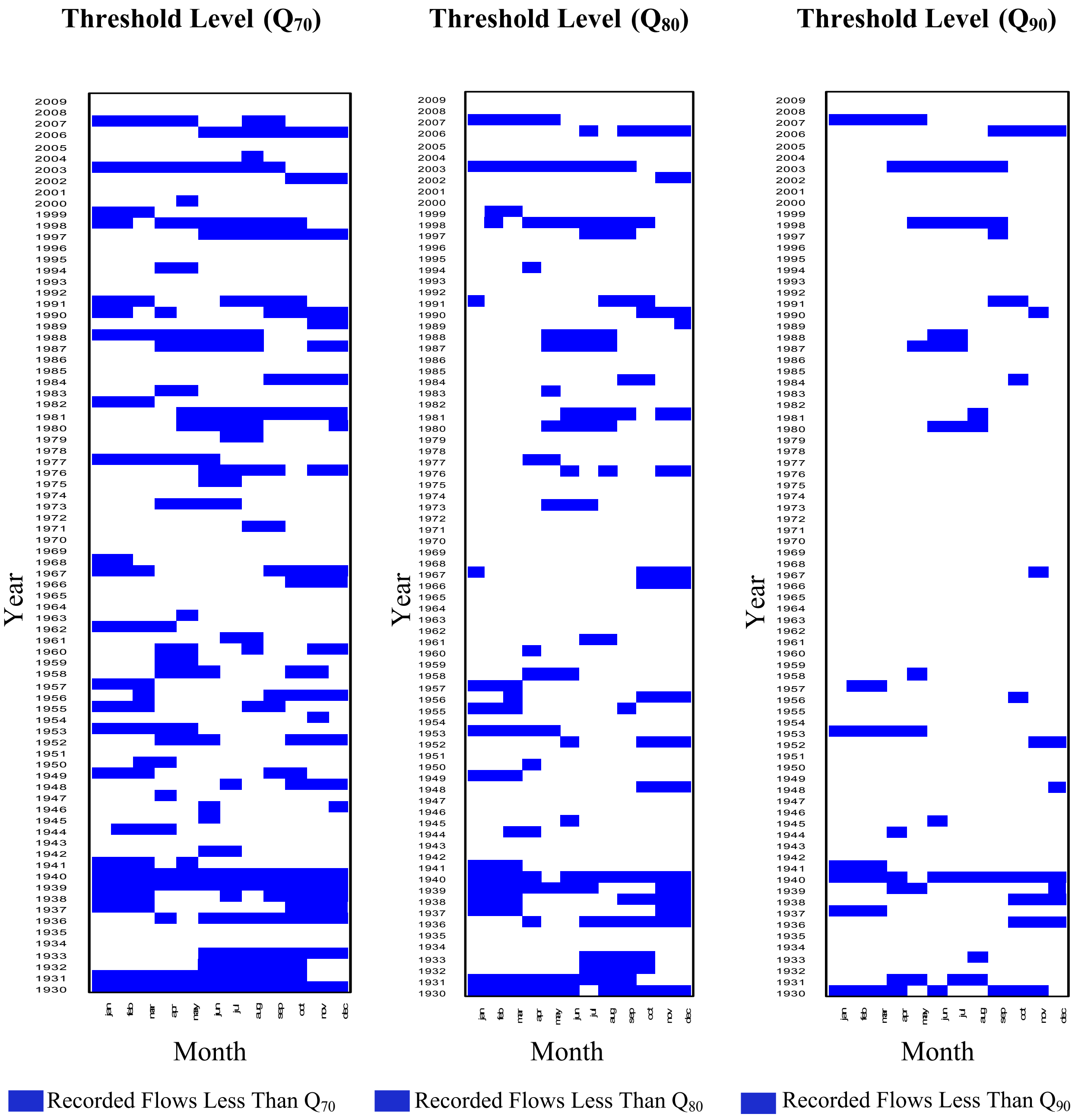


Figure 7.3: Threshold levels deficits captured in monthly time series of the Turtle River.

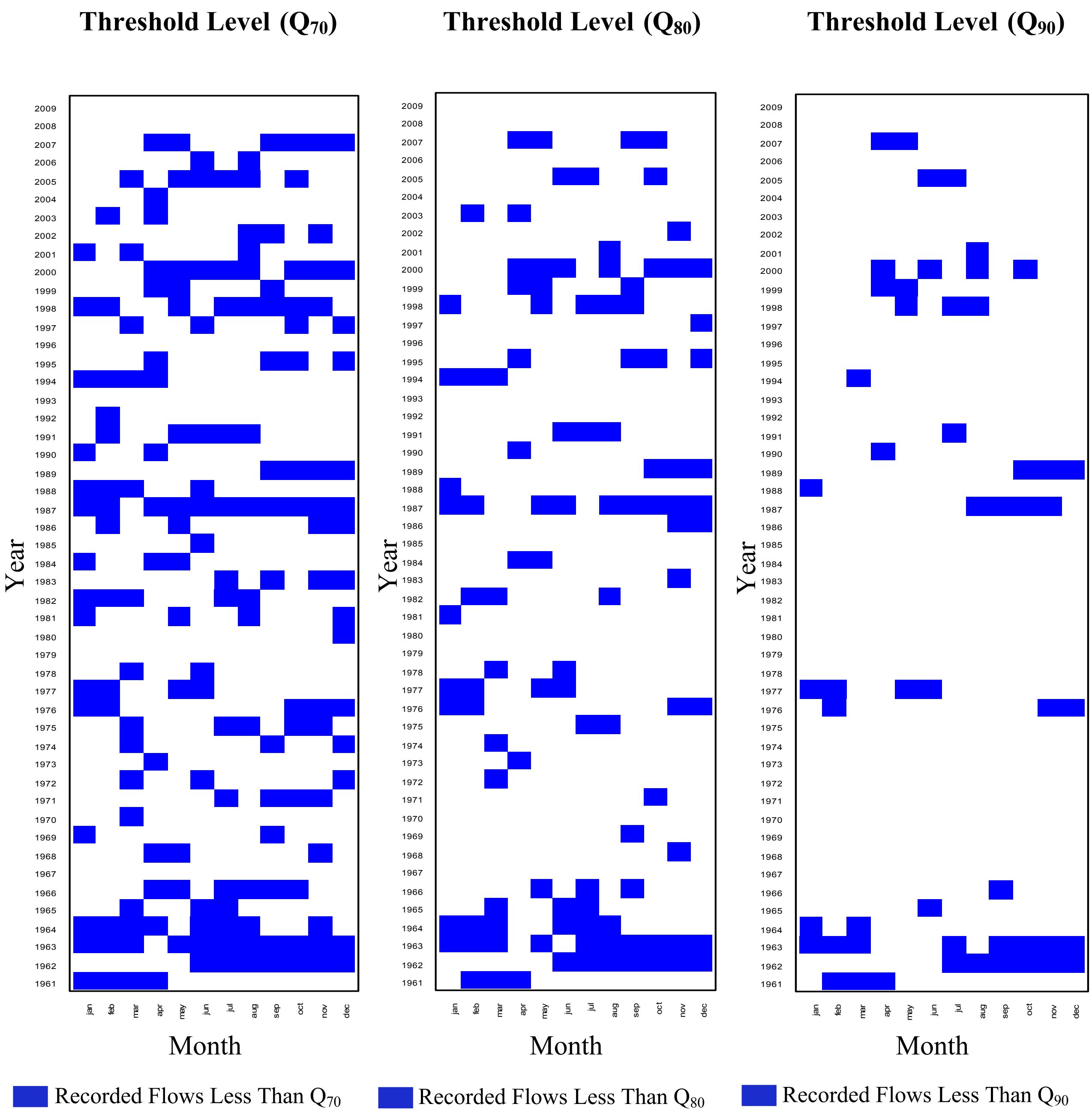


Figure 7.4: Threshold levels deficits captured in monthly time series of the Whitson River at Chelmsford.

Assessment concerning the selection of an appropriate threshold level to trigger the onset of a hydrological drought involves a measure of persistence. The threshold levels Q_{70}, Q_{80}, and Q_{90} were further investigated with the use of four rivers: English River, Missinaibi River, Turtle River and Whitson River at Chelmsford. These rivers are spread across the region (Figure 5.1), and contain lengthy records (Table 5.1) suitable for analysis. The first measure used for this assessment is that how much time it takes once a drought event has been triggered either by the threshold level of Q_{70}, Q_{80}, or Q_{90}, before the streamflow could be considered surplus (that is, the flow value exceeding the median flow (Q_{50})). In addition to the pictorial representation of these rivers in Figure 7.1 through Figure 7.4, the results pertaining to this assessment on these rivers are summarized in Table 7.2 and 7.3

Table 7.2: Number of drought events triggered by varying thresholds.

Name of the River	Record Length	Number of Drought Events Triggered by the Threshold Level		
	(Years)	Q_{70}	Q_{80}	Q_{90}
English River	80	60	39	14
Missinaibi River	80	117	76	38
Turtle River	80	57	38	19
Whitson River at Chelmsford	49	65	46	18
Mean Value	**72.3**	**75**	**50**	**22**

Note: English River ➔(60 - 39) = 21 and (39 - 14) = 25; Missinaibi River ➔(117 - 76) = 41 and (76 - 38) = 38; Turtle River ➔(57 - 38) = 19 and (38 – 19) = 19; Whitson River ➔(65 - 46) = 19 and (46 - 18) = 28.

Table 7.2 shows that as threshold level decreases to a less severe threshold level (i.e. Q_{90} to Q_{80} to Q_{70}), the number of drought events continued to increase but only at a slightly reduced rate than the previous increment in threshold levels (i.e., Q_{90} to Q_{80} and Q_{80} to Q_{70}). For example, in the case of English River, such a difference in the number of drought events for the reduction in threshold levels (Q_{90} to Q_{80}) and (Q_{80} to Q_{70}), was found respectively to be 25 and 21. The average increase in number of drought events for the case (Q_{90} to Q_{80}) and (Q_{80} to Q_{70}) was found respectively to be 27.5 and 25. This rate in increase in drought events is approximately 90% (25/27.5) from the more severe threshold to the lesser subsequent thresholds such as (Q_{90} to Q_{80}) and (Q_{80} to Q_{70}). It was previously noted that Q_{90} identifies the core of severe drought conditions as illustrated in Figures 7.1 to 7.4. It would be expected that lower threshold levels would extend the duration of drought events. Collectively, Table 7.2 and Figures 7.1 to 7.4, exhibit that the less severe threshold value (Q_{70}) captures a more complete picture of drought events but lead to occurrences of a substantial number of minor drought events of negligible impact. In other words, such an observation would indicate that negligible drought events of short duration are created at each subsequent lower threshold levels. Many of the events created would potentially be considered mutually dependent.

Table 7.3 also alludes to the fact that droughts with increasing severity of a threshold level invariably leads to longer time periods that are required by drought events to re-establish into surplus streamflows. On the average, the time to recover (Table 7.3) for threshold ranges (Q_{70} to Q_{80}), (Q_{80} to Q_{90}), and (greater than Q_{90}, which is also known as the drought initiation point), was respectively found to be 1.6, 2.6 and 6.0 months.

Persistence is also measured by the likelihood of a threshold level triggering a drought event that would lead to a more significant (i.e., severe) drought event (i.e., such a drought event has been identified by the threshold level of Q_{90}). Table 7.4 shows that using Q_{70} or Q_{80} as trigger point to initiate a drought event that would eventually results in to a Q_{90} drought event, only accounted, on the average, 29% and 44% of the time. Such an observation asserts that there is notable likelihood that a drought event triggered by Q_{80} would more likely persist into a more severe event, compared to the threshold Q_{70}. In other words, this observation implies that a drought event triggered by the threshold (Q_{80}), almost half the time would persist and would cause deficit streamflows to last, on the average, for up to six months.

Based on the foregoing observations, it can be generalized that the threshold (Q_{90}) neither addresses the slow onset of a drought nor the prolonged duration of a drought before termination. Identification of the entire drought progression from start to finish is of paramount importance in the drought preparedness planning.

The threshold level (Q_{70}) provides relatively a more complete assessment of the likelihood of occurrence of significant drought events. However, the likelihood that a drought event triggered by the threshold level (Q_{70}) to become a drought event (Q_{90}) with a frequency of occurrence of 1 in 10 years is approximately a quarter of the time. For the remainder of time, a multitude of drought events triggered by (Q_{70}) would be considered as false alarms because impacts of such drought events would be considered minor, and the recovery would generally be easy. It was further observed that drought events triggered by the threshold level Q_{70} also did not exceed the threshold of Q_{80}, and generally lasted, on the average, only 1.6 months.

Table 7.3: Drought development as a function of threshold levels and the degree of persistence of drought conditions.

Name of the River	Record Length (Years)	Average Duration in Months of Drought Recovery Time Required to Achieve Surplus flows (i.e., above the Median Q_{50}), for Specified Range of Threshold Values		
		Exceeds Q_{70}, but Less Than Q_{80}	Exceeds Q_{80}, but Less Than Q_{90}	Exceeds Q_{90}
English River	80	1.9	3.2	9.4
Missinaibi River	80	1.3	1.9	3.3
Turtle River	80	1.8	3.6	7.3
Whitson River at Chelmsford	49	1.4	1.8	4.0
Mean Value	**≅72**	**1.6**	**2.6**	**6.0**

Table 7.4: Persistence of Q_{70} and Q_{80} triggered drought.

Name of the River	Record Length (Years)	Percentage of Drought Events that Reached Q_{90} Status	
		Q_{70}	Q_{80}
English River	80	23%	36%
Missinaibi River	80	32%	50%
Turtle River	80	33%	50%
Whitson River at Chelmsford	49	28%	39%
Mean Value	**≅72**	**29%**	**≅ 44%**

The use of the threshold level (Q_{80}) to trigger a drought event contains features that may improve comprehension and subsequent applications in drought planning tools. Most notably, flows associated with Q_{80} are only exceeded 1 in 5 times (i.e., a probability of 0.2 (=1/5), which in other words implies the probability of recurrence of an event to be once in 5 year. This observation is congruent with current drought classification by the Canada Drought Monitor that includes a 5 to 10 year category to identify with moderate drought conditions. Governmental agencies also use similar triggers (Ouarda et al., 2008), who categorically noted that the $Q_{30,5}$ is applied today in Canada for flows utilized in regulated waste discharges. This trigger is the lowest flow recorded for 30 consecutive days (approximately 1 month) at a recurrence interval of 5 years. The threshold level (Q_{80}) has also been used in a multitude of studies to provide flows in a historical context for assessments (Tallaksen et al., 2004 and Vicente-Serranto et al., 2012). The use of threshold level (Q_{80}) may avoid the complexities associated with more severe threshold levels because such a level is less likely to be impacted by intermittent flows. In addition, such a threshold should be less susceptible to inaccuracies arising due to being out of the range of non-linear extreme values (that result from a lack of data points near the tails of the distribution).

7.2 Assessment of SSI Data Treatments to Achieve Standardized Normality

Providing standardized severity improves multisite comparisons (Sharma and Panu, 2009), a critical feature for the decision making in early warning and drought monitoring systems. The Z-score computed by the various SSI data treatments permits such multisite comparisons. The appropriateness of such comparisons ensures how accurately and consistently these treatments adhere to expectations of the normal distribution. The results summarized in Tables (7.5 to 7.7) for the untreated and treated (i.e., Log Normal Transformed, and the Fitted Gamma Distribution) data treatments, and their ability to accurately and consistently to satisfy the condition of a normal distribution.

The ability of each SSI data treatment to generate Z-scores that are identifiable with the normal distribution is determined using the Shapiro Wilk test and Anderson Darling test. Ranking of the computed test statistics revealed how often the selected data treatment failed to reject the alternative hypothesis (i.e., a sample is not from a normal distribution function). Ranking is completed based the strength of the test statistic summarized in Table 7.5 for all 12 months of the year at each site.

A review of results (Table 7.5) indicates that the Log Normal Transformation provides most consistent transformed data which are representative of the normal distribution, followed by the Fitted Gamma Distribution and subsequently Untreated data. All treatments contained, at least, one month at each site that failed to reject the alternative hypothesis.

It is apparent from the results of rejection rates (Table 7.6) of the alternative hypothesis for the normality test that the Fitted Gamma Distribution slightly outperforms the Log Normal Transformation. The rejection rates for Untreated data was much higher.

Table 7.5: Best ranked SSI data treatment rank at achieving conditions of a normal distribution.

Data Treatment	Percentage of Time Each Data Treatment Ranked First in its Ability to Achieve Normality*
Untreated	0%
Log Normal Transformation	70%
Fitted Gamma Distribution	50%

*Includes ties

Table 7.6: Data treatments overall frequency at failing to achieve normality.

Data Treatment	Rejection Rates for Each Data Treatment at Confirming Dataset Came from a Normal Distribution (Test Statistic value set at $P<0.05$)
Untreated	64%
Log Normal Transformation	26%
Gamma Fitted Distribution	23%

The Log Normal Transformation ranked higher and therefore achieved higher powers in the normality test than the Fitted Gamma Distribution. A further review into why ranking of data treatments (Table 7.5) are not consistent with the percent of achieved normality (Table 7.6), identified that the Log Normal Transformation often performed poorly at normalization whereas the Fitted Gamma Distribution performed well and vice versa. This tendency was further documented by seasonality traits of these data treatments during the specific investigation into the best performing data treatment for each month. Seasonal influence on monthly data treatment performance is not uncommon (Vincente-Serrano et al., 2012; Svensson et al., 2017). When the Log Normal Transformation and Fitted Gamma Distribution data treatments were used separately, only achieved approximately a quarter of the time the conditions of a normal distribution.

The results of normality tests at the monthly level (Table 7.7) show that the performance of each data treatment varied depending on the month and also the best performing data treatment varied for each month. When the best performing monthly data treatment was used, there was an increase in the SSI ability to achieve conditions of a normal distribution. It is further noted that the Fitted Gamma Distribution and the Log Normal Transformation respectively were found to perform unsatisfactorily (23% and 26%) in achieving normality (Table 7.7). On the other hand, the use of the best performing data treatment for each of 12 months was found to reduce the failure rate of achieving normality to 15.7% (Table 7.8).

Seasonality influences and their impacts on the effectiveness of the various data treatments are summarized in Table 7.8. From this table, it is apparent that the Log Normal Transformation was found to perform better for the summer months (June to October), while the Fitted Gamma Distribution appeared to perform better for the Winter Months (November to

May). None of the data treatments effectively represented conditions of a normal distribution for the month of March. Furthermore, the months that would be expected to experience snow ridden conditions and transitioning into snow melting conditions from snow pack (February, March, and April) resulted in the worst performance in Normality testing. It is plausible that a different data treatment altogether may improve the accuracy. It should be noted that seasonality influences may impact assessments differently between the northern and southern sites within the vast region of Northern Ontario.

For all streamflow datasets used in the analysis that contained sample size of less than 100 may result in a reduced ability for these tests to correctly reject the null hypothesis when the alternative hypothesis is true (Razali and Wah, 2011). The same study showed that of the Shapiro and Wilks test followed by the Anderson Darling test tend to demonstrate the greatest power in Normality testing (Razali and Wah, 2011). Another reason for best performance by the Shapiro Wilk test for Normality is due to the fact that this test was developed for small sample size (<50 as is the case in this thesis).

Table 7.7: Monthly data treatments and frequency of failing to achieve normality.

Month	Percentage of Failed Normality Tests for the Specified Month at All Sites (Test Statistic $P < 0.05$)			Best Performing Data Treatment
	Untreated Data	Treated Data		
		Log Normal	Gamma	
January	33.8%	32.5%	**11.3%**	Gamma
February	42.5%	41.3%	**21.3%**	Gamma
March	63.8%	56.3%	**55.0%**	Gamma
April	35.0%	40.0%	**18.8%**	Gamma
May	23.8%	37.5%	**10.0%**	Gamma
June	75.0%	**12.5%**	15.0%	LN
July	85.0%	**10.0%**	18.8%	LN
August	92.5%	**5.0%**	31.3%	LN
September	96.3%	**11.3%**	46.3%	LN
October	83.8%	**12.5%**	26.3%	LN
November	71.3%	27.5%	**8.8%**	Gamma
December	70.0%	26.3%	**11.3%**	Gamma
Average	64.4%	26.1%	**22.9%**	

Table 7.8: Summary of the best performing data treatments for each month.

Using Best Data Treatment		
Month	**Failed to Achieve Normality (Percentage of Time)**	**Best Performing Treatment by Month**
January	11.3%	Gamma
February	21.3%	Gamma
March	55.0%	Gamma
April	18.8%	Gamma
May	10.0%	Gamma
June	12.5%	LN
July	10.0%	LN
August	5.0%	LN
September	11.3%	LN
October	12.5%	LN
November	8.8%	Gamma
December	11.3%	Gamma
Average	**15.7%**	

7.3 Accuracy of Different Methods of Drought Analysis

The underlying assumption used in this thesis implies that the threshold level of Q_{80} is the most appropriate trigger for hydrological drought in Northern Ontario. Based on this trigger the most suitable SSI data treatment was determined. The initial SSI examination comprised of the typical application of a moderate drought being triggered at the Z-score of -1.0 (Z= -1). This application was followed by an SSI examination wherein a theoretical Z-score equivalent of a threshold level of Q_{80} triggers a drought at the Z-score of -0.84 (Z= -0.84). A comparison of Z = -1 and Z= -0.84 was made to ascertain on the use the threshold level of Q_{80} (Q_{TL}) to determine the appropriateness of these scores at identifying droughts in Northern Ontario.

The use of threshold levels (Q_{80} and Z= -1) in delineating (or identifying) a drought event for various data treatments provided identical results (49% to 61% of time as summarized in Table 7.9). Poor correlation between Q_{80} and Z= -1 reaffirmed that the use of a standard practice for the classification of SSI may not be appropriate in identifying the impacted sectors of drought in Northern Ontario. The SSI data treatments aim to achieve the equivalent standard to the threshold level Q_{80} such that it would be considered an appropriate trigger of SSI for the delineation of drought events in Northern Ontario. Since in this analysis the resulting SSI are assumed to adhere to the standard normal distribution, the various SSI are also reviewed based on the assumption that the exceedance probability of Q_{80} should theoretically match the standard normal distribution with that of Z= - 0.84.

Table 7.9: Correct characterization of drought using Z-Score of -1 in comparison to threshold level of Q_{80}.

Data Treatment	Percent Correct (%)								
	1976-77 Drought Event			1998 Drought Event			Averaged*		
	Initiation	Termination	Entirely Matching	Initiation	Termination	Entirely Matching	Initiation	Termination	Entirely Matching
Untreated	41	59	25	78	58	43	60	59	49
Log Normal Transformation	69	69	50	80	80	65	75	75	58
Fitted Gamma Distribution	75	72	53	80	75	60	78	74	57

* Average of Droughts Events 1976-77 and 1998

The results of SSI data treatments with the use of Z= - 0.84 to trigger a drought event were compared with the threshold level of Q_{80} (Table 7.10). An analysis of results affirms a substantial improvement with identical results being achieved 55% to 76% of the time. The Log Normal Transformation performs best at 76% matching results, followed by the Fitted Gamma Distribution and subsequently by the Untreated treatment. The 1998 drought event exhibits higher percentage of correct initiation then termination, while the opposite is true for the 1976/77 drought event.

Table 7.10: Drought characterization using the trigger of Z-Score of - 0.84 (the theoretical Z-Score equivalent of Q_{80}), in comparison to the threshold level of Q_{80}.

Data Treatment	Percentage Correct (%)								
	1976-77 Drought Event			1998 Drought Event			Average		
	Initiation	Termination	Entirely Matching	Initiation	Termination	Matching	Initiation	Termination	Matching
Untreated Data	69	69	56	80	65	53	75	67	55
Log Normal Transformation	84	88	72	90	90	80	87	89	76
Fitted Gamma Distribution	75	78	63	90	75	68	83	77	66

* Average of Droughts Events 1976-77 and 1998.

Inaccuracies arising from SSI data treatments that did not match entirely to the triggers set out by the threshold levels, resulted in notable influences on drought characterization (Tables 7.11 to 7.13). The instances where initiation and termination points did not match, exhibited least amount of impact, in general, in the case of the Log Normal Transformation. In terms of identifying the drought initiation, on the average, inaccuracies resulted in drought being triggered prematurely or delayed by 1.3 to 2.2 months. As for the termination, on the average, inaccuracies resulted in drought being terminated early or late by 1.5 to 2.3 months. Similarly, on the average, inaccurate drought duration estimates being too short or too long ranged by 1.5 to 3.3 months. The use of the best performing data treatment at some sites still resulted in imprecise match for the initiation, termination and duration. The corresponding use of the Log Normal Transformation with Z= - 0.84 also resulted in average variation of 1.3, 1.5 and 1.5 month respectively for the initiation, termination and duration. However, this could have been much worse if the least suitable data treatment was used then would have resulted in inaccuracies in the range of 2.2 to 3.3 months for the initiation, termination and duration. It is noted that results corresponding to the Atikokan River were removed from further analysis because drought events could have arguably required pooling for all SSI data treatments and thus would have resulted in the computations that would have skewed the foregoing analysis. In addition, for similar reasons, the Pipestone River was removed from results of the Fitted Gamma Distribution.

Table 7.11: Drought duration differences among various SSI data treatments.

Data Treatment	Average drought duration differences from SSI data treatments using the theoretical equivalent Z-score (= - 0.84) for Q_{80} compared to the results produced by using a threshold level of Q_{80} (Months)	
	1976/77	**1998**
Untreated	1.9	1.6
Log Normal Transformation	1.7	1.5
Gamma Fitted Distribution	2.2	2.2

Table 7.12: Drought initiation differences among various SSI data treatments.

Data Treatment	Average drought initiation differences from SSI data treatments using the theoretical equivalent Z-score (= - 0.84) for Q_{80} compared to the results produced by using a threshold level of Q_{80} (Months)	
	1976/77	**1998**
Untreated	1.8	1.9
Log Normal Transformation	1.6	1.3
Gamma Fitted Distribution	2.0	2.3

Table 7.13: Drought termination differences among various SSI data treatments.

Data Treatment	Average drought termination differences from SSI data treatments using the theoretical equivalent Z-score (= - 0.84) for Q_{80} compared to the results produced by using a threshold level of Q_{80} (Months)	
	1976/77	**1998**
Untreated	3.3	1.6
Log Normal Transformation	1.8	1.5
Gamma Fitted Distribution	2.0	1.5

7.3.1 Assessment of Severe and Extreme Droughts

Decisions concerning response and mitigation action are strongly influenced by the information obtained from the early warning and drought monitoring systems. Scale of the response is dependent on the assessments of drought severity. The potential for reduced accuracy of assessments is increased in severe and extreme drought conditions because of the lack of recorded years of streamflow data and also due to the dataset with minimal points near tails of the distribution. Severe and extreme conditions require estimations to be made at tails of the distribution and may potentially require that extrapolations be made beyond what has been recorded. The simplest method to assess the increasing severity of drought events is to compute the sum of drought severities (i.e. deficits) over a period of time. An intensity score can be obtained by averaging monthly SSI intensities as one would do for drought severities using the threshold method and dividing the resulting quantity by the duration. The appropriateness of such a score for assessments is evaluated.

Six drought events comprising of five month duration at six different sites are summarized in Table 7.14. The corresponding monthly intensities of the average SSI and computations of SSI on a five month time increment for the duration of these events are also presented in Table 7.14. These six events show that for severe to extreme events, computing average monthly SSI intensities was notably less severe than SSI intensities covering the same five month duration. However, all events show that the use of average intensities still identified conditions considered to be severe to extreme droughts. A review of the small sample exhibited that 33% of the time the drought categories are the same, and when that is not the case then generally the classification was off by one category less severe. Such an observation indicated that the use of probabilities of average intensities of SSI as being inappropriate. However, in terms of providing a general classification of ongoing conditions of drought, the use of average intensities of SSI may be acceptable. Nevertheless, such an approach may prove to be beneficial in the predication of droughts where general classifications may be deemed acceptable and also the results are likely to produce less false alarms.

An evaluation of the consistency of various SSI data treatments in the identification of severe and extreme drought conditions was conducted. The scores of monthly sample sets for each site were evaluated using the percentage of time scores were observed in the range defined as severe or extreme (Table 7.15). The values selected for investigation represent a Z-score of -1.64 and -2.33, respectively. The expected frequency distribution of Z-score values less than -1.64 is 5.0%, while the expected frequency distribution of Z-score values less than -2.33 is 1.0%.

The Fitted Gamma Distribution and the Log Normal Transformation (Table 7.15) contain 80% and 70% of the expected frequencies for Z-scores being less than -1.64, while the Untreated data treatment contained 19%. The ability to achieve the expected frequency of Z-scores of less than -2.33 was reduced for this extreme category. Only the Fitted Gamma Distribution was found to perform adequately by achieving 67% of the expected frequencies. All SSI data treatments underestimated the frequency of extreme events, and the precision appears to decrease with the more severe Z-score of -2.33.

Table 7.14: Comparing Fitted Gamma Distribution averaged intensities to Z-Scores computed from SSI with 5-month duration.

Name of the River	Drought Duration	*$SSI_{\text{5-Month Average}}$		**$SSI_{\text{5-Month Intensities}}$	
		Five-month Average Intensities	**Category**	**Five-month Intensities**	**Category**
Chippewa River	October 1976 to February 1977	-1.55	Severe	-2.68	Extreme
Nagagami River	October 1976 to February 1977	-2.12	**Extreme**	-2.07	**Extreme**
North French River	October 1976 to February 1977	-1.88	Severe	-2.31	Extreme
Pagwachuan River	October 1976 to February 1977	-1.86	**Severe**	-1.99	**Severe**
Whitefish River	May 1998 to September 1998	-1.63	Severe	-3.03	Extreme
Wolf River	May 1998 to September 1998	-1.90	Severe	-3.27	Extreme

* Averaged monthly intensities over a 5 month period ($SSI_{\text{5 Mo Average}}$)
** Intensity representing a 5 month period ($SSI_{\text{5 Mo Intensities}}$)

Table 7.15: Observed frequencies of Z = -1.64 and Z = -2.33 in comparison to expected.

Z-Score	Untreated Data	Log Normal Distribution	Fitted Gamma Distribution	Expected Frequency*
Observed Values Less Than Z = -1.64	0.96%	3.50%	4.00%	5.00%
Observed Values Less Than Z = -2.33	0.02%	0.36%	0.67%	1.00%

* The expected frequency distribution for Z-score values less than -1.64 is 5.0% and for Z-score values less than -2.33 is 1.0% .

The box plots (Figure 7.5 and 7.6) show the percentage of recurrences that each site experience drought events with less than both Z-score of -1.64 and -2.33. These box plots demonstrate that the fitted Gamma Distribution best represents the frequency of recurrence of severe to extreme drought conditions. In both instances, the fitted Gamma Distribution approaches the intended frequency of recurrence, but very rarely exceeded it. The Log Normal Transformation provided a slightly less representative percentage of recurrence than the fitted Gamma Distribution for both Z-score of -1.64 and -2.33. The Untreated treatment significantly underestimated the frequency of recurrence of Z-scores for both -1.64 and -2.33.

The frequencies of recurrence of the severe Z-scores less than -1.64 are well represented in order of best performance: the Fitted Gamma Distribution, followed by Log Normal Transformation. The Untreated SSI data treatment did not represent the frequency of recurrence of Z-scores exceeding -1.64. The fitted Gamma Distribution also performed well at identifying the frequency of recurrence of extreme droughts exceeding the Z-score of -2.33, which was followed by the Log Normal Transformation. Significant underestimates were made by the Untreated data for the Z-score of less than -2.33. It is noted that Untreated SSI data treatment did not identify extreme drought conditions, a critical feature of early warning and drought monitoring systems.

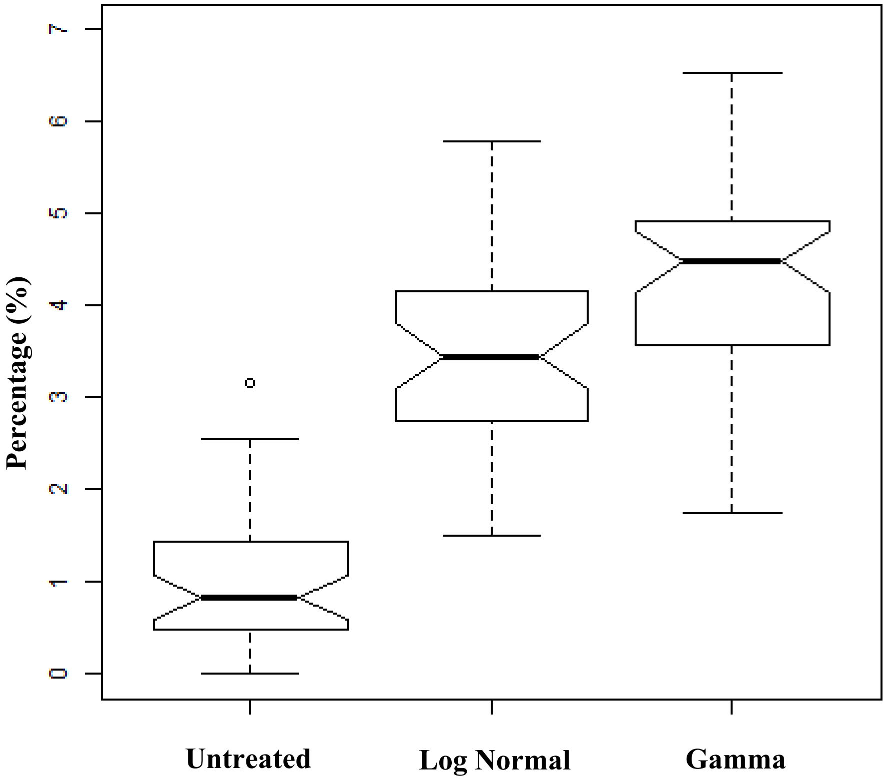


Figure 7.5: Boxplot of observed frequencies for Z-scores less than - 1.64 where the expected frequency is 5%.

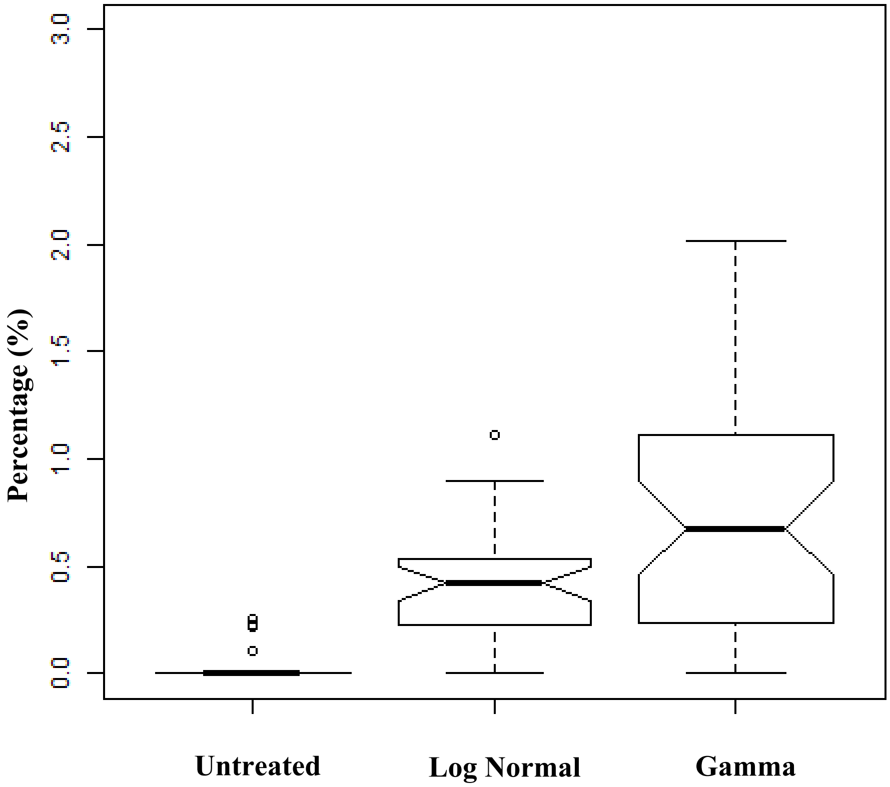


Figure 7.6: Boxplot of observed frequencies for Z-scores less than - 2.33 where the expected frequency is 1%.

The most significant finding was that all SSI data treatments failed to identify the extent of severe to extreme drought conditions resulting in a frequency of scores less than what was observed. Consistency and accuracy was found to be reduced with the assessment of extreme conditions. The selected SSI data treatments should be able to accurately and consistently identify the frequency of severe to extreme drought conditions, as inaccuracies and inconsistencies could result in significant consequences of being more vulnerable and being unprepared.

The above analysis alludes to the Gamma Distribution being a better distribution that simulates the behaviours of SSI responses in the hydrological drought scenario in Northern Ontario. The findings also indicates the results of Sharma and Panu (2010), in which they have shown the superiority of the Gamma probability density function to fit the monthly flows in Northern Ontario. When untreated data are being used, it tacitly assesses the data as being normally distributed.

Thus out of the Untreated, fitted Gamma Distribution and the Log Normal Transformation, the best results that preserve the characteristics of hydrological drought are obtained using the fitted Gamma Distribution.

CHAPTER 8: CONCLUSIONS AND RECOMMENDATIONS

The goal of this thesis is to provide an understanding of the implications of commonly used SSI data treatments for the characterization of drought in Northern Ontario, a region whose main industries are mining, logging and hydroelectric. The three streamflow data treatments that have been investigated include: Untreated (implicitly assumed to be normally distributed) and treated (i.e., Log Normal Transformation, and the Fitted Gamma Distribution). The intended use of the findings is to guide suitable applications of early warning systems and drought monitoring programs in an effort to effectively improve upon the drought planning and drought ameliorating processes in Northern Ontario.

Streamflow records of 40 catchments were used in evaluations, on the average, that represented 45 years of streamflow data on each catchment. Selection of a sample period for evaluations of historical regional drought required that a majority of catchments in the region contain records that registered the event(s). In addition, the respective drought event(s) needed to be supported by literature noting the economic, social and environmental impacts, and the Sample Periods, 1976/77 and 1998 were found to meet these criteria. These Sample Periods, as well as being significant events, complement the analysis by demonstrating the influence of seasonality.

Utilizing the recommended trigger threshold level of Q_{80} (established in this thesis), maintains sensitivity of the impacted sectors of drought in Northern Ontario. Utilizing the hydro-meteorological variable (i.e., streamflow) the threshold level is representative of social, economic and environmental systems. The threshold level Q_{80} was able to identify entire drought events from beginning to end, while being able to avoid the triggering of drought events that have negligible impacts. The threshold level of Q_{80} also has been found to be suitable to trigger responsive action set out in drought planning programs. A notable benefit is that Q_{80} may be associated with a recurrence interval of once in five years (i.e., probability of occurrence equal to 20%), which also conforms to the comprehensible scoring applied by the Canada Drought Monitor. The main limitation of any threshold level in terms of multisite comparisons is where different sites may still have varying drought durations and deficit volumes. In addition to presenting assessments with improved comprehension, the SSI data treatments provide standardized estimate of severity, which was found to enhance multisite comparisons.

Northern Ontario is highly influenced by seasonality, with snow pack contributing to the temperate hydrological characteristics of the region. Therefore, the use of monthly assessments helps to present a depiction of the transition drought seasons. Based on the results of investigations summarized in the thesis; it is recommended that the Fitted Gamma Distribution for the winter season months (November to May) and the Log Transformation for the Summer Seasons months (June to October) be utilized. It is to be noted that none of the data treatments were found to adequately represent the month of March, and both transformations showed less desirable results during the snow ridden and transitioning into snow melting months (February, March and April).

The use of these two data treatments for the respective seasons permitted normality to be rejected 15.7 % of the time. Further, by removing the month of March, normality was found to be rejected 12.0% of the time. Based on the results, it is recommended that each river for each month should be evaluated using the available data treatments in an effort to ascertain the best performing data treatment capable of representing catchment data for computing appropriate Z-scores that can be representative of the standard normal distribution. The data treatments ability to achieve normality was found to be an indicator of the accuracy in Z-score computations.

Each data treatment investigated is assessed for its ability to demonstrate an appropriate distribution of their computed Z-score values in severe to extreme drought conditions. The frequency distribution of severe and extreme Z-scores values that are less -1.64 and -2.33 are well represented by the Fitted Gamma Distribution, followed by the Log Normal Transformation and subsequently by Untreated data.

All SSI data treatments overlooked the number of severe and extreme droughts. This observation is more noticeable in the assessment of extreme drought conditions, where the anticipated frequency of extreme scores is significantly underestimated (Table 7.15). Underestimating of severe and extreme drought conditions is dangerous, as it leaves the region being assessed to remain more vulnerable and under prepared.

The difference in results of the drought assessment obtained while using Q_{80} in comparison to the Z-score of -1 for triggering drought reaffirms that the SSI classifications may not be appropriate in identifying drought with the impacted sectors in Northern Ontario. However, it was noted that the threshold level (Q_{80}) and its theoretical equivalent (Z-Score of -0.84) were found to produce better results. The Log Normal Transformation was found to perform best with 76% of identically matching results and followed by the Fitted Gamma Distribution with 66% of identically matching results. Untreated data treatment cases were found to provide less reliable results. When the results did not match precisely for the best performing Log Normal Transformation while using the equivalent Z-Score of - 0.84, initiation, termination and duration had an average difference of 1.3, 1.5 and 1.5 months, respectively. This indicates that approximately 25% of the time (when results do not match precisely) the likelihood of determination of the initiation, termination and duration will be imprecise approximately by a little over one month. Although, impreciseness of one month may appear small and inconsequential but not necessarily in terms of droughts where such a small under estimation could cause serious damage in drought preparedness, therefore, there is an opportunity to further improve upon the accuracy of initiation, termination and duration of a drought. Such differences were found to increase to the range of 2.2 to 3.3 months for the less suitable data treatments and thus emphasizing the need to use of most appropriate and optimal data treatments in drought assessment.

8.1 Recommendations for Future Research

Throughout the research process of this thesis, opportunities for further research were identified that are considered beyond the scope of this thesis. The most pertinent considerations for future research are outlined in bullet points as follows

- Investigate the use of fitting additional probability distributions
- Investigate the SSI at other time scales (2, 3, 4, 6 and 12 months)
- Increase the detail and extent of drought impacts in association with various levels of the SSI
- Investigate the ability of regional vulnerability to adapt in relation to frequency of severe to extreme droughts
- Generate a toolbox for a streamlined approach for best assessment of droughts
- Utilizing multiple distributions for the assessment of extreme tails
- Investigate the trend analysis to evaluate the influence of climate change across rivers in Northern Ontario
- How the SSI characterization relates to prediction assessments of droughts
- Delineation of an appropriate alternative to the drought termination trigger

CHAPTER 9: REFERENCES

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APPENDIX A-1: SUMMARY OF RESULTS FROM NORMALITY TESTS

Drought characteristics for early warning and drought monitoring systems are often conveyed in the form of standardized scores with the intent to improve comprehension by the general public, water managers, and governing administrations. Common applications of SSI are founded on the assumption that the computed standardized scores adhere to the standard normal (Gaussian) distribution. As a result, the accuracy of drought characteristics determined by the SSI is highly influenced by the ability of streamflow data to identify with the standard normal distribution. SSI data treatments are used to better identify streamflow data to the standard normal distribution. SSI data treatments such as Untreated and treated (i.e., Log Normal Transformed, and the Fitted Gamma Distribution) are assessed for their ability to satisfy the conditions of a normal distribution.

The Shapiro Wilk test and Anderson Darling test are used to evaluate the ability of each SSI data treatment to generate Z-scores that are identifiable with the normal distribution. These test are completed for each month of the year for each recording river station. Ranking of the computed test statistics revealed how often the selected data treatment failed to reject the alternative hypothesis (i.e., a sample is not from a normal distribution function). Ranking is completed based on the strength of the test statistic. The following tables provide supplementary detail to the respective results and discussions summarized in Section 7.2.

The Number of Months that Failed to Achieve Conditions of a Normal Distribution by Data Treatment

Hydrometric Station	Untreated	Log Normal Transformation	Fitted Gamma Distribution
Atikokan River near Atikokan	7	14	4
Aubinadong River above Sesabic Creek	18	2	7
Basswood River Near Winton	19	9	11
Batchawana River near Batchawana	13	19	6
Big Carp River near Sault St. Marie	19	3	1
Blackwater River at Beardmore	14	8	9
Blanche River above Englehart	19	3	2
Cat River below Wesley Lake	4	8	6
Cedar River below Wabaskang Lake	16	4	0
Chippewa Creek at North Bay	16	4	0
Coniston Creek Above Wanapitei River	17	0	9
English River at Umfreville	17	11	0
Goulais River near Searchmont	14	4	4
Junction Creek below Kelly Lake	16	2	2
Kwataboahegan River near the mouth	22	5	6
La Vase River at North bay	16	4	13
Long-Legged River below Long-Legged Lake	12	4	3
Little Pic River near Coldwell	13	10	8
Little White River near Bellingham	14	6	9
Little White River below Boland River	14	4	6
Missinaibi River at Mattice	16	11	5
Nagagami River at Highway No. 11	13	9	2
Namakan River at Outlet of Lac La Croix	18	6	11
Neebing River at Thunder Bay	22	5	9
North French River near the Mouth	17	4	5
Ogoki River above Whiteclay Lake	11	3	2
Pagwachuan River at Highway No. 11	12	10	7
Pic River near Marathon	14	8	4
Pipestone River at Karl Lake	17	2	3
Root River at Sault St. Marie	20	11	4
Serpent River at Highway No. 17	16	11	6
Sturgeon River at McDougall MILLS	14	2	3
Sturgeon River at outlet of Salvesen Lake	13	8	2
Sturgeon River at Upper Goose Falls	15	2	4
Troutlake River above Big Falls	4	13	4
Turtle River near Mine Centre	23	0	4
White Fish River at Nolalu	18	4	5
Whitson River at Chelmsford	20	4	13
Whitson River at Val Caron	18	0	9
Wolf River at Highway 17	17	12	3
Averaged of Failed Monthly Tests	**15.5**	**6.2**	**5.3**
Percentage of Failed Monthly Tests	**64%**	**26%**	**22%**

Note: A total of 24 months were tested, 12 using the Shapiro Wilks test and the 12 using the Anderson Darling test

Ranking of Data Treatments for their Ability
to Achieve Conditions of a Normal Distribution

Hydrometric Station	**Untreated**	**Log Normal Transformation**	**Fitted Gamma Distribution**
Atikokan River near Atikokan	3	4	2
Aubinadong River above Sesabic Creek	4	1	3
Basswood River Near Winton	4	1.5	2
Batchawana River near Batchawana	3	4	2
Big Carp River near Sault St. Marie	4	1	2
Blackwater River at Beardmore	4	2	2
Blanche River above Englehart	4	1	2
Cat River below Wesley Lake	3	4	2
Cedar River below Wabaskang Lake	4	2	2
Chippewa Creek at North Bay	4	2	2
Coniston Creek Above Wanapitei River	4	1	2
English River at Umfreville	4	3	1
Goulais River near Searchmont	4	2	2
Junction Creek below Kelly Lake	4	1	2
Kwataboahegan River near the mouth	4	1	2
La Vase River at North bay	4	1	2
Long-Legged River below Long-Legged Lake	3	2.5	2
Little Pic River near Coldwell	3.5	2	2
Little White River near Bellingham	3.5	1.5	2
Little White River below Boland River	3	1	2
Missinaibi River at Mattice	4	3	2
Nagagami River at Highway No. 11	3.5	2	2
Namakan River at Outlet of Lac La Croix	4	1.5	2
Neebing River at Thunder Bay	4	1	2
North French River near the Mouth	4	2	2
Ogoki River above Whiteclay Lake	3	2	1
Pagwachuan River at Highway No. 11	3	3	2
Pic River near Marathon	4	2	2
Pipestone River at Karl Lake	4	1	2
Root River at Sault St. Marie	4	3	1.5
Serpent River at Highway No. 17	3	2	2
Sturgeon River at McDougall MILLS	4	2	2
Sturgeon River at outlet of Salvesen Lake	4	3	2
Sturgeon River at Upper Goose Falls	4	1	2
Troutlake River above Big Falls	2.5	4	2
Turtle River near Mine Centre	4	1	2
White Fish River at Nolalu	4	1.5	2
Whitson River at Chelmsford	4	1	2
Whitson River at Val Caron	4	1	2
Wolf River at Highway 17	4	3	2
Average Rank	**3.7**	**2.0**	**2.0**

Note: Includes ties

APPENDIX A-2: SUMMARY RESULTS OF SSI SEVERE AND EXTREME SCORING DISTRIBUTIONS

Decisions resulting from drought monitoring and early warning systems rely more often on assessments of severe and extreme value drought conditions. Standardized scores (Z= -1.64 and Z= -2.33) are used to estimate accuracy of severe and extreme drought conditions. Drought conditions conveyed in terms of standardized scores as determined by SSI data treatments (Untreated and treated (i.e., Log Normal Transformed, and the Fitted Gamma Distribution)), are assessed for their ability to accurately identify the distribution of Z-scores in the severe and extreme range. The Z-scores of monthly sample sets for each site were evaluated using the percentage of time scores were observed in the range defined as severe or extreme. The expected frequency distribution of Z-score values less than -1.64 is 5.0%, while the expected frequency distribution of Z-score values less than -2.33 is 1.0%. The following tables provide supplementary detail to the respective results and discussions summarized in Section 7.3.1 and consist of the entire set of samples depicted in respective Boxplots (Figures 7.5 and 7.6).

SSI Frequency Distribution of Severe Conditions by Data Treatment

Z-Score Counts Less than Z= -1.64

Hydrometric Station	Untreated	Log Normal Transformation	Fitted Gamma Distribution	Record Length (Years)
Atikokan River near Atikokan	6	6	21	27
Aubinadong River above Sesabic Creek	1	18	7	30
Basswood River Near Winton	10	40	47	80
Batchawana River near Batchawana	10	16	20	37
Big Carp River near Sault St. Marie	2	10	15	30
Blackwater River at Beardmore	6	19	21	38
Blanche River above Englehart	2	26	13	37
Cat River below Wesley Lake	11	10	21	41
Cedar River below Wabaskang Lake	4	13	23	37
Chippewa Creek at North Bay	3	73	14	35
Coniston Creek Above Wanapitei River	1	17	13	29
English River at Umfreville	16	30	62	83
Goulais River near Searchmont	6	15	21	42
Junction Creek below Kelly Lake	2	16	14	33
Kwataboahegan River near the mouth	2	21	16	39
La Vase River at North bay	2	13	9	37
Long-Legged River below Long-Legged Lake	3	6	17	30
Little Pic River near Coldwell	6	19	22	39
Little White River near Bellingham	6	27	26	57
Little White River below Boland River	4	15	13	30
Missinaibi River at Mattice	6	24	44	84
Nagagami River at Highway No. 11	13	22	38	60
Namakan River at Outlet of Lac La Croix	16	27	41	76
Neebing River at Thunder Bay	1	44	16	46
North French River near the Mouth	4	20	20	43
Ogoki River above Whiteclay Lake	8	18	21	38
Pagwachuan River at Highway No. 11	3	12	22	43
Pic River near Marathon	9	11	29	41
Pipestone River at Karl Lake	1	21	23	44
Root River at Sault St. Marie	3	7	25	39
Serpent River at Highway No. 17	7	11	24	68
Sturgeon River at McDougall Mills	4	17	23	44
Sturgeon River at outlet of Salvesen Lake	7	15	28	42
Sturgeon River at Upper Goose Falls	0	12	5	26
Troutlake River above Big Falls	14	10	29	38
Turtle River near Mine Centre	3	37	42	85
White Fish River at Nolalu	3	11	10	29
Whitson River at Chelmsford	3	34	16	49
Whitson River at Val Caron	9	20	17	35
Wolf River at Highway 17	2	15	24	40

SSI Frequency Distribution of Severe Conditions by Data Treatment

Z-Score Counts Less than Z= -2.33

Hydrometric Station	Untreated	Log Normal Transformation	Fitted Gamma Distribution	Record Length (Years)
Atikokan River near Atikokan	1	0	8	27
Aubinadong River above Sesabic Creek	0	2	0	30
Basswood River Near Winton	0	4	9	80
Batchawana River near Batchawana	1	0	7	37
Big Carp River near Sault St. Marie	0	1	1	30
Blackwater River at Beardmore	0	2	3	38
Blanche River above Englehart	0	2	2	37
Cat River below Wesley Lake	0	2	8	41
Cedar River below Wabaskang Lake	0	2	0	37
Chippewa Creek at North Bay	0	1	3	35
Coniston Creek Above Wanapitei River	0	1	0	29
English River at Umfreville	0	4	8	83
Goulais River near Searchmont	0	2	7	42
Junction Creek below Kelly Lake	0	3	0	33
Kwataboahegan River near the mouth	0	2	1	39
La Vase River at North bay	0	1	1	37
Long-Legged River below Long-Legged Lake	0	1	0	30
Little Pic River near Coldwell	0	4	1	39
Little White River near Bellingham	0	4	5	57
Little White River below Boland River	0	4	5	30
Missinaibi River at Mattice	1	6	7	84
Nagagami River at Highway No. 11	0	1	4	60
Namakan River at Outlet of Lac La Croix	0	5	11	76
Neebing River at Thunder Bay	0	2	2	46
North French River near the Mouth	0	2	4	43
Ogoki River above Whiteclay Lake	1	2	3	38
Pagwachuan River at Highway No. 11	0	2	2	43
Pic River near Marathon	0	1	6	41
Pipestone River at Karl Lake	0	2	0	44
Root River at Sault St. Marie	0	0	5	39
Serpent River at Highway No. 17	0	3	8	68
Sturgeon River at McDougall Mills	0	1	4	44
Sturgeon River at outlet of Salvesen Lake	0	1	5	42
Sturgeon River at Upper Goose Falls	0	2	0	26
Troutlake River above Big Falls	0	0	8	38
Turtle River near Mine Centre	0	4	3	85
White Fish River at Nolalu	0	2	4	29
Whitson River at Chelmsford	0	3	2	49
Whitson River at Val Caron	0	0	1	35
Wolf River at Highway 17	0	0	4	40

APPENDIX A-3: SUMMARY OF DROUGHT CHARACTERISTICS FROM SSI AND THRESHOLD LEVELS

The threshold level of $Q_{80,}$ as applied in this thesis, is determined to be the most appropriate trigger for hydrological drought in Northern Ontario, and consequently forms the basis for determining the most suitable SSI data treatment.

SSI data treatments such as Untreated and treated (i.e., Log Normal Transformed, and the Fitted Gamma Distribution) are assessed for their ability to accurately characterize drought when compared to characterizations determined by the threshold level of Q_{80}. SSI are compared to the threshold level of Q_{80} using two different standardized scores. The first standardized score of $Z= -1$ is representative of moderate drought conditions, and is commonly applied by SSI to trigger drought. The second standardized score of $Z= -0.84$ is the theoretical Z-score equivalent of the threshold level Q_{80} (representative threshold of drought in Northern Ontario).

The initiation and termination dates are determined for each of the two selected drought periods (1976/77 and 1998) for Q_{80}, $Z= -1$ and $Z= -0.84$. The corresponding results from $Z= -1$, $Z= -0.84$, and Q_{80}, for initiation and termination dates, along with drought durations, are directly compared. In order to evaluate the impacts on severity and intensity; the Q_{80} initiation and termination dates are then applied to the predetermined monthly record of the SSI treated data sets. The following tables provide supplementary detail to the respective results and discussions summarized in Section 7.3.

Drought Summary Characteristics 1976

Threshold Level in Comparison to the Untreated Treatment

	Threshold Level of Q_{80}					Untreated Treatment				
Hydrometric Station	**Onset**	**Termination**	**Duration**	**Averaged Intensity***	**Sum of Intensities***	**Onset**	**Termination**	**Duration**	**Averaged Intensity***	**Sum of Intensities***
Atikokan River near Atikokan	-	-	-	-	-	-	-	-	-	-
Aubinadong River above Sesabic Creek	-	-	-	-	-	-	-	-	-	-
Basswood River Near Winton	01/08/1976	30/06/1977	11	-1.52	-16.68	01/11/1976	30/06/1977	8	-1.72	-13.73
Batchawana River near Batchawana	01/07/1976	28/02/1977	8	-1.61	-12.89	01/09/1976	28/02/1977	6	-1.87	-11.22
Big Carp River near Sault St. Marie	-	-	-	-	-	-	-	-	-	-
Blackwater River at Beardmore	01/10/1976	28/02/1977	5	-1.29	-6.43	01/09/1976	31/01/1977	5	-1.10	-5.49
Blanche River above Englehart	01/11/1976	28/02/1977	4	-1.29	-5.17	01/12/1976	28/02/1977	3	-1.43	-4.28
Cat River below Wesley Lake	01/12/1976	30/04/1977	5	-1.92	-9.62	01/12/1976	30/06/1977	7	-1.67	-11.67
Cedar River below Wabaskang Lake	01/08/1976	31/08/1977	13	-1.27	-16.53	01/10/1976	30/07/1977	10	-1.36	-13.56
Chippewa Creek at North Bay	01/10/1976	28/02/1977	5	-1.16	-5.78	01/10/1976	31/12/1976	3	-1.30	-3.89
Coniston Creek Above Wanapitei River	-	-	-	-	-	-	-	-	-	-
English River at Umfreville	01/06/1976	30/03/1977	10	-1.31	-13.05	01/11/1976	30/03/1977	5	-1.55	-7.77
Goulais River near Searchmont	01/07/1976	28/02/1978	8	-1.54	-12.29	01/09/1976	28/02/1977	6	-1.77	-10.61
Junction Creek below Kelly Lake	01/04/1977	30/06/1977	3	-1.22	-3.67	01/04/1977	30/06/1977	3	-1.22	-3.67
Kwataboahegan River near the mouth	01/10/1976	31/01/1977	4	-0.97	-3.90	01/11/1976	30/11/1976	1	-1.22	-1.22
La Vase River at North bay	01/10/1976	28/02/1977	5	-0.99	-4.93	01/11/1976	31/12/1976	2	-1.23	-2.46
Long-Legged River below Long-Legged Lake	-	-	-	-	-	-	-	-	-	-
Little Pic River near Coldwell	01/10/1976	28/02/1977	5	-1.56	-7.81	01/10/1976	28/02/1977	5	-1.56	-7.81
Little White River near Bellingham	01/07/1976	28/02/1977	8	-1.27	-10.19	01/10/1976	28/02/1977	5	-1.45	-7.25
Little White River below Boland River	-	-	-	-	-	-	-	-	-	-
Missinaibi River at Mattice	01/09/1976	28/02/1977	6	-1.83	-10.98	01/09/1976	28/02/1977	6	-1.83	-10.98
Nagagami River at Highway No. 11	01/10/1976	27/02/1977	5	-1.63	-8.13	01/10/1976	28/02/1977	5	-1.63	-8.13
Namakan River at Outlet of Lac La Croix	01/09/1976	31/07/1977	11	-1.47	-16.20	01/10/1976	30/06/1977	9	-1.60	-14.38
Neebing River at Thunder Bay	01/07/1976	28/02/1977	8	-0.90	-7.23	01/10/1976	28/02/1977	5	-1.08	-5.41
North French River near the Mouth	01/10/1976	28/02/1977	5	-1.45	-7.25	01/10/1976	28/02/1977	5	-1.45	-7.25
Ogoki River above Whiteclay Lake	01/07/1976	30/03/1977	9	-1.23	-11.06	01/07/1976	28/02/1977	8	-1.26	-10.09
Pagwachuan River at Highway No. 11	01/10/1976	28/02/1977	5	-1.38	-6.92	01/10/1976	28/02/1977	5	-1.38	-6.92
Pic River near Marathon	01/09/1976	28/02/1977	6	-1.49	-8.97	01/10/1976	28/02/1977	5	-1.63	-8.15
Pipestone River at Karl Lake	01/10/1976	28/02/1977	5	-1.20	-6.00	01/10/1976	28/02/1977	5	-1.20	-6.00
Root River at Sault St. Marie	01/06/1976	28/02/1977	9	-1.33	-12.00	01/09/1976	28/02/1977	6	-1.52	-9.10
Serpent River at Highway No. 17	01/07/1976	28/02/1977	8	-1.37	-10.93	01/10/1976	28/02/1977	5	-1.61	-8.07
Sturgeon River at McDougall Mills	01/06/1976	31/08/1977	15	-1.31	-19.69	01/08/1976	30/06/1977	11	-1.47	-16.17
Sturgeon River at outlet of Salvesen Lake	01/08/1976	31/08/1977	13	-1.38	-17.95	01/11/1976	30/07/1977	9	-1.57	-14.16
Sturgeon River at Upper Goose Falls	-	-	-	-	-	-	-	-	-	-
Troutlake River above Big Falls	01/07/1976	30/06/1977	12	-1.53	-18.34	01/07/1976	30/05/1977	11	-1.59	-17.48
Turtle River near Mine Centre	01/04/1977	31/05/1977	2	-0.99	-1.97	01/05/1977	31/05/1977	1	-1.06	-1.06
White Fish River at Nolalu	-	-	-	-	-	-	-	-	-	-
Whitson River at Chelmsford	01/11/1976	28/02/1977	4	-1.19	-4.76	01/11/1976	28/02/1977	4	-1.19	-4.76
Whitson River at Val Caron	01/11/1976	28/02/1977	4	-1.27	-5.08	01/11/1976	28/02/1977	4	-1.27	-5.08
Wolf River at Highway 17	01/09/1976	28/02/1977	6	-1.19	-7.12	01/11/1976	28/02/1977	4	-1.39	-5.56

* Intensity scores for threshold level of Q_{80} are based on the Untreated SSI Z-Scores

Note: The drought intensity, which is the ratio of severity to duration, is also a positive entity. However, if the flow sequences are standardized or converted to SSI, then all values below the truncation level become negative, rendering severity to be negative and correspondingly, drought intensity also to be negative. In other words, the drought intensity turns out to be tantamount to SSI or Z score, which has been reported as negative in the thesis.

Drought Summary Characteristics 1976

Threshold Level in Comparison to the Log Normal Transformation

	Threshold Level of Q_{80}					Log Normal Transformation				
Hydrometric Station	**Onset**	**Termination**	**Duration**	**Averaged Intensity***	**Sum of Intensities***	**Onset**	**Termination**	**Duration**	**Averaged Intensity***	**Sum of Intensities***
Atikokan River near Atikokan	-	-	-	-	-	-	-	-	-	-
Aubinadong River above Sesabic Creek	-	-	-	-	-	-	-	-	-	-
Basswood River Near Winton	01/08/1976	30/06/1977	11	-3.07	-3.07	01/08/1976	30/06/1977	11	-3.07	-33.78
Batchawana River near Batchawana	01/07/1976	28/02/1977	8	-2.65	-21.18	01/08/1976	28/02/1977	7	-2.89	-20.21
Big Carp River near Sault St. Marie	-	-	-	-	-	-	-	-	-	-
Blackwater River at Beardmore	01/10/1976	28/02/1977	5	-1.64	-8.22	01/09/1976	31/01/1977	4	-1.84	-7.36
Blanche River above Englehart	01/11/1976	28/02/1977	4	-1.64	-6.55	01/12/1976	28/02/1977	3	-1.87	-5.60
Cat River below Wesley Lake	01/12/1976	30/04/1977	5	-2.52	-12.61	01/12/1976	30/06/1977	7	-2.11	-14.77
Cedar River below Wabaskang Lake	01/08/1976	31/08/1977	13	-1.77	-23.00	01/08/1976	30/08/1977	13	-1.77	-23.00
Chippewa Creek at North Bay	01/10/1976	28/02/1977	5	-1.72	-8.60	01/10/1976	28/02/1977	5	-1.72	-8.60
Coniston Creek Above Wanapitei River	-	-	-	-	-	-	-	-	-	-
English River at Umfreville	01/06/1976	30/03/1977	10	-1.81	-18.10	01/06/1976	30/03/1977	10	-1.81	-18.10
Goulais River near Searchmont	01/07/1976	28/02/1977	8	-2.76	-22.06	01/07/1976	28/02/1977	8	-2.76	-22.06
Junction Creek below Kelly Lake	01/04/1977	30/06/1977	3	-1.42	-4.26	01/04/1977	30/06/1977	3	-1.42	-4.26
Kwataboahegan River near the mouth	01/10/1976	31/01/1977	4	-1.28	-5.10	01/11/1976	31/01/1977	3	-1.40	-4.21
La Vase River at North bay	01/10/1976	28/02/1977	5	-1.54	-7.70	01/11/1976	31/12/1976	2	-2.56	-5.12
Long-Legged River below Long-Legged Lake	-	-	-	-	-	-	-	-	-	-
Little Pic River near Coldwell	01/10/1976	28/02/1977	5	-0.88	-4.40	01/09/1976	28/02/1977	6	-1.97	-11.83
Little White River near Bellingham	01/07/1976	28/02/1977	8	-1.95	-15.62	01/07/1976	28/02/1977	8	-1.95	-15.62
Little White River below Boland River	-	-	-	-	-	-	-	-	-	-
Missinaibi River at Mattice	01/09/1976	28/02/1977	6	-3.53	-21.17	01/09/1976	28/02/1977	6	-3.53	-21.17
Nagagami River at Highway No. 11	01/10/1976	27/02/1977	5	-2.33	-11.67	01/10/1976	28/02/1977	5	-2.33	-11.67
Namakan River at Outlet of Lac La Croix	01/09/1976	31/07/1977	11	-2.39	-26.24	01/09/1976	30/06/1977	10	-2.53	-25.26
Neebing River at Thunder Bay	01/07/1976	28/02/1977	8	-1.97	-15.80	01/07/1976	28/02/1977	8	-1.97	-15.80
North French River near the Mouth	01/10/1976	28/02/1977	5	-2.04	-10.20	01/10/1976	28/02/1977	5	-2.04	-10.20
Ogoki River above Whiteclay Lake	01/07/1976	30/03/1977	9	-1.67	-15.05	01/06/1976	28/02/1977	9	-1.68	-15.15
Pagwachuan River at Highway No. 11	01/10/1976	28/02/1977	5	-2.04	-10.18	01/10/1976	28/02/1977	5	-2.04	-10.18
Pic River near Marathon	01/09/1976	28/02/1977	6	-2.38	-14.27	01/09/1976	28/02/1977	6	-2.38	-14.27
Pipestone River at Karl Lake	01/10/1976	28/02/1977	5	-1.56	-7.81	01/10/1976	28/02/1977	5	-1.56	-7.81
Root River at Sault St. Marie	01/06/1976	28/02/1977	9	-2.66	-23.95	01/06/1976	28/02/1977	9	-2.66	-23.95
Serpent River at Highway No. 17	01/07/1976	28/02/1977	8	-2.51	-20.06	01/08/1976	28/02/1977	7	-2.73	-19.14
Sturgeon River at McDougall Mills	01/06/1976	31/08/1977	15	-1.90	-28.51	01/08/1976	30/06/1977	11	-2.27	-25.02
Sturgeon River at outlet of Salvesen Lake	01/08/1976	31/08/1977	13	-2.33	-30.31	01/08/1976	30/08/1977	13	-2.33	-30.31
Sturgeon River at Upper Goose Falls	-	-	-	-	-	-	-	-	-	-
Troutlake River above Big Falls	01/07/1976	30/06/1977	12	-2.01	-24.12	01/07/1976	30/05/1977	11	-2.12	-23.29
Turtle River near Mine Centre	01/04/1977	31/05/1977	2	-1.04	-2.07	01/05/1977	31/05/1977	1	-1.14	-1.14
White Fish River at Nolalu	-	-	-	-	-	-	-	-	-	-
Whitson River at Chelmsford	01/11/1976	28/02/1977	4	-1.79	-7.16	01/11/1976	28/02/1977	4	-1.79	-7.16
Whitson River at Val Caron	01/11/1976	28/02/1977	4	-1.97	-7.87	01/11/1976	28/02/1977	4	-1.97	-7.87
Wolf River at Highway 17	01/09/1976	28/02/1977	6	-1.92	-11.55	01/09/1976	28/02/1977	6	-1.92	-11.55

* Intensity scores for threshold level of Q_{80} are based on the Log Normal Transformation SSI Z-Scores

Note: The drought intensity, which is the ratio of severity to duration, is also a positive entity. However, if the flow sequences are standardized or converted to SSI, then all values below the truncation level become negative, rendering severity to be negative and correspondingly, drought intensity also to be negative. In other words, the drought intensity turns out to be tantamount to SSI or Z score, which has been reported as negative in the thesis.

Drought Summary Characteristics 1976

Threshold Level in Comparison to the Fitted Gamma Distribution

	Threshold Level of Q_{80}					**Fitted Gamma Distribution**				
Hydrometric Station	**Onset**	**Termination**	**Duration**	**Averaged Intensity***	**Sum of Intensities***	**Onset**	**Termination**	**Duration**	**Averaged Intensity***	**Sum of Intensities***
Atikokan River near Atikokan	-	-	-	-	-	-	-	-	-	-
Aubinadong River above Sesabic Creek	-	-	-	-	-	-	-	-	-	-
Basswood River Near Winton	01/08/1976	30/06/1977	11	-2.50	-27.53	01/08/1976	30/06/1977	11	-2.50	-27.53
Batchawana River near Batchawana	01/07/1976	28/02/1977	8	-2.32	-18.59	01/08/1976	28/02/1977	7	-2.52	-17.62
Big Carp River near Sault St. Marie	-	-	-	-	-	-	-	-	-	-
Blackwater River at Beardmore	01/10/1976	28/02/1977	5	-1.56	-7.79	01/10/1976	31/01/1977	4	-1.72	-6.88
Blanche River above Englehart	01/11/1976	28/02/1977	4	-1.54	-6.17	01/12/1976	28/02/1977	3	-1.74	-5.21
Cat River below Wesley Lake	01/12/1976	30/04/1977	5	-2.37	-11.84	01/08/1976	30/07/1977	12	-1.84	-22.09
Cedar River below Wabaskang Lake	01/08/1976	31/08/1977	13	-1.63	-21.25	01/08/1976	30/08/1977	13	-1.63	-21.25
Chippewa Creek at North Bay	01/10/1976	28/02/1977	5	-1.55	-7.75	01/10/1976	28/02/1977	5	-1.55	-7.75
Coniston Creek Above Wanapitei River	-	-	-	-	-	-	-	-	-	-
English River at Umfreville	01/06/1976	30/03/1977	10	-1.68	-16.79	01/06/1976	30/03/1977	10	1.11	11.15
Goulais River near Searchmont	01/07/1976	28/02/1977	8	-2.36	-18.89	01/07/1976	28/02/1977	8	-2.36	-18.89
Junction Creek below Kelly Lake	01/04/1977	30/06/1977	3	-1.39	-4.17	01/04/1977	30/06/1977	3	-1.39	-4.17
Kwataboahegan River near the mouth	01/10/1976	31/01/1977	4	-1.22	-4.90	01/11/1976	31/01/1977	3	-1.31	-3.94
La Vase River at North bay	01/10/1976	28/02/1977	5	-1.38	-6.92	01/10/1976	28/02/1977	5	-1.38	-6.92
Long-Legged River below Long-Legged Lake	-	-	-	-	-	-	-	-	-	-
Little Pic River near Coldwell	01/10/1976	28/02/1977	5	-2.18	-10.89	01/09/1976	28/02/1977	6	-1.83	-10.97
Little White River near Bellingham	01/07/1976	28/02/1977	8	-1.74	-13.91	01/07/1976	28/02/1977	8	-1.74	-13.96
Little White River below Boland River	-	-	-	-	-	-	-	-	-	-
Missinaibi River at Mattice	01/09/1976	28/02/1977	6	-2.95	-17.73	01/09/1976	28/02/1977	6	-2.95	-17.73
Nagagami River at Highway No. 11	01/10/1976	27/02/1977	5	-2.12	-10.59	01/10/1976	28/02/1977	5	-2.12	-10.59
Namakan River at Outlet of Lac La Croix	01/09/1976	31/07/1977	11	-2.08	-22.87	01/09/1976	30/07/1977	11	-2.08	-22.87
Neebing River at Thunder Bay	01/07/1976	28/02/1977	8	-1.61	-12.85	01/07/1976	28/02/1977	8	-1.61	-12.85
North French River near the Mouth	01/10/1976	28/02/1977	5	-1.88	-9.38	01/10/1976	28/02/1977	5	-1.88	-9.38
Ogoki River above Whiteclay Lake	01/07/1976	30/03/1977	9	-1.55	-13.91	01/06/1976	28/02/1977	9	-1.55	-13.98
Pagwachuan River at Highway No. 11	01/10/1976	28/02/1977	5	-1.86	-9.30	01/10/1976	28/02/1977	5	-1.86	-9.30
Pic River near Marathon	01/09/1976	28/02/1977	6	-2.11	-12.66	01/09/1976	28/02/1977	6	-2.11	-12.66
Pipestone River at Karl Lake	01/10/1976	28/02/1977	5	-1.47	-7.34	01/10/1976	28/02/1977	5	-1.47	-7.34
Root River at Sault St. Marie	01/06/1976	28/02/1977	9	-2.24	-20.12	01/06/1976	28/02/1977	9	-2.24	-20.12
Serpent River at Highway No. 17	01/07/1976	28/02/1977	8	-2.14	-17.10	01/08/1976	28/02/1977	7	-2.31	-16.15
Sturgeon River at McDougall Mills	01/06/1976	31/08/1977	15	-1.72	-25.75	01/06/1976	30/06/1977	13	-1.86	-24.18
Sturgeon River at outlet of Salvesen Lake	01/08/1976	31/08/1977	13	-2.02	-26.28	01/08/1976	30/08/1977	13	-2.02	-26.28
Sturgeon River at Upper Goose Falls	-	-	-	-	-	-	-	-	-	-
Troutlake River above Big Falls	01/07/1976	30/06/1977	12	-1.89	-22.70	01/07/1976	30/05/1977	11	-1.98	-21.83
Turtle River near Mine Centre	01/04/1977	31/05/1977	2	-1.03	-2.06	01/05/1977	31/05/1977	1	-1.12	-1.12
White Fish River at Nolalu	-	-	-	-	-	-	-	-	-	-
Whitson River at Chelmsford	01/11/1976	28/02/1977	4	-1.61	-6.42	01/11/1976	28/02/1977	4	-1.61	-6.42
Whitson River at Val Caron	01/11/1976	28/02/1977	4	-1.75	-7.02	01/11/1976	28/02/1977	4	-1.75	-7.02
Wolf River at Highway 17	01/09/1976	28/02/1977	6	-1.71	-10.24	01/09/1976	28/02/1977	6	-1.71	-10.24

* Intensity scores for threshold level of Q_{80} are based on the Fitted Gamma Distribution SSI Z-Scores

Note: The drought intensity, which is the ratio of severity to duration, is also a positive entity. However, if the flow sequences are standardized or converted to SSI, then all values below the truncation level become negative, rendering severity to be negative and correspondingly, drought intensity also to be negative. In other words, the drought intensity turns out to be tantamount to SSI or Z score, which has been reported as negative in the thesis.

Drought Summary Characteristics 1998

Threshold Level in Comparison to the Untreated Treatment

	Threshold Level of Q_{80}					Untreated Treatment				
Hydrometric Station	**Onset**	**Termination**	**Duration**	**Averaged Intensity***	**Sum of Intensities***	**Onset**	**Termination**	**Duration**	**Averaged Intensity***	**Sum of Intensities***
Atikokan River near Atikokan	01/06/1997	30/11/1998	18	-1.15	-20.73	01/04/1998	30/09/1998	6	-1.48	-8.86
Aubinadong River above Sesabic Creek	01/08/1997	28/02/1998	7	-1.16	-8.12	01/10/1997	28/02/1998	5	-1.35	-6.76
Basswood River Near Winton	01/05/1998	31/10/1998	6	-1.10	-6.62	01/05/1998	31/08/1998	4	-1.22	-4.87
Batchawana River near Batchawana	01/05/1998	31/05/1998	1	-1.70	-1.70	01/05/1998	31/05/1998	1	-1.70	-1.70
Big Carp River near Sault St. Marie	01/04/1998	31/05/1998	2	-1.31	-2.63	01/04/1998	31/05/1998	2	-1.31	-2.63
Blackwater River at Beardmore	01/05/1998	31/08/1998	4	-1.43	-5.73	01/05/1998	31/05/1998	1	-1.85	-1.85
Blanche River above Englehart	01/05/1998	30/06/1998	2	-1.63	-3.25	01/05/1998	30/06/1998	2	-1.63	-3.25
Cat River below Wesley Lake	01/04/1998	30/09/1998	6	-1.32	-7.89	01/04/1998	30/09/1998	6	-1.32	-7.89
Cedar River below Wabaskang Lake	01/11/1998	31/03/1999	5	-0.90	-4.50	01/03/1999	31/03/1999	1	-1.00	-1.00
Chippewa Creek at North Bay	01/05/1998	31/05/1998	1	-1.73	-1.73	01/05/1998	31/05/1998	1	-1.73	-1.73
Coniston Creek Above Wanapitei River	01/05/1998	31/05/1998	1	-1.28	-1.28	01/05/1998	31/05/1998	1	-1.28	-1.28
English River at Umfreville	01/04/1998	30/09/1998	6	-1.37	-8.21	01/05/1998	31/08/1998	4	-1.59	-6.37
Goulais River near Searchmont	01/05/1998	31/05/1998	1	-1.59	-1.59	01/05/1998	31/05/1998	1	-1.59	-1.59
Junction Creek below Kelly Lake	01/05/1998	31/05/1998	1	-1.08	-1.08	01/05/1998	31/05/1998	1	-1.08	-1.08
Kwataboahegan River near the mouth	01/05/1998	31/08/1998	4	-1.20	-4.82	01/05/1998	30/07/1998	3	-1.36	-4.07
La Vase River at North bay	01/05/1998	31/08/1998	4	-1.01	-4.03	01/05/1998	31/05/1998	1	-1.54	-1.54
Long-Legged River below Long-Legged Lake	01/12/1998	30/06/1999	7	-1.17	-8.21	01/01/1999	30/06/1999	6	-1.20	-7.23
Little Pic River near Coldwell	01/05/1998	30/09/1998	5	-1.12	-5.62	01/05/1998	30/07/1998	3	-1.35	-4.05
Little White River near Bellingham	01/05/1998	31/05/1998	1	-1.47	-1.47	01/05/1998	31/05/1998	1	-1.47	-1.47
Little White River below Boland River	01/05/1998	31/05/1998	1	-1.29	-1.29	01/05/1998	31/05/1998	1	-1.29	-1.29
Missinaibi River at Mattice	01/05/1998	31/07/1998	3	-1.30	-3.91	01/05/1998	30/06/1998	2	-1.50	-3.00
Nagagami River at Highway No. 11	01/05/1998	31/08/1998	4	-1.43	-5.73	01/05/1998	31/07/1998	3	-1.60	-4.80
Namakan River at Outlet of Lac La Croix	01/05/1998	30/11/1998	7	-1.30	-9.13	01/05/1998	31/10/1998	6	-1.39	-8.35
Neebing River at Thunder Bay	01/04/1998	30/09/1998	6	-0.95	-5.69	01/04/1998	31/05/1998	2	-1.48	-2.95
North French River near the Mouth	01/05/1998	31/05/1998	1	-1.90	-1.90	01/05/1998	31/05/1998	1	-1.90	-1.90
Ogoki River above Whiteclay Lake	01/06/1998	31/12/1998	7	-1.21	-8.50	01/07/1998	30/09/1998	3	-1.50	-4.50
Pagwachuan River at Highway No. 11	01/05/1998	31/07/1998	3	-1.45	-4.36	01/05/1998	31/07/1998	3	-1.45	-4.36
Pic River near Marathon	01/05/1998	30/09/1998	5	-1.30	-6.48	01/05/1998	31/07/1998	3	-1.62	-4.85
Pipestone River at Karl Lake	01/07/1998	31/03/1999	9	-1.21	-10.91	1998-011-01	31/03/1999	5	-1.32	-6.61
Root River at Sault St. Marie	01/04/1998	31/05/1998	2	-1.25	-2.50	01/04/1998	31/05/1998	2	-1.25	-2.50
Serpent River at Highway No. 17	01/05/1998	31/05/1998	1	-1.31	-1.31	01/05/1998	31/05/1998	1	-1.31	-1.31
Sturgeon River at McDougall Mills	01/04/1998	30/09/1998	6	-1.30	-7.78	01/04/1998	31/08/1998	5	-1.37	-6.86
Sturgeon River at outlet of Salvesen Lake	01/09/1998	31/05/1999	9	-1.02	-9.20	01/12/1998	31/05/1999	6	-1.14	-6.82
Sturgeon River at Upper Goose Falls	01/05/1998	31/05/1998	1	-1.51	-1.51	01/05/1998	31/05/1998	1	-1.51	-1.51
Troutlake River above Big Falls	01/08/1998	31/08/1999	13	-1.22	-15.85	01/10/1998	31/08/1999	11	-1.28	-14.06
Turtle River near Mine Centre	01/04/1998	31/10/1998	7	-1.26	-8.82	01/04/1998	30/09/1998	6	-1.35	-8.10
White Fish River at Nolalu	01/05/1998	30/09/1998	5	-1.00	-5.02	01/05/1998	30/06/1998	2	-1.15	-2.30
Whitson River at Chelmsford	01/05/1998	31/05/1998	1	-4.25	-4.25	01/05/1998	31/05/1998	1	-1.55	-1.55
Whitson River at Val Caron	01/05/1998	31/05/1998	1	-1.40	-1.40	01/05/1998	31/05/1998	1	-1.40	-1.40
Wolf River at Highway 17	01/05/1998	30/09/1998	5	-1.26	-6.31	01/05/1998	31/08/1998	4	-1.40	-5.61

* Intensity scores for threshold level of Q_{80} are based on the Untreated SSI Z-Scores

Note: The drought intensity, which is the ratio of severity to duration, is also a positive entity. However, if the flow sequences are standardized or converted to SSI, then all values below the truncation level become negative, rendering severity to be negative and correspondingly, drought intensity also to be negative. In other words, the drought intensity turns out to be tantamount to SSI or Z score, which has been reported as negative in the thesis.

Drought Summary Characteristics 1998

Threshold Level in Comparison to the Log Normal Transformation

	Threshold Level of Q_{80}					Log Normal Transformation				
Hydrometric Station	**Onset**	**Termination**	**Duration**	**Averaged Intensity***	**Sum of Intensities***	**Onset**	**Termination**	**Duration**	**Averaged Intensity***	**Sum of Intensities***
Atikokan River near Atikokan	01/06/1997	30/11/1998	18	-1.69	-30.50	01/10/1997	28/02/1998	5	-1.62	-8.12
Aubinadong River above Sesabic Creek	01/08/1997	28/02/1998	7	-1.72	-12.04	01/10/1997	28/02/1998	5	-2.08	-10.40
Basswood River Near Winton	01/05/1998	31/10/1998	6	-1.67	-10.05	01/06/1998	31/10/1998	5	-1.85	-9.26
Batchawana River near Batchawana	01/05/1998	31/05/1998	1	-3.10	-3.10	01/05/1998	31/05/1998	1	-3.10	-3.10
Big Carp River near Sault St. Marie	01/04/1998	31/05/1998	2	-1.90	-3.80	01/04/1998	31/05/1998	2	-1.90	-3.80
Blackwater River at Beardmore	01/05/1998	31/08/1998	4	-2.08	-8.33	01/05/1998	31/08/1998	4	-2.08	-8.33
Blanche River above Englehart	01/05/1998	30/06/1998	2	-2.38	-4.75	01/05/1998	30/06/1998	2	-2.38	-4.75
Cat River below Wesley Lake	01/04/1998	30/09/1998	6	-1.76	-10.59	01/04/1998	30/09/1998	6	-1.76	-10.59
Cedar River below Wabaskang Lake	01/11/1998	31/03/1999	5	-0.82	-4.11	DNR	DNR	DNR	DNR	DNR
Chippewa Creek at North Bay	01/05/1998	31/05/1998	1	-2.79	-2.79	01/05/1998	31/05/1998	1	-2.79	-2.79
Coniston Creek Above Wanapitei River	01/05/1998	31/05/1998	1	-1.88	-1.88	01/05/1998	31/05/1998	1	-1.88	-1.88
English River at Umfreville	01/04/1998	30/09/1998	6	-2.03	-12.19	01/05/1998	30/09/1998	5	-2.26	-11.31
Goulais River near Searchmont	01/05/1998	31/05/1998	1	-2.76	-2.76	01/05/1998	31/05/1998	1	-2.76	-2.76
Junction Creek below Kelly Lake	01/05/1998	31/05/1998	1	-1.15	-1.15	01/05/1998	31/05/1998	1	-1.15	-1.15
Kwataboahegan River near the mouth	01/05/1998	31/08/1998	4	-1.88	-7.52	01/05/1998	31/08/1998	4	-1.88	-7.52
La Vase River at North bay	01/05/1998	31/08/1998	4	-1.73	-6.94	01/05/1998	30/11/1998	7	-1.64	-11.46
Long-Legged River below Long-Legged Lake	01/12/1998	30/06/1999	7	-1.28	-8.98	01/01/1999	30/06/1999	6	-1.34	-8.04
Little Pic River near Coldwell	01/05/1998	30/09/1998	5	-1.79	-8.97	01/05/1998	30/09/1998	5	-1.79	-8.97
Little White River near Bellingham	01/05/1998	31/05/1998	1	-1.97	-1.97	01/05/1998	31/05/1998	1	-1.97	-1.97
Little White River below Boland River	01/05/1998	31/05/1998	1	-1.53	-1.53	01/05/1998	31/05/1998	1	-1.53	-1.53
Missinaibi River at Mattice	01/05/1998	31/07/1998	3	-1.78	-5.33	01/05/1998	30/06/1998	3	-1.78	-5.33
Nagagami River at Highway No. 11	01/05/1998	31/08/1998	4	-1.90	-7.61	01/05/1998	31/08/1998	4	-1.90	-7.61
Namakan River at Outlet of Lac La Croix	01/05/1998	30/11/1998	7	-1.97	-13.81	01/05/1998	31/10/1998	6	-2.15	-12.89
Neebing River at Thunder Bay	01/04/1998	30/09/1998	6	-1.59	-9.56	01/04/1998	30/09/1998	6	-1.59	-9.56
North French River near the Mouth	01/05/1998	31/05/1998	1	-2.80	-2.80	01/05/1998	31/05/1998	1	-2.80	-2.80
Ogoki River above Whiteclay Lake	01/06/1998	31/12/1998	7	-1.68	-11.74	01/06/1998	30/09/1998	4	-2.02	-8.10
Pagwachuan River at Highway No. 11	01/05/1998	31/07/1998	3	-2.24	-6.71	01/05/1998	31/07/1998	3	-2.62	-7.87
Pic River near Marathon	01/05/1998	30/09/1998	5	-1.92	-9.60	01/05/1998	30/09/1998	5	-1.92	-9.60
Pipestone River at Karl Lake	01/07/1998	31/03/1998	9	-1.65	-14.87	01/07/1998	31/03/1999	9	-1.65	-14.87
Root River at Sault St. Marie	01/04/1998	31/05/1998	2	-1.85	-3.70	01/04/1998	31/05/1998	2	-1.85	-3.70
Serpent River at Highway No. 17	01/05/1998	31/05/1998	1	-1.40	-1.40	01/05/1998	31/05/1998	1	-1.40	-1.40
Sturgeon River at McDougall Mills	01/04/1998	30/09/1998	6	-1.89	-11.35	01/04/1998	30/09/1998	6	-1.89	-11.35
Sturgeon River at outlet of Salvesen Lake	01/09/1998	31/05/1999	9	-1.12	-10.08	01/10/1998	31/05/1999	8	-1.14	-9.16
Sturgeon River at Upper Goose Falls	01/05/1998	31/05/1998	1	-2.00	-2.00	01/05/1998	31/05/1998	1	-2.00	-2.00
Troutlake River above Big Falls	01/08/1998	31/08/1999	13	-1.34	-17.41	01/09/1998	31/08/1999	12	-1.38	-16.57
Turtle River near Mine Centre	01/04/1998	31/10/1998	7	-2.32	-16.23	01/04/1998	30/10/1998	7	-2.32	-16.23
White Fish River at Nolalu	01/05/1998	30/09/1998	5	-1.93	-9.65	01/05/1998	30/09/1998	5	-1.93	-9.65
Whitson River at Chelmsford	01/05/1998	31/05/1998	1	-2.07	-2.07	01/05/1998	31/05/1998	1	-2.07	-2.07
Whitson River at Val Caron	01/05/1998	31/05/1998	1	-1.87	-1.87	01/05/1998	31/05/1998	1	-1.87	-1.87
Wolf River at Highway 17	01/05/1998	30/09/1998	5	-2.29	-11.45	01/05/1998	30/09/1998	5	-2.29	-11.45

* Intensity scores for threshold level of Q_{80} are based on the Log Normal Transformation SSI Z-Scores

Note: The drought intensity, which is the ratio of severity to duration, is also a positive entity. However, if the flow sequences are standardized or converted to SSI, then all values below the truncation level become negative, rendering severity to be negative and correspondingly, drought intensity also to be negative. In other words, the drought intensity turns out to be tantamount to SSI or Z score, which has been reported as negative in the thesis.

Drought Summary Characteristics 1998

Threshold Level in Comparison to the Fitted Gamma Distribution

	Threshold Level of Q_{80}					**Fitted Gamma Distribution**				
Hydrometric Station	**Onset**	**Termination**	**Duration**	**Averaged Intensity***	**Sum of Intensities***	**Onset**	**Termination**	**Duration**	**Averaged Intensity***	**Sum of Intensities***
Atikokan River near Atikokan	01/06/1997	30/11/1998	18	-1.57	-28.31	01/04/1998	31/10/1998	7	-2.29	-16.03
Aubinadong River above Sesabic Creek	01/08/1997	28/02/1998	7	-1.56	-10.94	01/10/1997	28/02/1998	5	-1.86	-9.30
Basswood River Near Winton	01/05/1998	31/10/1998	6	-1.41	-8.45	01/06/1998	31/10/1998	5	-1.62	-8.10
Batchawana River near Batchawana	01/05/1998	31/05/1998	1	-2.63	-2.63	01/05/1998	31/05/1998	1	-2.63	-2.63
Big Carp River near Sault St. Marie	01/04/1998	31/05/1998	2	-1.73	-3.47	01/04/1998	31/05/1998	2	-1.73	-3.47
Blackwater River at Beardmore	01/05/1998	31/08/1998	4	-1.83	-7.34	01/05/1998	30/09/1998	5	-1.73	-8.65
Blanche River above Englehart	01/05/1998	30/06/1998	2	-2.14	-4.28	01/05/1998	30/06/1998	2	-2.14	-4.28
Cat River below Wesley Lake	01/04/1998	30/09/1998	6	-1.64	-9.87	01/04/1998	30/09/1998	6	-1.64	-9.87
Cedar River below Wabaskang Lake	01/11/1998	31/03/1999	5	-0.88	-4.39	DNR	DNR	DNR	DNR	DNR
Chippewa Creek at North Bay	01/05/1998	31/05/1998	1	-2.45	-2.45	01/05/1998	31/05/1998	1	-2.45	-2.45
Coniston Creek Above Wanapitei River	01/05/1998	31/05/1998	1	-1.70	-1.70	01/05/1998	31/05/1998	1	-1.70	-1.70
English River at Umfreville	01/04/1998	30/09/1998	6	-1.82	-10.92	01/05/1998	30/09/1998	5	-2.01	-10.04
Goulais River near Searchmont	01/05/1998	31/05/1998	1	-2.36	-2.36	01/05/1998	31/05/1998	1	-2.36	-2.36
Junction Creek below Kelly Lake	01/05/1998	31/05/1998	1	-1.16	-1.16	01/05/1998	31/05/1998	1	-1.16	-1.16
Kwataboahegan River near the mouth	01/05/1998	31/08/1998	4	-1.69	-6.75	01/05/1998	31/08/1998	4	-1.69	-6.75
La Vase River at North bay	01/05/1998	31/08/1998	4	-1.52	-6.08	01/05/1998	31/08/1998	4	-1.52	-6.08
Long-Legged River below Long-Legged Lake	01/12/1998	30/06/1999	7	-1.29	-9.01	01/01/1999	30/06/1999	6	-1.34	-8.02
Little Pic River near Coldwell	01/05/1998	30/09/1998	5	-1.60	-7.99	01/05/1998	30/09/1998	5	-1.60	-7.99
Little White River near Bellingham	01/05/1998	31/05/1998	1	-1.84	-1.84	01/05/1998	31/05/1998	1	-1.84	-1.84
Little White River below Boland River	01/05/1998	31/05/1998	1	-1.50	-1.50	01/05/1998	31/05/1998	1	-1.50	-1.50
Missinaibi River at Mattice	01/05/1998	31/07/1998	3	-1.66	-4.99	01/05/1998	30/06/1998	3	-1.66	-4.99
Nagagami River at Highway No. 11	01/05/1998	31/08/1998	4	-1.77	-7.09	01/05/1998	31/08/1998	4	-1.77	-7.09
Namakan River at Outlet of Lac La Croix	01/05/1998	30/11/1998	7	-1.76	-12.33	01/05/1998	31/10/1998	6	-1.91	-11.43
Neebing River at Thunder Bay	01/04/1998	30/09/1998	6	-1.42	-8.51	01/04/1998	30/06/1998	3	-1.73	-5.20
North French River near the Mouth	01/05/1998	31/05/1998	1	-2.52	-2.52	01/05/1998	31/05/1998	1	-2.52	-2.52
Ogoki River above Whiteclay Lake	01/06/1998	31/12/1998	7	-1.55	-10.88	01/06/1998	30/09/1998	4	-1.83	-7.32
Pagwachuan River at Highway No. 11	01/05/1998	31/07/1998	3	-2.01	-6.03	01/05/1998	31/07/1998	3	-2.01	-6.03
Pic River near Marathon	01/05/1998	30/09/1998	5	-1.75	-8.77	01/05/1998	30/09/1998	5	-1.75	-8.77
Pipestone River at Karl Lake	01/07/1998	31/03/1998	9	-1.54	-13.82	01/07/1998	31/03/1999	9	-1.54	-13.82
Root River at Sault St. Marie	01/04/1998	31/05/1998	2	-1.66	-3.32	01/04/1998	31/05/1998	2	-1.66	-3.32
Serpent River at Highway No. 17	01/05/1998	31/05/1998	1	-1.41	-1.41	01/05/1998	31/05/1998	1	-1.41	-1.41
Sturgeon River at McDougall Mills	01/04/1998	30/09/1998	6	-1.72	-10.30	01/04/1998	1998-09-31	6	-1.72	-10.30
Sturgeon River at outlet of Salvesen Lake	01/09/1998	31/05/1999	9	-1.13	-10.20	01/10/1998	31/05/1999	8	-1.17	-9.32
Sturgeon River at Upper Goose Falls	01/05/1998	31/05/1998	1	-1.89	-1.89	01/05/1998	31/05/1998	1	-1.89	-1.89
Troutlake River above Big Falls	01/08/1998	31/08/1999	13	-1.34	-17.42	01/09/1998	31/08/1999	12	-1.38	-16.54
Turtle River near Mine Centre	01/04/1998	31/10/1998	7	-1.93	-13.51	01/04/1998	30/10/1998	7	-1.93	-13.51
White Fish River at Nolalu	01/05/1998	30/09/1998	5	-1.64	-8.19	01/05/1998	30/09/1998	5	-1.64	-8.19
Whitson River at Chelmsford	01/05/1998	31/05/1998	1	-1.93	-1.93	01/05/1998	31/05/1998	1	-1.93	-1.93
Whitson River at Val Caron	01/05/1998	31/05/1998	1	-1.75	-1.75	01/05/1998	31/05/1998	1	-1.75	-1.75
Wolf River at Highway 17	01/05/1998	30/09/1998	5	-1.97	-9.84	01/05/1998	30/09/1998	5	-1.97	-9.84

* Intensity scores for threshold level of Q_{80} are based on the Fitted Gamma Distribution SSI Z-Scores

Note: The drought intensity, which is the ratio of severity to duration, is also a positive entity. However, if the flow sequences are standardized or converted to SSI, then all values below the truncation level become negative, rendering severity to be negative and correspondingly, drought intensity also to be negative. In other words, the drought intensity turns out to be tantamount to SSI or Z score, which has been reported as negative in the thesis.