Locating priority groundwater monitoring locations in the Central Mackenzie Valley using thermal and optical band Landsat imagery

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**Introduction**

The Central Mackenzie Valley (CMV) of the Northwest Territories, located between Great Bear and Great Slave Lake, is a region of active shale oil exploration due to the vast reserves held by the Canol Oil Formation. In advance of this exploration, it is important that baseline environmental assessments are obtained for the region so that any negative impacts resulting from oil exploration operations can be quantified.

The initial state of the hydrogeologic (subsurface water) system is one of those important baseline parameters, and because of the challenges associated with the establishment of field equipment, has gone largely unmeasured. A sparse population of groundwater monitoring wells have provided some initial estimates of hydraulic head and water table depth in the region (Golder Associates, 2015). However, given the extensive size of the lease areas (Figure 1), little can

*Figure 1. Study Site Leases in the CMV (AMEC, 2014).*
be inferred from these measurements regarding the system as a whole. Additionally, the harsh winter climate in the region has caused many of the wells to freeze or cease operation.  

Hydraulic fracturing (fracking) is the process by which shale oil is extracted from the ground. Historically, there has much skepticism surrounding this method of oil extraction due to its poorly understood environmental impacts. Of particular concern in this work is the impact that fracking may have on groundwater supplies in the CMV, especially in the event of a leak or spill within the subsurface. Not only does oil itself pose a risk to groundwater supplies, but so do the chemical constituents that make up fracking fluid. The proposed research aims to identify groundwater-surface water (GW-SW) interaction points within the CMV; these locations may be most vulnerable to the surface expression of contamination in the event of subsurface contamination. The purpose of identifying these regions is to identify priority monitoring locations – locations that should be continually monitored once fracking operations commence so that changes from baseline conditions, if any occur, may be quickly detected.  

Expense, lack of road access, remoteness, and freezing of equipment make in situ research in this region very challenging. Certainly, it is required in order to establish a thorough monitoring system, but if priority monitoring locations can be established ahead of time, this makes the transition to in situ work much easier. The work described in the sections to follow will utilize multispectral and thermal band datasets obtained from Landsat-5/8 imagery to locate priority monitoring locations and to gain insight into the hydrogeological regime in the area. Additionally, the work will provide first estimates of initial and boundary conditions that will inform future subsurface numerical models constructed for the region.  

Groundwater-surface water interaction points are identified by the presence of icings (also commonly referred to as aufeis). Icings are sheet-like masses of ice which can form on pre-existing
river ice, or on the land surface. Three main types of icings are identified: ground type, spring type, and river type. River icings, which form when groundwater discharges through a body of river ice and laps onto a frozen river surface, are not considered in this study. Only land-fast (spring and ground type) icings are considered. These two types of icings are differentiated by the source of groundwater in which they are derived. Spring icings are formed from groundwater springs – where water tends to be sourced from sub-permafrost, deep groundwater reserves – and are often annually recurring features (Carey, 1973; Yoshikawa 2007). Ground icings, which tend to be temporary or intermittent features, are formed when water in the active layer becomes ‘trapped’ between a downward propagating freezing front and the top of the permafrost table (Carey, 1973). The entrapment of water in the shallow subsurface results in a temporary increase in hydrostatic head at that locality, forcing pressurized water to discharge at the surface. This concept is illustrated in Figure 2.

It is noted that the mechanics and physical properties governing icing formation, particularly land fast icings, are still poorly understood when compared to the detailed

Figure 2. Formation of ground icings (Carey, 1973).
understanding that characterizes many other hydrogeological processes. This is likely due to the nature of icings to occur in subarctic, permafrost bearing climates which are not heavily populated. However, for the purposes of identifying GW-SW interaction points, a detailed understanding of formation processes is not essential. In situ work to follow will aim to provide a more detailed analysis of icing formation processes in the CMV region.

Remote geophysical instruments have been effective at monitoring and mapping icing distribution in regions where field instrumentation is difficult. The vast majority of remote sensing research focused on icing distribution in North America has examined river type icings in the Brooks Range of Alaska and Northern Yukon. Shusun et al. (1997) used single-look SAR (Synthetic Aperture Radar) from ERS-1 to monitor the seasonal growth of icings in the Inishak and Echooka river valleys. This study concluded that icings could be separated from other land cover types by observing low coherence values, noisy phase patterns, and large changes in radar backscatter. Yoshikawa et al. (2007) used a combination of NIR/SWIR and thermal infrared data derived from Landsat imagery, and SAR data derived from RADARSAT and ERS-1/2 to examine icing dynamics in another region of the Brooks Range. SAR imagery was able to discriminate icings in the late winter and spring based on surface roughness and wetness characteristics. Some discrete spring locations could be identified by Landsat thermal band data, but the authors note that the coarse spatial resolution of this dataset did result in some difficulty in accomplishing this. Thermal infrared cameras yielded better results.

The most extensive remote sensing study pertaining not specifically to river type icings was carried out by Morse and Wolfe (2014) with the goal of determining icing recurrence over a 24 year period. This work utilized an entire Landsat scene in the Great Slave Lake Region of the NWT, collected for 24 consecutive years. The methodology they developed is used extensively for
the work described in this paper. Morse and Wolfe sequence a series of algorithms (described in more detail in the sections to follow) that extract icings from late spring imagery using multispectral, NIR, and SWIR1 sensors. They establish icing recurrence intervals in order to pinpoint regions which are at risk of infrastructural damage.

Other works not specifically concerned with icings have attempted to use thermal infrared datasets to delineate spring and groundwater discharge zones. Most of these studies are situated in regions that experience summers with high amounts of solar radiation as cold discharging groundwater represents itself as a stark contrast against a hot landscape (Barron and Van Niel, 2009). As such, groundwater discharge is not as easily detectable at Northern latitudes during the summer. Fewer studies have attempted to delineate winter discharge zones where a snowpack is present, yet it was shown to be very effective in a study conducted by Sass et al. (2014). This work derived at-satellite brightness temperature from the Landsat thermal infrared band for a study area in the Prairie Parkland of Northern Alberta. It was found that there was good correlation between known spring locations and warm zones (presumably discharge zones) within the snowpack.

Icings to be identified as priority monitoring locations in the CMV should be a) icings that are annually recurring, and b) icings that are of both spring and ground type; it is expected that contaminant transport processes within these two discharge types will be different. Identification of icing type through the use of remote sensing tools presents a new challenge. Due to the nature of ground icings to have only a finite supply of water (Carey, 1973), it is anticipated that in the late winter, spring icings will still be discharging warm groundwater, reaching peak formation in the early spring (Yoshikawa et al. 2007), and that ground icings will have already reached peak formation. This distinction between the two icing types is the basis for the hypothesis presented.
here: that late winter thermal anomalies derived from the Landsat thermal band may be able to
differentiate icing types when the effects of other land cover types (vegetation, surface water
bodies) are muted. Presumably, spring icings will appear in zones that are warmer against the
surrounding snowpack due to the property of the snow pack amplify the heat signature through
exchange of sensible heat and heat of fusion during melting induced by groundwater (Becker,
2006). Ground icings then, should appear in colder zones due to a lack of discharging water in the
late winter. The specific objectives laid out for this work are as follows:

I. Determine the locations and extent of icings and thermal anomalies.

II. Determine the strength of the relationship between the occurrence of icings and thermal
anomalies.

III. Differentiate between ground and spring type icings based on their thermal characteristics.

IV. Determine the strength of the relationship between the occurrence of icings and surficial
geology.

Objective IV will be used as an initial verification technique for the mapping of icings; it is
expected that icings will occur over the most permeable materials as they are most conducive to
subsurface water transport.

**Study Area**

The Central MacKenzie Valley is inhabited by the small towns of Norman Wells (population
~750) and Tulita (population ~400), both of which are located on the east side of the Mackenzie
River. The rest of the valley is largely uninhabited, except by small First Nations who are a part of
the Sahtu Settlement Area (SSA) that occupies 283,171 sq. km within the CMV (Golder Associates,
2015). The CMV is part of the Taiga Plains eco-region, characterized by boreal forests interspersed
with peat plateaus and sparsely vegetated bogs. The center of the valley is a relatively flat plain, bounded by the Mackenzie Mountains to the west, Great Bear Lake to the east, and the Mackenzie River in the center flowing North to the Arctic Ocean.

Arctic air masses moving south along the river valley tend to result in fairly consistent mean monthly air temperatures for the CMV south of Inuvik. There is also little variability in the spatial distribution of heat in the valley due to the long hours of daylight and low sun angle experienced during the summer months (Dyke, 2000). Precipitation is variable within the region, noted as being less prominent within the Eastern Basins (Kokelj, 2001). There are a total of 11 basins which drain into the Mackenzie River. The largest of these is the Great Bear Lake Northwestern, occupying 27,428 sq. km east of the Mackenzie River, and the smallest is the Carcajou, occupying 9,108 sq. km west of the Mackenzie River (Kokelj, 2001). A report compiled by AMEC in 2014 identifies the region as a transition zone between the discontinuous and continuous permafrost zones, with permafrost thicknesses ranging from 50m to 143m in the Norman Wells area. Detailed information regarding the climate, state of permafrost, and bedrock and surficial geology may be obtained from the baseline evaluations of Golder Associates in 2015, AMEC in 2014, and Rudolph et al. in 2016.

The specific area examined in this work does not occupy the entirety of the CMV, nor any specific watershed. Rather, it encompasses leases which have established groundwater monitoring systems, as shown in Figure 1. The satellite imagery used, obtained from the USGS, covers WRS-2 Path 56, Row 14, and contains the towns of both Norman Wells and Tulita. The Mackenzie Mountains are removed from the study area as river (also called valley-type) icings are not the focus of this work, and topographic relief introduces a significant amount of complications and uncertainties to the derivation of land surface temperature. This is in part due to the property
of high relief areas to experience thermal inversion during the winter months. The work presented here will likely be refined to examine smaller watersheds with high resolution imagery if the methodology yields acceptable agreement with proposed field verification. The area used for the analysis presented here, shown in Figure 3, occupies approximately 6,800 sq km.

![Figure 3. True colour composite of the entire summer Landsat scene (2009); study area delineated by red polygon.](image)

**Methods**

**Icing Extraction**

Three Landsat images per dataset for each of the three years (2004, 2009, and 2016) are utilized in this study. A late spring image is used to discriminate icings, a late winter image to delineate thermal anomalies, and a summer image to generate a water mask used in the icing
discrimination process. The images used within this study are listed in Table 1. Locating three images from the same year proved difficult due to the persistent cloud cover in the study area and the poor temporal coverage of Landsat-5 during the winter. The selected years were chosen because three images were available for those years, and cloud cover over the study area was less than 5 percent.

Table 1. Landsat scenes used for analysis.

<table>
<thead>
<tr>
<th>Year</th>
<th>Summer Image</th>
<th>Winter Image</th>
<th>Spring Image</th>
<th>Landsat Sensor</th>
<th>Snow Depth*</th>
</tr>
</thead>
<tbody>
<tr>
<td>2004</td>
<td>Aug 17th</td>
<td>April 17th</td>
<td>May 29th</td>
<td>L5-TM</td>
<td>35cm</td>
</tr>
<tr>
<td>2009</td>
<td>July 30th</td>
<td>March 24th</td>
<td>May 17th</td>
<td>L5-TM</td>
<td>31cm</td>
</tr>
<tr>
<td>2016</td>
<td>July 1st</td>
<td>Feb 8th</td>
<td>May 14th</td>
<td>L8-OLI/TIRS</td>
<td>29cm</td>
</tr>
</tbody>
</table>

*Snow depth recorded by Environment Canada at the Norman Wells Climate Station for the date of the late winter image

A simplified schematic of the pre-analysis processing of the imagery is shown in Figure 4. As aforementioned, the late spring image is used to discriminate icings optically because the snowpack has largely been depleted, yet icings still remain. Both the spring and summer images are converted from digital numbers to Top of Atmosphere Reflectance (TOA) using PCI Geomatica Software. All subsequent processing and analysis is performed in ArcGIS and/or ArcPy 10.3.

The processing steps used to automatically extract icings closely follow the methodology developed by Morse and Wolfe in 2014. After being converted to TOA and clipped to the extent of the study area, the Normalized Difference Snow Index (NDSI) is applied to the image:
Figure 4. Workflow applied to datasets to generate icings and thermal anomalies.
\[
(1) \text{NDSI} = \frac{\text{Green} - \text{SWIR1}}{\text{Green} + \text{SWIR1}}
\]

(Hall, et al. 1995)

Using a threshold value of 0.4, as shown in Figure 5a, ice, snow, water, and marl water are separated from the rest of the land cover types. This algorithm is founded on the principle that snow and ice will absorb most of the incoming short-wave radiation, and reflect in the visible portion of the electromagnetic spectrum. Multiple studies have confirmed the effectiveness of the NDSI for this purpose (Salomonson and Appel, 2004; Yun-gang and Chuang, 2006; Hall et al. 1995). All values exceeding 0.4 are isolated from the image and used to mask the original

![Figure 5a. Bimodal distribution of the NDSI, separated by a threshold value of 0.4.](image1)

![Figure 5b. 2016 NDSI Result.](image2)

multispectral TOA conversion, as shown in Figure 5b. At this point in the processing, ice now needs to be separated from snow, water, and turbid water. The MDSII (Maximum Difference Snow and Ice Index) is applied to the image:

\[
(2) \text{MDSII} = \text{Green}^2 - \text{SWIR1}^2
\]
In a similar manner to the NDSI, threshold values of the MDSII can be used to discriminate ice from other land cover types. For a study area near Great Slave Lake, NWT, Morse and Wolfe determine a value of 0.144 to be used for discrimination of ice when some snow is still present in the scene, and a value of 0.040 to be used when no snow is present. These threshold values are found to be appropriate for this study area as well. All late-spring scenes used to extract icings are snow free, therefore the MDSII threshold value will separate ice from marl water. The distribution has not been rescaled in this study, therefore a threshold value of 144, rather than 0.144 is used for the discrimination. Values in excess of this threshold are considered to be ice, and are extracted from the image. Figure 6 shows a subset of the imagery where the MDSII is separated into ice and non-ice features, as well as the histogram indicating the threshold value used.

**Figure 6a.** Distribution of the MDSII, separated by a threshold value of 144.

**Figure 6b.** 2016 MDSII Result.
The MDSII extracts all ice in the study area, including ice on water bodies that may not have been completely melted. In order to remove this ice from the result, a water mask is generated using an image from the summer of that year. As the extent and location of thaw ponds and Thermokarst lakes may be variable in this area, separate water masks are generated for each year (rather than just one), in order to most closely approximate the position of surface water bodies at that time. Use of the MDSII to discern marl water also assists with the removal of non-permanent water features that may not be removed by the water mask. To generate the water mask, the NDWI (Normalized Difference Water Index) algorithm is applied to the summer TOA conversion:

$$NDWI = \frac{Green - NIR}{Green + NIR}$$

(McFeeters, 1996)

The result of this algorithm is a range of values from -1 to 1, where positive values are considered to be water. These values are extracted and converted to polygons. As some variability also exists within the stage of rivers and lakes, the polygon mask is grown outwards by 1.5 pixels (45m) to at least partially account for ice that may otherwise have been classified as an icing when it was actually surface water ice (Morse and Wolfe, 2014). The MDSII result is converted from raster format to polygon format, and the water mask is erased from the MDSII polygons to leave only land-fast icings, shown in Figure 7.

*Figure 7. Result of NWDI with icings overlain (2016).*
**Thermal Anomaly Delineation**

The spring image is also used to compute a Normalized Difference Vegetation Index (NDVI) that is then used, in part, to identify land-surface temperature in the late winter imagery. A winter NDVI is not suitable for this purpose because the majority of vegetation is snow-covered and therefore does not represent an accurate spectral reflectance. However, vegetation may still play a role in the collection of the thermal infrared data, and thus is computed from spring imagery when icings are observed and when vegetation is no longer snow covered. A sample of the NDVI result is shown in Figure 8. The NDVI algorithm relies on the property of more dense vegetation to reflect more light in the near-infrared part of the spectrum, and is as follows:

\[
NDVI = \frac{NIR - Red}{NIR + Red}
\]

(Rouse, et al. 1973)

Late winter imagery is used to delineate thermal anomalies which are hypothesized to have some correlation to the occurrence of icings. Because the snow pack is very thick in the late winter, it is suspected that it will serve to insulate discharging groundwater, prevent rapid freezing and growth of icings, and warm the surrounding snowpack. To the knowledge of this work, this hypothesis has not been tested in situ on spring or ground type icings and is formed on the basis that heat produced during the freezing of discharging groundwater can dissipate quickly when the

![Figure 8. 2016 NDVI Result.](image-url)
snowpack is thin or not present, and will be impeded when the snow pack is thick due to the property of the snowpack to act as a strong thermal insulator and absorber of sensible heat (Becker, 2006). This hypothesis is supported by the results of Diaz et al. (2015) which examined the land surface temperature product derived from the VIIRS satellite in snow covered regions. This study concludes that the relationship between absolute ground surface temperature and air temperature above the surface are much better correlated over barren ground than they are when snow covers the ground. This is due to the constancy of the ground temperature when snow is present, and reflects the inability of latent heat to escape. Furthermore, this ability of the snow pack to act as an insulator is demonstrated in relation to active layer dynamics, where it serves to delay or prevent complete freezing of the active layer due to the entrapment of heat (Atchley et al. 2016; McKenzie and Voss, 2013). Thus, it is hypothesized that discharging groundwater and spring icings will be associated with strong, warm, thermal anomalies in the late winter. Ground icings may or may not be associated with warm anomalies. As ground icings generally have a limited supply of water – unlike spring icings which have a continuous supply – they may already have exhausted their water supply at this stage of the winter (Carey, 1973). In this case, they may be represented by cold anomalies as the surrounding snowpack, without a supply of warm water, is not expected to produce a warm thermal signal.

In order to categorize thermal properties of the study area, the thermal infrared bands of Landsat satellites are converted to land-surface temperature through a series equations which manipulate digital numbers into degrees Celsius, then Z-scores, then thermal anomalies. Band 10 from Landsat-8 OLI/TIRS, or Band 6 from Landsat-5 TM, are used as the inputs for this portion of the processing. The water mask generated for the icing analysis is also used to remove water bodies from the late winter image. This is done to ensure that lake and river ice do not appear as
cold anomalies in the distribution. The coldest anomalies present should be the result of icings which are not discharging warm groundwater. To derive land surface temperature, the digital numbers of the image are first converted to Spectral Radiance:

\[
R_\lambda = R_{\text{mult}} \times DN + R_{\text{add}}
\]

where

- \( R_\lambda \) = Spectral radiance
- \( R_{\text{mult}} \) = Sensor radiance multipier (gain coefficient)
- \( R_{\text{add}} \) = Sensor radiance add (bias coefficient)
- \( DN \) = unaltered digital number

(Chander, et al. 2009)

Then to temperature in degrees Kelvin:

\[
T_u = \frac{K_2}{\ln \frac{K_1}{R_u} + 1}
\]

where

- \( T_u \) = Temperature (°K)
- \( K_2 \) = Thermal constant 2 (°K)
- \( K_1 \) = Thermal constant 1 (mW cm\(^{-2}\)sr\(^{-1}\)μm\(^{-1}\))
- \( R_u \) = Spectral Radiance

(Wukelic, et al. 1989)

Sensor bias and gain coefficients, as well as thermal constants, are obtained from the sensor metadata. In the previous equation, ‘1’ is an assumed emissivity applicable when the determination of absolute temperature is not required.
These equations achieve at-satellite brightness temperature, but do not account for the effects that vegetation may play in the thermal signature. Generally, lower NDVI values are associated with higher at-satellite brightness temperatures (Julien et al. 2011); in this study area this phenomena is likely attributed to the re-emittance of long-wave radiation by barren ground.

To account for interference related to vegetation density, at-satellite brightness temperatures are converted to land surface temperatures using the earlier described NDVIs. First, the NDVI is used to compute a proportion of vegetation (a scaled NDVI):

\[
(7) \quad P_v = \left[ \frac{\text{NDVI} - \text{NDVI}_{min}}{\text{NDVI}_{max} - \text{NDVI}_{min}} \right]^2
\]

(Carlson and Ripley, 1997)

Then the proportion of vegetation is used to determine an emissivity for vegetation:

\[
(8) \quad e = 0.004 \times P_v + 0.986
\]

(Cuenca and Sobrino, 2004)

At-satellite brightness temperature and the emissivity values are then used in conjunction to determine the land-surface temperature, as shown in Figure 9:

\[
(9) \quad LST = \frac{B_T}{1 + \omega \times \left( \frac{B_T}{P} \right) \times \ln(e)}
\]

where

\[
LST = \text{Land surface temperature (°C)}
\]

\[
B_T = \text{At satellite brightness temperature (°C)}
\]

\[
e = \text{Emissivity of vegetation}
\]

\[
\omega = \text{Wavelength of emitted radiance (µm)}
\]

\[
P = h \cdot \frac{c}{s}
\]
\[ h = \text{Planck's constant} \ (1.438 \times 10^{-34} \text{ m K}) \]
\[ c = \text{Velocity of light} \ (2.2998 \times 10^8 \text{ m s}^{-1}) \]
\[ s = \text{Boltzmann constant} \ (1.38 \times 10^{-23} \text{ J K}^{-1}) \]

(Avdan and Jovanovska, 2016)

The result of the land-surface temperature takes into account the emissivity of vegetation in order to mute its contribution to thermal signature. At this point, anomalies could be classified. However, if anomalies are to be compared over different time periods, they must be standardized to account for differences in the distributions of temperature at different times. Not all images have the same range of temperatures, nor do all temperature values overlap. As determining absolute temperatures is not the goal of this work, statistical comparison is made possible by converting land-surface temperatures into Z-scores:

\[ (10) \quad Z = \frac{T_i - T_m}{\sigma} \]
where
\[
Z = Z - \text{score}
\]
\[
T_i = \text{Pixel temperature} \ (°C)
\]
\[
T_m = \text{Mean temperature of all pixels} \ (°C)
\]
\[
\sigma = \text{Standard deviation of temperature distribution}
\]

(Van Niel et al. 2004)

This method was also used by Barron and Van Niel in 2009 to classify groundwater discharge zones using thermal anomalies from different time periods. This statistical conversion is suitable for normally distributed data only, and therefore is appropriate for the land-surface temperature datasets. An example of the Z-score result is shown in Figure 10. Z-scores of ‘0’ represent the mean of the data. Positive Z-scores represent temperatures warmer than the mean, with the highest positive score being the strongest warm anomaly. Conversely, negative Z-scores represent temperatures colder than the mean, with the highest negative score being the strongest cold anomaly.

The Z-scores are then reclassified from floating point to integer type data in order to assign ranks of strength to the anomalies. The reclassification scheme is shown in Table 2. After reclassification, and shown in Figure 11, the ranked groups are converted into polygons for the analysis described in the next section. The reclassification scheme is arbitrary but is the same for

<table>
<thead>
<tr>
<th>Z-Score</th>
<th>Integer</th>
<th>Reclassification</th>
</tr>
</thead>
<tbody>
<tr>
<td>3+</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>2 TO 3</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>1 TO 2</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>0 TO 1</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>0 TO -1</td>
<td>-1</td>
<td></td>
</tr>
<tr>
<td>-1 TO -2</td>
<td>-2</td>
<td></td>
</tr>
<tr>
<td>-2 TO -3</td>
<td>-3</td>
<td></td>
</tr>
<tr>
<td>-3+</td>
<td>-4</td>
<td></td>
</tr>
</tbody>
</table>

Table 2. Reclassification scheme used to convert Z-Scores to singular integer values.
all late winter images regardless of the distribution, thus making them suitable for statistical comparison.

**Results**

The number of discrete icings, as well as the areal extent of icings, was calculated for each year. A subset of this result, underlain by the thermal anomalies, is shown in Figure 16. Icings separated by one or more pixels are considered to be discrete. It is possible that icings within close proximity to one another were part of a larger icing that degenerated, however, this cannot be definitively determined from the imagery. The total areal extent of all icings are 35, 34, and 32 square kilometers for years 2016, 2009, and 2004 respectively. The occurrence of icings, by count as well as by areal extent, was compared to the occurrence of thermal anomalies using a Kolmogorov–Smirnov goodness of fit test. The discrete distributions represented by the icing count and size are inferred to be continuous for the purposes of the statistical test. These distributions are shown in Figure 12. The K-S tests reveals that neither of two distributions differ significantly at a level of 0.05. This result is expected as the curves follow the same trend in both cases. The greatest count and areal coverage of icings always occurs within

*Figure 11. Thermal anomalies, reclassified from Z-Scores to integer values where anomalies become stronger in the both the increasing positive and negative directions.*
the weak anomalies (1 and -1), and decreases moving in the positive and negative anomaly directions.

Given the similarity of these two distributions, it was anticipated that there must also be a strong correlation between icing area and count. Indeed, these two variables are strongly correlated for all sampled years, yielding positive correlation coefficients of 0.91, 0.89, and 0.87 for years 2016, 2009, and 2004 respectively.

![Graphs showing distribution of discrete icings and icing coverage by area over thermal anomalies.](image)

*Figure 12. Distribution of discrete icings (left) and icing coverage by area (right) in relation to thermal anomalies.*

Icing recurrence, or overlap, for all possible year combinations, is shown in Figure 13. These results were determined by performing an intersect of icings for each overlap range. If an icing was found to be within 30m (one pixel) of an icing from a different year, but not quite overlapping, it was included in the intersect as a way to partially account for effects that topographic variation and snowpack density may play in the surface expression of the icing. Given that the purpose of establishing icing recurrences is to locate priority monitoring sites, a intersect threshold value of 30m is assumed to be reasonable. It is determined that the overlap of icings by area are 28.8, 25.0, and 34.8 percent of the total area for overlap ranges 2016-2009, 2016-2004,
and 2009-2004 respectively. The overlap of icings for all years is determined to be 12.5%, or 11.1 square km.

The three-year recurring icings are examined in greater detail as they represent the most promising locations for field monitoring sites, and they are the only icings which can be compared year to year for their representation in thermal anomalies. The strong anomalies (2, 3, 4, -2, -3, -4), which, because they have been converted to z-scores, will always represent approximately 32% of the scene, are amalgamated into strong warm, and strong cold zones. They are then compared to the three-year recurring icing count and areal extent as shown in Table 3. No strong relationship was found between either the count or extent with the strong anomalies. The weak (-1, 1) anomalies are not considered in this comparison; If recurring icings are able to be identified based on winter thermal anomalies, it should be because they are correlated with strong anomalies only. This is considered further in the discussion.

Surficial geology datasets, obtained from the Geological Survey of Canada Open File 7289, are also related to the distribution of icings. Primary texture

Figure 13. Icing Overlap (recurrence) by area for all possible year combinations.

Figure 14. Primary surficial texture classification within the study region.
Table 3. Comparison of the area represented by strong anomalies to the discrete count of icings in those areas and the percent area of total icings.

<table>
<thead>
<tr>
<th>Year</th>
<th>Warm Area (sq. m)</th>
<th>Cold Area (sq. m)</th>
<th>Warm Icings*</th>
<th>Cold Icings*</th>
<th>Warm Icings (%)</th>
<th>Cold Icings (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2016</td>
<td>131722</td>
<td>8292388</td>
<td>121</td>
<td>1097</td>
<td>74.9</td>
<td>6.9</td>
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<tr>
<td>2009</td>
<td>395491</td>
<td>661477</td>
<td>81</td>
<td>235</td>
<td>5.9</td>
<td>4.1</td>
</tr>
<tr>
<td>2004</td>
<td>1759459</td>
<td>1186829</td>
<td>260</td>
<td>127</td>
<td>10.7</td>
<td>13.3</td>
</tr>
</tbody>
</table>

* Discrete count of icings occurring separately within strong warm and strong cold zones

As shown in Figure 14, the greatest proportion of icings, by area, is found in bedrock outcrops and sand for all years considered. The same is true of the size of icings; largest icings are located in bedrock outcrops.

Figure 15. Percent of total icing area for each year (left), and average discrete icing size for each year (right) compared to the primary surficial texture class.
within bedrock outcrops and sand. Correlation coefficients are used to characterize the relationship between the three-year recurring icings and the surficial geology, and it is found that a strong positive correlation (0.82) exists between the three-year recurring icings and the exposure of bedrock at the surface.

Figure 16. Subset of the final results – icings and thermal anomalies, for each year.

Discussion

Distinguishing Spring and Ground Type Icings

As aforementioned, it was anticipated that icings would be segregated into either strong warm (2, 3, 4), or strong cold anomalies (-2, -3, -4) and that this property could be used to distinguish spring from ground icings. This discernment is important when establishing field monitoring sites as different mechanisms and physical processes within these two types of icings...
may affect the way that contaminants are moved to the surface. This hypothesis forms its basis from the previously reviewed literature on icing phenomena, which indicates that ground icings may exhaust their supply of groundwater at some point during the winter and that spring icings have a continuous supply through the winter, reaching peak formation in the late spring (Carey, 1973; Kane, 1981; Yoshikawa et al. 2007). Weak anomalies (1, -1) would then represent unaffected snowpack – snow that does not contain either active or inactive icings. As the majority of icings did fall within weak warm and cold anomalies, this suggests that the presence of icings, whether discharging groundwater or not, does not strongly affect the land surface temperature in the majority of cases. The icings falling in the weak warm may be discharging enough warm groundwater to fall above the mean temperature, but not enough to appear in the strong warm. Similarly, the icings falling in the weak cold may affect the LST enough to fall below the mean, but not enough to appear in the strong cold. It is possible that the mean of the data (the 0 level Z-Score) could distinguish ground from spring icings, however, the results provide insufficient evidence to support this conclusion. If an icing were classified as spring type because it fell just above the mean Z-Score of 0, it may in fact be a ground icing that is still discharging warm water in the late winter or that has a low ice content. The same argument may be made for an icing classified as ground type because it fell just below the mean. Perhaps this is in fact a spring type icing which is discharging a small amount of groundwater on that particular day. These examples are to say that because the weak anomalies represent values closest to the mean, their contrast is not sufficient to discriminate icing types. Additionally, if the icings are distinguished from one another using the entire dataset, there is likely room for a large degree of error in classifying those icings which lie in the weak anomalies. So, the icings which do fall into strong warm and cold anomalies may be more definitively classed as either spring or ground type based on current
definitions of their physical occurrence, but because the majority do not fall into these strong anomalies, it is concluded that thermal anomalies may not be an ideal variable for discriminating icing type. It should also be noted that there are other factors besides discharging groundwater that may play a role in determining land surface temperature. These include snow pack density and differential thermal insulation (Diaz et al. 2015). Several measures were taken to try and account for variation in the expression of the anomalies. These included: Conversion to LST rather than brightness temperature, removal of water bodies from the distribution, selection of images with a similar snow depth, selection of cloud-free images, selection of images taken at the same time of day, and conversion of absolute temperatures to Z-scores for standardization.

Recurring Icings

As the initial results described above do not provide promising evidence for classifying icings based on thermal anomalies, the 3-year recurring icings are examined in more detail. The fact that the vast minority of icings observed in the study region (12.5% by area) recur in each observed year suggests that the majority of icings are intermittent or temporary. Though it is possible for ground type icings to recur in the same location year to year, it is expected that these recurring icings are more likely spring type as there is greater evidence to suggest that springs yield recurring icings (Yoshikawa, et al. 2007). The hypothesis described in the previous section is re-tested but using only the 3-year recurring icings; no relationship was found between either extent or count with the strong anomalies. This result is not surprising given that the majority of icings from all years coincide with weak anomalies. As the results indicated in Table 3 are so variable, no definitive conclusions are drawn regarding the type of icings that 3-year recurrences are likely to be. This does not mean that the 3-year recurring icings aren’t of spring type, but it does suggest a
large degree of variability in the hydrogeological regime, and that spring and ground type icings may not simply be distinguished based on the amount of water they are discharging in the late winter. Nonetheless, these 3-year recurring icings do provide promising locations for field monitoring, where further in-situ work may be able to classify their type more definitively. It has been demonstrated by field observations that ground icings contain more organic material (appearing brown in color) than due spring icings (Carey, 1973), and also that carbonate precipitates are found in spring-derived icings (Hall, 1980). These variables warrant further investigation in the CMV. In this work, the observations that a) 87.5% of the icings by area do not recur in all years, and b) upon visual inspection, the distribution of anomalies is not consistent, further supports the conclusion that these icings are intermittent and occur in different places on an annual basis.

*Characteristics of the Hydrogeologic System*

Though the distribution of icings within their respective anomalies is similar, the overall distribution of icings is highly inconsistent. However, this inconsistency does not appear to affect the overall areal coverage of icings from year to year. The consistency in the total areal coverage of icings suggests that the water available from the subsurface during winter is also consistent. Yoshikawa et al. (2007) concludes that icings monitored in the Brooks Range of Alaska are not nearly as sensitive to climate change as they are to source groundwater properties. It is suspected that this is also the case for icings in the CMV. As there have been numerous studies in the last few decades detailing dramatic climate changes in Northern latitudes, yet icing coverage remains consistent in the CMV, this lends evidence to the idea that climatic changes are not adversely affecting the amount of groundwater discharge during the winter. This information in itself is
invaluable, as it provides an indication of the amount of groundwater that discharges to the surface during the winter. This metric can be used in part to characterize the overall hydrologic system of the area, and to determine what proportion of water available in the system is derived from a subsurface source. Areal coverage on its own is not particularly useful for this purpose, therefore, an empirical equation first proposed by Sokolov in 1973 is used to compute the volume of icings:

\[ V = b \times F^n \]

where \( V \) = volume of icings,

\( b \) and \( n \) = aufeis growth coefficients, and

\( F \) = the area of icing coverage, derived from satellite imagery

Empirical coefficients to be used in this equation were determined for an aufeis field in the Brooks Range of Alaska in 1981 by Hall and Roswell:

\[ V = 0.96 \times F^{1.09} \]

These coefficients are used here to establish an initial estimate of the volume represented by icings in the Central Mackenzie Valley region. This information is not used for any further analysis in this study, but simply to provide a baseline for the volume of discharging water that may be used to better understand the hydrogeologic system, and to establish initial or boundary conditions used in future numerical models. Using this equation, total volumes of icings are found to be 161, 159, and 149 million cubic meters for years 2016, 2009, and 2004 respectively. In situ studies would be required to refine these coefficients for more precise use in the CMV, and/or to assess the applicability of the Brooks Range coefficients for use in this study area.
**Surficial Geology**

As shown in numerous studies, and in particular for regions where icings develop (Romanovskii et al., 1996), groundwater discharges at the surface where materials are most permeable. Therefore, it was hypothesized that icings would also occur in areas of higher permeability geology as they are sourced from groundwater. This hypothesis is well supported by the results indicated in Figure 15. Sand, having one of the highest hydraulic conductivities of all subsurface materials, is very proficient at transporting subsurface water and yielded the second highest amount of icings (by area) for all years. Bedrock outcrops yielded the highest amount of icings for all years. Bedrock in the region is primarily late Devonian to early Cretaceous shale and sandstone (Rudolph, et al. 2016). Some of the sandstone formations in the area have been confirmed to contain productive aquifers, and therefore should be able to easily disperse water at the surface. Bedrock shale, whether or not it contains water, is a highly impermeable lithology. This implies that fractures within shale formations could provide more conductive transportation routes for subsurface water. Bedrock outcrops and sand are also representative of the largest icings in the study area, for all years. This suggests that more permeable materials may provide a more consistent flow of subsurface water, allowing icings to grow larger than they would in less permeable materials.

The exposed bedrock in the area requires further investigation to determine the extent and nature of possible fractures that are dispelling water. The Geological Survey of Canada has mapped, in detail, a system of thrust faults and folds in the region that may be related to the discharge of water. However, given that icings can be as small as 900 sq. meters, small localized fractures are expected to play an important role. It is also possible that the presence of bedrock at the surface may be a good indicator of whether an icing is of spring or ground type. Since bedrock
does not strictly freeze, it does not satisfy the criteria for the development of a ground type icing. Additionally, it is found that the correlation between the three-year recurring icings and the presence of bedrock is 0.82. This provides further evidence to suggest that these recurring icings are primarily of spring type. Therefore, it is proposed that of the three-year recurring icings, field monitoring sites should contain a good mix of icings that occur over exposed bedrock, and icings that occur over sand.

**Conclusions**

This work aimed to accomplish a few main goals through the outlined objectives:

1. To provide suggestions of groundwater discharge locations to be monitored in advance of shale oil and fracturing development; these monitoring zones should contain icings which recur, and icings which are of both spring and ground type.
2. To provide a better understanding of the variability associated with the hydrogeological regime in the area.
3. To provide, through initial estimates of the contribution of discharging groundwater to the overall hydrogeologic system, boundary or initial conditions for subsurface numerical and freeze thaw models.

This work did not have the goal of determining definitive mechanisms and physical conditions governing the formation of icings. Rather, it used the limited available literature on spring and ground type icings and aufeis to develop a methodology that would indicate where further in situ data and monitoring would be beneficial. Objectives I-III were accomplished through the manipulation and analysis of Landsat-5/8 datasets. Objective IV, to distinguish
between ground and spring type icings using thermal characteristics, could not be entirely accomplished.

There are a few important limitations that are noted within this work. Firstly, temporal coverage of Landsat data for this region was limited; this was due to the need for images from specific time periods, with specific snow depths, and with no cloud cover. Ideally, recurrence intervals would have been computed for smaller time intervals had the appropriate data been available. Secondly, the spatial resolution for Landsat optical bands are 30m by 30m. Therefore, icings smaller than this could not be resolved by the image algebra techniques. The spatial resolution of Landsat thermal bands is 120m by 120m. Therefore, discharging groundwater may not have been discretely detected even if an icing was present within that 120m pixel. The computation of LST may also be afflicted by variations in factors such as snow pack density and differential thermal insulation. Thirdly, in situ data regarding icings or their formation is not, to the knowledge of this work, currently available for this specific study region. Therefore, field verification of the results given here cannot be provided.

Despite these limitations, some very important conclusions are drawn from this remote study:

1. The amount of winter groundwater discharging in this region is stable from year to year, even though the spatial distribution of icings is not.
2. Ground and spring icings may not function in the same way across all regions; that is to say that ground icings may still discharge water late in the winter, and spring icings may undergo periods of little or no discharge.
3. Due to variability in the distribution of recurring icings within thermal anomalies, and the large overall proportion of icings in weak anomalies for all years, thermal data should not be used to
definitively distinguish ground and spring type icings. It should be used only to make suggestions as to the mechanisms governing their formation.

4. Icings are well correlated with the occurrence of sand (a highly permeable material), and bedrock (a material that is suspected to contain fractures). The presence or absence of bedrock at the surface may be used to establish icing type in situ.

Given these conclusions, the goals of the work have been largely accomplished. Next steps will include the establishment of field monitoring locations based on the results given here, further investigation on the role of bedrock fractures in icing occurrence, and the repetition of this methodology with higher resolution optical imagery for a more localized zone.
References


