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Road Salt Use Analysis in the Context of Changing Winter Weather Conditions

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ROAD SALT USE ANALYSIS IN THE CONTEXT OF CHANGING WINTER WEATHER CONDITIONS

By

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An Abstract of the Thesis Presented
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The research is inspired by the past and current patterns of road salt use, changing weather patterns, and management strategies in Maine. The historical road salt application has led to long-term impacts on the environment pressing the need for strategic use of road salt. Winter Severity Indices (WSIs) find their application in the field by aiding in interpreting weather forecasts and planning for strategic salt application. This study uses existing indices: Accumulated Winter Season Severity Index (AWSSI), Strategic Highway Research Program (SHRP) index, Illinois Salt days index, and Accumulated Freezing Degree Days to quantify long-term changes in winter weather conditions. Statistical models based on Principal Component Analysis, Quantile, and quasi-Poisson regression provide estimates of trends, interdependence between weather variables and salt use, derivation of weather indices model with high salience towards the use of road salt. Results show the existing index and changing baselines linked to salt application practice explain most of the variability (R^2 greater than 80%) in salt usage from 1991 to 2020. The leading components of WSIs parse Maine's weather variability into short-term and long-term patterns showing increasing severity, in general, along coastal regions.

The research also investigates the prevalence of rising chlorides in groundwater in Maine. The impact assessment is based on the water quality data set analysis to get estimates of the local risk of well contamination due to chlorides. Qualitative analysis of chlorides in well and appropriate co-variates representing the proximate environment are also presented. We find general patterns of increasing chlorides with decreasing distance to high-priority roads. In addition, the local risk of wells for chloride contamination and arsenic mobilization provide substantial grounds for further study. The results from this study will help state and local road maintenance agencies understand the regional disparity in winter severity and implement informed road salt application decisions in potential contamination zones.

DEDICATION

This thesis is dedicated to my parents. For their endless love, support and encouragement.

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INTRODUCTION AND LITERATURE SURVEY

1.1 Introduction

During winter, in regions with a cold climate, snow, and ice accumulated along the road surface adversely affect traffic safety and mobility. In particular, the snow and ice make roads slippery and reduce pavement friction, causing slower speeds, reduced roadway capacity, and increasing crash risk. Road maintenance authorities employ deicing and anti-icing practices to prevent ice formation and accumulation on road surfaces. These practices involve applying solid or liquid salt on the roads before, during, or after a storm to prevent or break the ice bond, improve traction, and promote melting. The resulting mix is easier to plow and clear the roads of snow and ice.

Approximately 35 million metric tons of salt are applied to roads for wintertime maintenance worldwide [49]. This rate continues to rise due to the expansion of the maintained wintertime road miles, higher public demand for safer driving conditions, and increased precipitation in cold regions due to climate change [49]. In 2020, highway deicing accounted for about 43 percent of all salt consumed in the United States [44]. The winter road maintenance alone accounts for about 20 percent of state Department of Transportation (DOT) maintenance budgets.

The Maine DOT used 155,568 tons of rock salt for snow and ice control activities in the winter of 2019-2020 [10]. This material cost amounts to $10.7 million of the state budget. without accounting for more than three thousand gallons of salt brine used during the road pre-treatment. Furthermore, these figures represent road salt use from Maine DOT only and exclude the material used by other agencies, such as Maine Turnpike Authority, Municipalities, Counties, and private sectors. Although proven to improve traffic mobility, the historical road salt application can leave long-term impacts on the environment.

In the following sections of this chapter, we discuss some recognized effects of road salt use. Important winter severity indices used to relate to climate and winter road maintenance are reviewed, along with a discussion of previous work. Related wintertime severe weather conditions and meteorological variables are presented. Finally, the objectives and contributions of this work will be presented.

1.2 Impacts of Winter Road Salt use

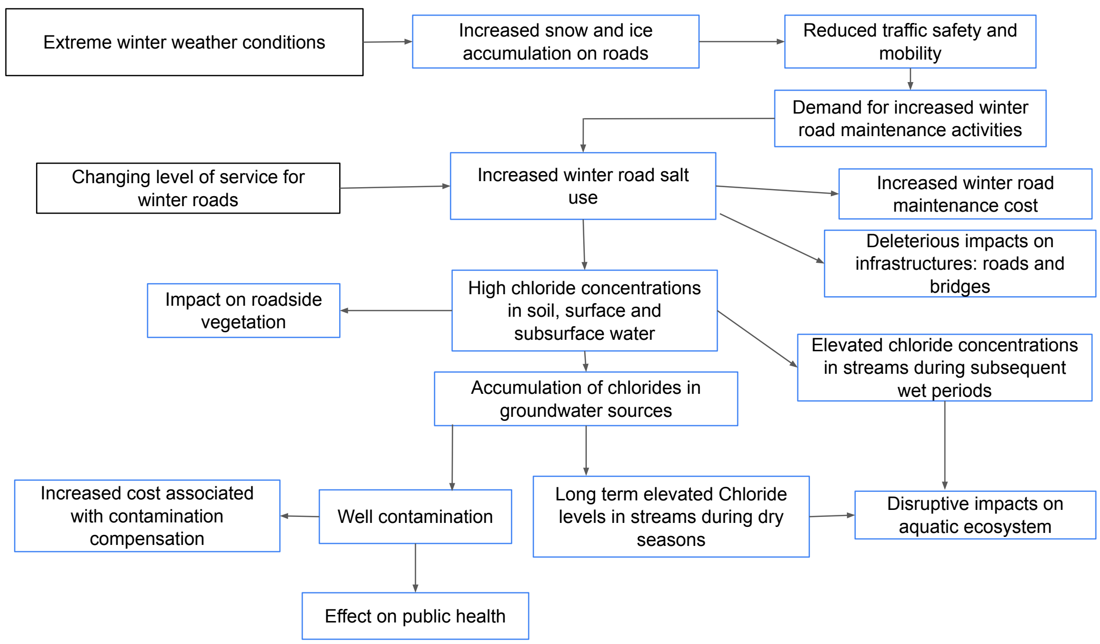


Figure 1.1: Flow chart showing cause and effect relation between extreme winter weather conditions, winter road salt use, and its impacts.

The road salt, which most commonly is sodium chloride, is 40% sodium and 60% chloride with up to 5% of trace elements or possible contaminants [46]. The chloride ions move with water seeping through soil, joining streams, and accumulating in groundwater systems. They are gradually discharged into streams over the years as base flows affecting the streams, especially in dry seasons, even after the period of salt application. Maine Department of Environmental Protection (MDEP) reports alarmingly high levels of chloride concentrations for aquatic life in most of the Maine streams, with the chloride levels exceeding the acute criterion during the wet months and chronic criterion during the drier months [37].

Maine's private and public water supply is heavily sourced from groundwater. It contributes to around 40% of Maine's household private water supply and 94% of the public water systems. Considering this heavy reliance on groundwater sources, the public health risk from elevated sodium and chloride levels is serious. The elevated sodium levels in drinking water are associated with health risks of high blood pressure and cardiovascular disease. The effects of elevated chlorides are secondary such as a salty taste in water and corroded pipes, pumping, and plumbing fixtures [6]. Additionally, in the state of Maine, well owners whose water supply has been adversely affected by public construction, reconstruction, or maintenance of roads (including road salt application) are redressed by the state [1]. With increasing demands on the level of service for winter roads and no check on salt use, these claims and associated compensation continue to rise. Maine DOT has spent around $5.3 million on resolving well claims during 2006-2020 [11]. In addition to water systems, the effect of winter road salt has been realized on road infrastructures, public vehicles, and roadside vegetation. Frequent road salt use causes corrosion to concrete, metal members, reinforcement bars, and other essential bridge components. Likewise, the salts develop corrosion in the vehicle metal parts and deteriorate pavement by accelerating the normal deterioration caused by freeze-thaw cycles in winter, shortening the lifespan of asphalt. Roadside plants and trees show inhibition of general growth, followed by specific injuries to foliage and limbs, and, at times, plant death in response to increased salt concentration in soil [25].

The flow chart, shown in Figure 1.1, summarizes the cause and effect relation between winter weather conditions, winter road salt use, and impacts on roadside soil, vegetation, infrastructures, and water systems.

1.3 Winter Severity Indices

Wintertime road conditions comprise a complex array of weather phenomena, ranging from icing, frost, frozen rain, and black ice, to name a few. Thus, the amount and timing of applied road salt are closely linked to winter weather severity. As such, numerous Weather Severity Indices (WSI)s have been developed with a view to (a) anticipate salt usage, (b) interpret weather forecasts within the context of potentially hazardous conditions on roads, and (c) plan and schedule salt application on roads.

This section includes a detailed description of the severity indices established to aid efficient ice and snow control activities in several countries and states with cold climates. The indices are introduced in detail, along with the type of variables included, and weather triggers accounted for.

1. Maine DOT index (Not currently in use) [30]

   The Maine Department of Transportation (Maine DOT) developed a point-based WSI in 2009 using daily historical weather information from 1980 to 2006. The index assigns various values to weather conditions: daily values of minimum and maximum temperatures and derived parameters: daily snowfall and precipitation values, including freezing rain. The first derived parameter is freezing rain equivalent, defined by:

$$\begin{aligned} Freezing\ Rain\ Equivalent = \frac{30}{30 + DeltaT^2} + [&Daily\ Precipitation\ Total - \\ &Daily\ Snowfall\ (10:1\ ratio)\ Equivalent\ Precipitation] \end{aligned} \tag{1.1}$$

   where DeltaT is the maximum temperature less thirty (Tmax – 30).

   This parameter considers freezing rain events by converting freezing rain into an equivalent snowfall amount throughout a winter season.

The second parameter is modified snowfall, and the definition is as follows:

$$\begin{aligned} Modified\ Daily\ Snowfall = & [Estimated\ Daily\ Snowfall\ (ratio) \\ & - Measured\ Daily\ Snowfall] * 1.25 \\ & + Measured\ Daily\ Snowfall \end{aligned}$$

To calculate the second parameter, first, estimated values of daily snowfall are obtained by using daily values of precipitation with predetermined snow to liquid ratios. The remainder of the precipitation is assumed to be freezing rain and added to modified rainfall using a factor of 1.25 for accounting for increased maintenance costs. The points are seasonally accumulated and then adjusted based on their statistical properties. The lowest seasonal point (zero) corresponds to the Zero WSI point, and the highest value corresponds to the WSI point of near 100.

The developed WSI is a good indicator of winter severity for the study period 2005 to 2008 across all five DOT regions. However, discrepancies appeared when relating to the maintenance cost. Maine later did not adopt the index due to the requirement for a significant expansion in data collection efforts [20].

2. Winter Severity Index from Strategic Highway Research Program (SHRP) [4]

   A study conducted by Strategic Highway Research Program (SHRP) in 1993 developed a severity index to help highway agencies efficiently allocate winter maintenance resources and ensure adequate safety. The SHRP index computes parameters for temperature, snowfall, and the likelihood of frost based on daily weather records and provides a seasonal value varying from -50 to + 50, where -50 implies severe winter with maximum ice and snow control and +50 implies warm winter with no need of snow and ice control. Weather data are summed from daily records from National Weather Service and then averaged for each month from November 1 to March 31 to eliminate the influence of the month length.

The index is computed using the equation:

$$WI_{SHRP} = -25.58\sqrt{T_{index}} - 35.68\ln(\frac{S_{daily}}{10}+1) - 99.5\sqrt{\frac{d_{freez1}}{T_{range1}+1}} + 50 \qquad (1.2)$$

where

$$t_{seasonindex} = Average\ t_{dayindex}\ over\ season,\ (0 \leq t_{seasonindex} \leq 1),$$

$$\begin{aligned} t_{dayindex} &= 0,\ if minimum\ daily\ temperature\ (T_{min})\ is\ above\ 32°F \\ &= 2,\ if\ daily\ maximum\ temperature\ (T_{max}) \leq 32°F, \end{aligned}$$

$S_{daily} = Mean\ daily\ values\ of\ snowfall\ (millimeters),$

$d_{freeze1} = Mean\ daily\ values\ of\ no.\ of\ days\ with\ T_{min} \leq 32°F,$

$T_{range1} = Mean\ monthly\ T_{max}\ minus\ the\ Mean\ monthly\ T_{min}(°C)$

Since T_{range1} was determined to have a similar but inverse distribution to relative humidity, the term $\sqrt{\frac{d_{freez1}}{T_{range1}+1}}$ reflects the likelihood of frost [41]. The weights for specific terms with temperature, snowfall, and the likelihood of frost in the equation are assigned according to their significance to the maintenance costs. Since its development, the SHRP index has been actively used in transportation agencies for more than two decades [13]. The index is now actively used by Kansas and New Hampshire state DOTs for winter maintenance operations [13, 33, 12].

A comparison of the index values with winter maintenance cost data from 40 states showed a strong log-linear relationship exists between cost and index. However, the index does not address regional characteristics that influence maintenance activities since it was developed in general to be used in all states. To address this issue, some transportation agencies outside the US have modified the index to better represent the local winter conditions. An example is a work by the Ontario Ministry of Transportation, which modified SHRP by substituting freezing rain for the likelihood of frost [31].

3. Illinois DOT index : Salt days [8]

   The Illinois DOT index was developed by Illinois State Water Survey as a user-oriented climatic variable indicating the number of days when road salt is required. It is computed as the number of days requiring snow and ice work by summing the cold days and snow days. The formula for index computation is:

$$WI_{Illinois} = D_{snow} + D_{cold} \tag{1.3}$$

   where D_{snow} is the number of days with snowfall accumulation greater than or equal to 0.5 inches (1.3 cm) and D_{cold} is the number of days with daily mean temperature between 15° F and 30° F (9° to -1° C). The index was also incorporated into a study explaining the temporal and spatial variability of salt use on highways in the Province of Ontario, Canada [3].

4. Accumulated Winter Season Severity Index (AWSSI) [32]

   AWSSI was developed in 2015 for application in general sectors, including transportation. It is a point-based index that computes winter seasonal severity by accumulating points for daily values of minimum, maximum temperatures, and snowfall amounts and depths. Unlike other indices, which often compute seasonal severity based on fixed calendar months, AWSSI accumulates daily severity from an evaluated onset day through an evaluated cessation day of the winter season. The winter onset day is defined as the day when any one of the three criteria is met: 1) daily maximum temperature $\leq 32°F$ $(0°C)$, 2) daily snowfall $\geq$ 0.1in. (0.25 cm), or 3) it is December 1. The cessation day is when the last of the four conditions are met: 1) daily maximum temperature $\leq 32°F$ $(0°C)$ no longer occurs, 2) daily snowfall $\geq$ 0.1 in. (0.25 cm) no longer occurs, 3) daily snow depth $\geq$ 1.0 in. (2.5 cm) is no longer observed, or 4) it is March 1. This allows the index to add points for the impacts of any offset or long winter season and accurately estimate seasonal severity.

Once the accumulation period in winter is defined, daily points of AWSSI are computed based on thresholds of maximum and minimum temperature, snowfall, and snow depth shown in Figure 1.2. The point thresholds were designed to give greater weight to rare or extreme occurrences with trace snowfall and depths treated as zero, not accumulating severity points. The following expressions highlight the point accumulation process:

$$AWSSI = \sum [Daily\ Temp\ Scores + Daily\ Snow\ scores] \tag{1.4}$$

where,

$$Daily\ Temp\ score = Min\ Temperature\ Score + Max\ Temperature\ Score, and$$

$$Daily\ Snow\ score = Snowfall\ score + Snow\ depth\ score$$

AWSSI Point Thresholds				
	Temperature (°F)		Snow (in)	
Points	**Max**	**Min**	**Fall**	**Depth**
1	25 to 32	25 to 32	0.1 to 0.9	1
2	20 to 24	20 to 24	1.0 to 1.9	2
3	15 to 19	15 to 19	2.0 to 2.9	3
4	10 to 14	10 to 14	3.0 to 3.9	4 to 5
5	5 to 9	5 to 9	-	6 to 8
6	0 to 4	0 to 4	4.0 to 4.9	9 to 11
7	-1 to -5	-1 to -5	5.0 to 5.9	12 to 14
8	-6 to -10	-6 to -10	-	15 to 17
9	-11 to -15	-11 to -15	6.0 to 6.9	18 to 23
10	-16 to -20	-16 to -20	7.0 to 7.9	24 to 35
11	-	-21 to -25	-	-
12	-	-	8.0 to 8.9	-
13	-	-	9.0 to 9.9	-
14	-	-	10.0 to 11.9	-
15	<-20	-26 to -35	-	36+
18	-	-	12.0 to 14.9	-
20	-	<-35	-	-
22	-	-	15.0 to 17.9	-
26	-	-	18.0 to 23.9	-
36	-	-	24.0 to 29.9	-
45	-		>=30.0	-

Reprinted from "Barbara E Mayes Boustead, Steven D Hilberg, Martha D Shulski, and Kenneth G Hubbard. The accumulated winter season severity index (awssi). Journal of Applied Meteorology and Climatology, 54(8):1693–1712, 2015."

Figure 1.2: Points accumulated in daily AWSSI totals, based on thresholds of daily temperature, snowfall, and snow depth data.

The AWSSI index is new in the field of transportation, and its implementation for maintenance activities or material use is not tested yet. A noteworthy limitation in the index is it does not explicitly include freezing rain events, which are reported as liquid precipitation or mixed precipitation events, not snow events.

5. WSI for provincial highway system in Ontario, Canada [31]

   In 2016, a study was conducted to develop a winter severity index for highway systems in Ontario, Canada. The index is a province-wide and simple-to-use winter severity index that effectively explains temporal and spatial variations in winter road maintenance activities. Based on the previous studies and data availability, six weather conditions were selected for inclusion in the index:1) Snowfall, 2) Road Weather Information System Pavement Warnings, 3) Rain with low temperatures, 4) Blowing snow, 5) Series of cold days, and 6) Warm weather adjustment factor. The first five conditions represent weather conditions that trigger the maintenance activity. The sixth variable is a warm-weather adjustment factor that represents the times of the year when the average mean temperature remains above freezing for an extended period and reduces daily weather severity.

   Rather than combining these conditions into a single equation, the authors designed the index such that each day during the study period is characterized as a single weather condition out of the six conditions and is provided the associated weather-severity score. The hierarchy of day's weather triggers is the same as the numerical order of the weather conditions listed. Accordingly, the daily weather scores were accumulated for a 14-day period that aligned with the reporting period of maintenance activities across all maintenance regions in Ontario. Thresholds and scores for each weather trigger were calculated using an optimization algorithm. The developed index was found to have a good fit with the maintenance activity across all maintenance regions in Ontario.

6. Weather index in Denmark [26, 41]

The Danish severity index, developed by Knudsen in 1994, uses meteorological data continuously available from a large network of road weather stations covering 13 out of 14 Danish counties. The frequency of daily instances of freezing road surface temperature, frost conditions, thaw and freeze cycles, snowfall, and snowdrifts are included in the index equations. The index is equation is:

$$WI_{Dane} = \sum_{Oct15}^{Apr15} WI_{DaneDay} \tag{1.5}$$

where

$$\begin{aligned}
WI_{DaneDay} =& x_{freeze}(1 + x_{frost} + x_{refreeze} + x_{snow} + x_{drift}) \\
x_{freeze} =& 1,\ if\ the\ road\ temperature\ is\ below\ 0.5^{\circ}C\ at\ any\ moment\ within\ a\ 24- \\
& hour\ period,\ otherwise\ 0. \\
x_{frost} =& the\ number\ of\ times\ the\ road\ temperature\ drops\ below\ 0^{\circ}C,\ provided \\
& that\ it\ is\ at\ the\ same\ time\ lower\ than\ the\ air\ dew\ point\ for\ at\ least \\
& 3\ hours,\ with\ an\ interval\ of\ at\ least\ 12\ hours \\
x_{refreeze} =& the\ number\ of\ times\ the\ road\ temperature\ drops\ below\ 0^{\circ}C \\
& (from\ at\ least\ 0.5^{\circ}C\ to\ \breve{}0.5^{\circ}C)\ within\ a\ 24-hour\ period. \\
x_{snow} =& 1, if\ a\ snowfall\ of\ at\ least\ 1\ cm\ is\ reported\ within\ a\ 24-hour\ period, \\
& otherwise\ 0. \\
x_{drift} =& 1,\ if\ some\ noteworthy\ snowdrift\ has\ occurred,\ otherwise\ 0.
\end{aligned}$$

The parameters $x_{refreeze}$, x_{frost} and $x_{refreeze}$ are averaged over all road weather stations within a county. With this, daily values of severity indices are calculated for individual counties.

7. Noriks index for Norway [29]

   The Noriks index is developed to accurately represent the weather and climate conditions in the Norwegian climate. The index equation is:

$$NORIKS = [Temperature\, rise + Temperature\, Fall + Precipitation + Drifting\, snow] \tag{1.6}$$

   The elements in the equation represent the frequency of instances of different weather conditions. Temperature rise represents the number of instances of an increase in temperature. Such increasing temperature can occur in connection with a change from cold and clear weather to cloudy and humid weather leading to frost formation. Temperature fall gives information on the frequency of cases when the lowering road surface temperature drops below freezing and leads to ice formation or frost formation in case of decreasing air humidity. Precipitation term represents snow, snow mixed with rain, and freezing rain. Drifting snow represents conditions when the loose snow along the road is swept with the blowing wind. The three key elements define a snowdrift event: 1) occurrence of snowfall, 2) air temperature remains below freezing and no rainfall, and 3) wind speed during a 24-hr period exceeds 7 m/s.

8. GAB index for Sweden [17]

   The GAB index is based on three weather parameters: snow, frost, and black ice. The index equation is:

$$GAB = A * snow + B * frost + C * blackice \tag{1.7}$$

   Snow includes snow or rain events occurring below 0 ℃ are considered. Frost is the number of occasions with risk of frost formation, for at least a 2-hr duration with a time interval of at least 4-hr. Black ice is the number of occasions when the temperature drops from above 0 ℃ to below 0 ℃ and the road surface remains dry. The parameters A, B, and C take a value of either 0 or 1 depending on whether or not the respective criteria are satisfied. The daily GAB values can be summed up for the entire season or a short period to accumulate the severity. The index also offers flexibility to change the influence of the three weather parameters on maintenance activity by treating the parameters A, B, and C as weights.

Common Weather events and variables used in context of winter road maintenance

Winter road maintenance agencies develop the WSIs to represent winter's severity accurately. They incorporate parameters that pertain to characteristic weather conditions that lead to snow and ice formation on roads. As a general rule, WSIs are designed to reflect the relative importance of weather events and their severity on road maintenance. Point-based indices, such as AWSSI, design the point assignments to reflect the relative importance. Some indices use relative weights to achieve the same. SHRP assigns 35%, 35%, and 30% to temperature index, snowfall, and frost, and the weights reflect relative importance in maintenance cost. GAB index assigns weights to reflect the influence of snow, frost, and black ice on maintenance activity.

The inclusion of weather parameters in indices varies with the differing perceptions of the severity and the prevalence of winter weather conditions in the target region. Table 1.1 shows the winter weather conditions included in the indices discussed.

Index	Weather events included
Maine DOT [30]	Snowfall, Freezing rain, Low temperature
SHRP [4]	Snowfall, Low temperature, Likelihood of frost
Illinois DOT [8]	Snowfall, Freeze
AWSSI [32]	Snowfall, Snow depth,Low temperature
$WI_{Ontario}$ [31]	Snowfall, Freeze, Rain with low temperature, Blowing snow, Series of cold days
$WI_{Denmark}$ [26]	Snowfall, Freeze, Refreeze, Frost, Snow drift
NORIKS [29]	Snowfall, Rain, Freeze and thaw, Snow drift
GAB [16]	Snowfall, Rain, Frost, Black Ice

Table 1.1: Winter Severity Indices and weather events included.

Snowfall is a significant critical weather event and is recognized in all the indices. Cold temperature is also recognized, followed by freezing events and frost. Freezing rain occurs when snowfall passes through a thick, warm layer above a thin layer of freezing air. Such raindrops immediately freeze after contact with pavements forming a layer of ice. The formed ice layer appears white or translucent due to the entrapped air. Both near-freezing temperature and precipitation variables are included to identify freezing rain events. Freeze events occur when the temperature reaches a freezing point and freezes moisture already present on the road. Frosting results from the water vapor present in the air when the air temperature reaches the dew point. The ice layer formed is transparent and is termed black ice. Snowdrift represents the events when the snow is carried by blowing wind carrying snow onto the road surface.

Weather variables	Parameters included in index computation
Temperature	Minimum, maximum and mean air temperature Road surface temperature Dew point temperature
Precipitation	Amount of snowfall or rainfall Duration of snow fall or rainfall Snow depth accumulation Frequency of days with snow or freezing rain Frequency of days with light, medium and heavy snowfall
Wind	Wind speed

Table 1.2: Weather variable and their representative parameters in WSI.

The meteorological variables and parameters common to the indices are shown in Table 1.2. Three significant meteorological variables in use are temperature, precipitation, and wind. Temperature and precipitation are the most versatile meteorological variables in the index computation. Temperature-based parameters like minimum, maximum, or mean air temperature and, at times, road surface temperature are compared against freezing temperature, 32° F or 0° C, to determine if freezing events occurred during a particular day. Dew point temperature and minimum air temperature have been used to determine the occurrence of frost. As for precipitation, the amount, duration, or intensity of all the forms are used: snowfall, rainfall, and freezing rain. The frequency of days with these precipitation events is also included. Wind speed is used to determine visibility severity from drifting snow.

1.4 Related work in relating indices to winter road maintenance

Numerous past studies have focused on relating winter maintenance with meteorological data and severity indices. The objective is to evaluate degree of maintenance activity and cost and minimize the resources and expenses. The SHRP index, developed to relate to winter highway maintenance in the United States, showed strong relation to maintenance cost data at 40 states from 1985/86 to 1988/89 [4]. Gustavsson (1996) compared three different winter severity indices: the modified Hulme index [45], the COST 309 winter index [48] and the GAB [17] index used in Sweden, in relation to winter road maintenance but concluded that none of the indices fully explained the maintenance activity [16]. Another study used various indices based on snowfall amount and frequency of sleet observations, black ice formation, freezing rain, and frost formations in Finland; however, the equations developed did not perform satisfactorily in all regions [28].

With innovations in measuring real-time road surface conditions, severity indices that require continuous road weather data are being introduced. These, however, prevent the applicability of models to regions with only basic meteorological stations. In this setting, Venäläinen (2001) experimented with estimating the road salting cost in Finland by using only air temperature, which is reliably measured at most stations [47]. Linear regression models developed using monthly air temperature provided reasonable estimates of annual salting amounts with 60% variance explained.

The need for road salt application primarily stems from the severe winter weather conditions. As such, any variances in patterns of the winter weather itself can bring about variability in the patterns of road salt application. The link between changing patterns of the wintertime severity and road salt application in recent years, brought upon by climate change, can help make informed salt application decisions. The WSIs can be applied in assessing the spatio-temporal variations in winter weather. Several state DOTs apply severity indices to compare maintenance cost geographically and temporally.

1.5 Objective of Thesis

This research aims to understand the cause and effect relation of road salt with winter weather and associated groundwater contamination in Maine. The first objective of the work is to study the spatial and temporal patterns in historical (1991-2020) winter weather severity in Maine. A suite of established severity indices, AWSSI, SHRP, Illinois Salt days index, and Accumulated Freezing Degree Days (AFDD), is calculated at 12 stations and analyzed for this. Given that extreme weather events govern the road salt application, weather triggers for road ice and snow accumulation are also included. The indices and weather events are estimated using the basic daily meteorological variables, such as snowfall, rain and ambient air temperature.

The second objective is to characterize the appropriateness of the indices, events, and patterns on road salt application. The influence of indices and events on historical road salt amounts is studied. The results are used to suggest a suitable model that would adequately explain road salt use in Maine.

Finally, the third goal is to assess chlorides (Cl) levels on groundwater wells in Maine using well-sampling tests from 2001 to 2020. Incidence of wells exceeding Cl thresholds is used to estimate local risk to surrounding wells. The influence of hydro-geological factors in the mobility of road salt away from roads to groundwater systems is discussed.

The organization of the remaining chapters is as follows. Weather and road salt-related analyses are discussed in Chapter 2. The groundwater contamination assessment is provided in Chapter 3. Chapter 4 discusses the findings of this research, the perspectives for future research, and summarizes the major contributions and conclusions of the work.

CHAPTER 2
ROAD SALT USE ANALYSIS IN THE CONTEXT OF CHANGING WINTER WEATHER CONDITIONS

2.1 Introduction

An in-depth understanding of historical patterns in WSIs, with high salience towards winter road salt use, can help better understand the historical salt use patterns. This information is vital for working towards efficient salt application decisions and anticipating and adapting to potential impacts on water systems. At present, Maine DOT uses the point-based index, AWSSI [32], to compare seasonal severity with winter road maintenance cost and materials [10]. AWSSI offers an advantage over other indices in adjusting for longer/ shorter or offsets winter seasons by implementing sets of criteria to estimate the winter onset and end date. The index is relatively new in traffic safety and winter road maintenance. As such, the long-term performance of the index, especially in the context of winter road salt, has not been explored yet.

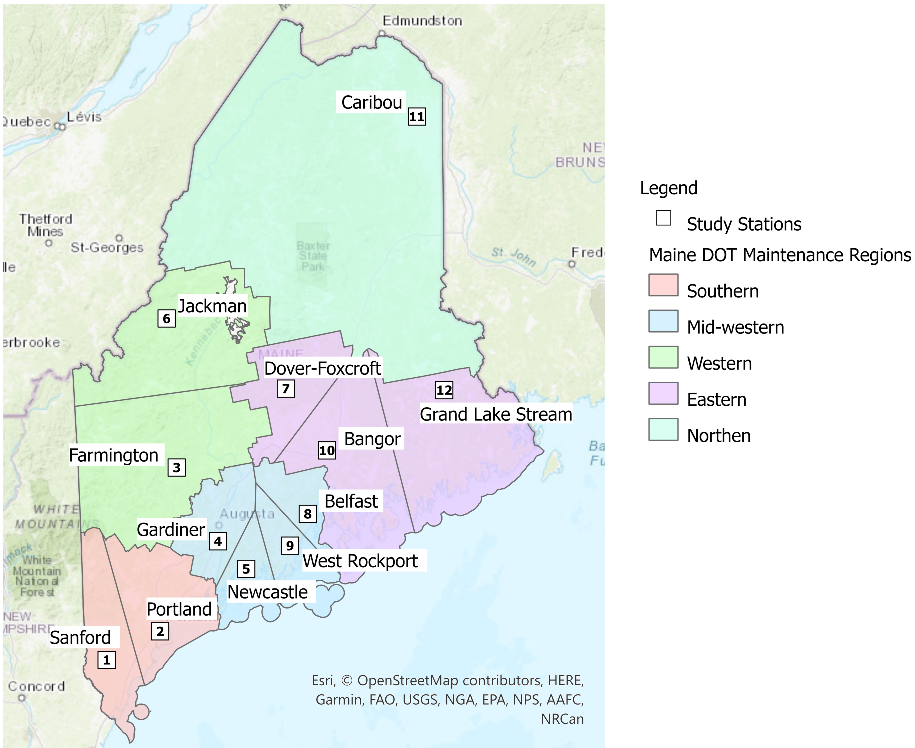
This chapter aimed to provide insight into the appropriateness of AWSSI and three other established indices: SHRP, Illinois Salt Days Index, and Accumulated Freezing Degree Days (AFDD), to Maine's climate and road salt application. The index SHRP [4] was developed to reduce winter maintenance costs on U.S. highways in general. Similarly, the Salt Days index [8], developed for Illinois DOT, was built to relate to winter road salt application in specific. AFDD measures how long and cold it has been. Additionally, given that much of the salt use is carried out on an event-by-event basis; the count of weather situations is a critically important measure of the severity. Hence, the weather events and their influence on road salt will be discussed.

In addition to winter weather, the variability in road salt use is induced by non-weather factors such as changing road salt practices, increasing winter road maintained miles and increasing the level of service for winter road maintenance. Thus models for road salts based solely on weather indices are incomplete. To overcome this, we present a method of combined models that linearly combines estimates from individual WSI models to improve accuracy.

The historical severity data at multiple stations presents challenges for analysis due to the high dimensions and inherent multi-collinear severity values. The method of Principal Component Analysis (PCA) can be used with high dimensional data to aid in data visualisation and subsequent data analysis. It re-expresses multivariate data into new sets of uncorrelated features that preserve most of the available information in the first few features and can be used in regression analysis. The results from PCA can also be analyzed to study the spatial and temporal patterns in the original variables.

Likewise, the information on trends of the weather indices and various weather conditions across the state help authorities anticipate salt use decisions. The trend analysis is performed using Quantile Regression (QR) and quasi-Poisson Regression approach. These approaches are discussed in detail later in the chapter. To summarize, the main contributions of this chapter are:

- Characterizing principal patterns of space-time variability in winter severity and their relationship with road salt use,
- Combined WSI model to forecast road salt use for improved accuracy
- Investigating quantile specific trends to study and identify any diverse trends across the distribution of indices,
- Understanding the trends in the frequency of winter weather conditions prevalent in Maine



In regions with more than one meteorological station, smaller areas were delineated using Thiessen polygons.

Figure 2.1: Study station located across Maine DOT maintenance regions.

2.2 Study Area and Data

The data used for this study consists of salt and climate data from 1991 to 2020. Seasonal salt use data are obtained from Maine DOT [10] and reflected only Maine DOT's share of winter material use. Climate data consists of daily meteorological data recorded at GHCN (Global Historical Climate Network) stations across Maine [34]. The data are accessed from the cli-MATE online data portal [7]. The meteorological data are collected at 12 weather stations in Maine: 1) Sanford, 2) Portland, 3) Farmington, 4) Gardiner, 5) New Castle, 6) Jackman, 7) Dover-Foxcroft, 8) Belfast, 9) West-Rockport, 10) Bangor, 11) Caribou and 12) Grand Lake Stream.

Additionally, daily mean temperature, minimum dew point temperature, and precipitation values for the stations are obtained from PRISM Climate Data [38]. These additional data contribute to the estimation of frost events. Locations of the study stations across Maine DOT maintenance regions are shown in Figure 2.1. We divide the DOT maintenance regions into smaller sub-regions by constructing Thiessen polygons around the weather stations. The regional severity is computed using weather data at the station.

Selected Weather Triggers for Road Salt Application in Maine

Ice formations on road surfaces result from freezing temperatures and moisture (water) availability on the surface. Although road ice formation during snowfall and rain is typical, moisture from the groundwater seepage and snow that had initially melted on the warm road surface also form ice if the temperature lowers below freezing. In this study, four events leading to road ice formations are used to study their influence on road salt use in Maine.

- Freezing rain days

  When falling rain passes through a below-freezing air layer near the road surface, it freezes into clear glaze ice as soon as it hits the road. Parameters corresponding to freezing rain are included in several state DOTs indices, including past indices developed for Maine DOT. In this study, freezing rain days correspond to the days that receive rainfall and have daily mean air temperatures near freezing $(25°F - 32°F)$.

- Frost days without precipitation

  To account for the events when the moisture from roadside snow or groundwater seepage leads to road ice formations, we consider frost day events without precipitation. These are computed as the days when the minimum air temperature and mean dew point temperature are below freezing temperature $32°F$.

- Snow days below and above freezing temperatures

  Snow events are split into two sub-events to investigate the influence of snow days during freezing and non-freezing conditions separately.

2.2.1 Calculation of Severity Indices

Seasonal values of all winter severity indices and events, shown in Table 2.2, are calculated at 12 stations for each winter from 1991 to 2020. AWSSI, SHRP, and Salt days are calculated using the computation methods described in the literature review. The formula is presented in Table 2.1. The AWSSI index computation is based on estimated winter onset and cessation day for each seasons during the study period. The criteria for start and end period along with obtained seasonal length are presented in Appendix A.1.

Accumulated Freezing degree days are calculated as a sum of average daily Fahrenheit degrees below freezing for the winter season. Daily accumulated snowfall below 4 inches is classified as light snowfall, snowfall between 4 and 12 inches as moderate snowfall, and that above 12 inches is considered heavy snowfall in this study.

This study defines freezing rain days as days with more than trace rainfall and average air temperature between $25°F$ to $32°F$. Frost days without precipitation are described as days with zero precipitation(snow and rain) and minimum air temperature below the mean dew point temperature. Snow days during freezing and non-freezing temperatures are calculated as days with snow during and or above the freezing range ($25°F$ to $32°F$). Table 2.2 shows the meteorological variables used in the computation for indices and metrics.

Indices	Computation Formula
AWSSI [32]	$AWSSI = \sum[Daily\ Temp\ Scores + Daily\ Snow\ scores]$, where $Daily\ Temp\ score = T_{min}\ score + T_{max}\ score$ $Daily\ Snow\ score = Snowfall\ score + Snow\ depth\ score$
WI_{SHRP} [4]	$WI_{SHRP} = -25.58\sqrt{T_{index}} - 35.68ln(\frac{S_{daily}}{10} + 1) - 99.5\sqrt{\frac{d_{freez1}}{T_{range1}+1}} + 50$, where $t_{seasonindex} =\ Average\ t_{dayindex}\ over\ season, (0 <= t_{seasonindex} <= 1)$ $t_{dayindex} = 0, T_{min}\ is\ above\ 32^oF$; 1, if $T_{max} > 32^oF$ while $T_{min} <= 32^oF$; 2, if $T_{max} <= 32^oF$ $S_{daily} = Mean\ daily\ values\ of\ snowfall\ (millimeters)$ $d_{freeze1} = Mean\ daily\ values\ of\ no.\ of\ days\ with\ T_{min} <= 32^oF$ $T_{range1} = Mean\ monthly\ T_{max} minus\ the\ Mean\ monthly\ T_{min} (^oC)$
Illinois Salt days Index [8]	$Salt\ days = D_{snow} + D_{cold}$, where $D_{snow} = Number\ of\ days\ with\ snowfall > 0.5 inches$ $D_{cold} = Number\ of\ days\ with\ T_{mean} between\ (15-30)^oF$

Table 2.1: Computation formula for indices AWSSI, SHRP Index and Illinois Salt days index.

Indices	Items	Precipitation			Air Temperature			
		Rainfall	Snowfall	Snowdepth	Minimum	Maximum	Mean	Dew point
Winter Severity Indices	AWSSI	-	x	x	x	x	-	-
	SHRP	-	x	-	x	x	-	-
	Illinois Salt day Index	-	x	-	-	-	x	-
	AFDD	-	-	-	-	-	x	-
Weather triggers	Freezing rain days	x	-	-	-	-	x	-
	Snow days with freezing temperature	-	x	-	-	-	x	-
	Snow days with non--freezing temperature	-	x	-	-	-	x	-
	Frost days	-	-	-	x	-	-	x
Snow days	Light snow (less than 4 in.)	-	x	-	-	-	-	-
	Moderate snow (between 4 and 12 in.)	-	x	-	-	-	-	-
	Heavy snow (greater than 12 in.)	-	x	-	-	-	-	-

Table 2.2: Study indices and metrics with the meteorological variables included in the computation.

2.3 Methods

2.3.1 Principal Component Analysis (PCA) of indices

The method of PCA has two essential applications. First, it can identify, through a reduction of data, the recurring and independent modes of variation within an extensive, noisy data set, thereby summarizing the essential information of the data set so that the meaningful and descriptive conclusions can be made [19]. Second, the analysis sorts the initially correlated data into new variables, designated as Principal Components (PCs), which are linear combinations of the original variables. The linear transformation is performed so that the most significant variance in the initial data is found on the first principal component, and each subsequent component is orthogonal to the last and has a lesser variance. In this way, the PCs obtained are uncorrelated and ordered so that the first few components retain most of the variation present in all of the original variables. PCA is adopted in this study since it helped reduce the winter severity indices available at 12 study stations to a few uncorrelated variables that still represent the original severity variation in the data.

Below is a brief description of the computation involved in PCA:

With the data matrix for an index, i, with a dimension of 12 variables (stations) and 30 samples (years), the data are first centered on the means of each variable. The first principal component (Y_1) is defined by the linear combination of the initial variables X_1, X_2, ...,X_{12} as

$$Y_1 = a_{1\,1}X_1 + a_{1\,2}X_2 + ... + a_{1\,12}X_{12} \tag{2.1}$$

The first principal component is calculated to account for the greatest possible variance in the data set. This is obtained by choosing large values for weights $a_{1\,1}, a_{1\,2}, ...a_{1\,12}$ with the constraint that their sum of squares is 1.

$$a_{1\,1}^2 + a_{1\,2}^2 + ... + a_{1\,12}^2 = 1 \tag{2.2}$$

The second principal component is calculated in the same way, with the condition that it is uncorrelated with (i.e., perpendicular to) the first principal component and accounts for the next highest variance.

$$Y_2 = a_{2\,1}X_1 + a_{2\,2}X_2 + ... + a_{2\,12}X_{12} \tag{2.3}$$

This continues until 12 principal components have been calculated, equal to the original number of variables. The sum of variances in all principal components will equal the sum of the variances of all of the variables. That is, all of the original information has been explained or accounted for. It is essential to note that the new variables, or principal components, are mathematical and do not necessarily have to have physical relevance.

Using Horn's Parallel Analysis criterion [22], the number of components to be retained to capture maximum variance in the selected indices is either only one or two. Thus, the first two components, which represent the severity at 12 stations, are retained for each index. The PCA results are then employed in subsequent analyses as discussed below.

2.3.2 Spatial and temporal patterns in winter severity in Maine

The PCA solution of an index comprises two results: 1) new uncorrelated principal components for the historical period, and 2) rotated principal component loading scores from the original variables. The loading scores, representing the weight from original variables, highlight varying contributions from multiple stations towards combined severity. The scores provide information on spatial patterns of severity existent between the stations. The time series of the first two retained PCs help understand the temporal trend in weather variability.

2.3.3 Winter Severity Indices and Road Salt Use

Multiple Regression models are fit for natural log-transformed salt use data using the retained principal components of the individual WSIs as the explanatory variables. An upward temporal trend component' Year' is also added to account for changing baselines linked to deicing practices and level of service in winter road maintenance over the years. The equations for the regression model are:

$$Model\ 1 : log(Salt) = \beta_{01} + \beta_{11} AWSSI\ PC1 + \beta_{21} AWSSI\ PC2 + \beta_{31} Year$$

$$Model\ 2 : log(Salt) = \beta_{02} + \beta_{12} SHRP\ PC1 + \beta_{22} SHRP\ PC2 + \beta_{32} Year$$

$$Model\ 3 : log(Salt) = \beta_{03} + \beta_{13} Illinois\ Salt\ days\ index\ PC1 + \beta_{23} Illinois\ Salt\ days\ index\ PC2 + \beta_{33} Year$$

$$Model\ 4 : log(Salt) = \beta_{04} + \beta_{14} AFDD\ PC1 + \beta_{24} AFDD\ PC2 + \beta_{34} Year$$

The model performance, coefficient and significance of predictors are studied to understand relation between weather, non-weather factors and road salt use.

2.3.4 Influence of selected weather events

To measure the influence of the selected weather triggers, we fit log-transformed linear regression models for road salt with the retained PCs of the weather events without any component for non-weather factors. The general regression equation fitted for the seasonal frequency of a weather event, i, is:

$$log(Salt) = \beta_{0i} + \beta_{1i} * Weather\ event\ PC1 + \beta_{2i} * Weather\ event\ PC2$$

2.3.5 Linearly combined WSI models

Several non-weather factors, such as changing maintenance practices over the years, can bring variability in road salt use. Due to the challenges in quantifying the non-weather factors, road salt models based solely on weather severity are often of interest. The individual WSI models perform differently due to varying winter weather conditions considered in the index. As an alternative, several incomplete WSI-based models can be combined linearly to improve accuracy. The constrained least-squares regression combination method [2, 14, 36] facilitates a linear weighted combination of individual models, with the weight adding up to unity. This combination weighs in the accuracy over explainability of models. The weights represent the relative contribution from individual models.

The development structure of AWSSI is such that it assigns severity points based on the minimum and maximum temperatures and snow depths. However, it does not address the severity of freezing rain and frost days. Accordingly, we select the leading components from the index AWSSI and weather events, freezing rain days and frost days without precipitation, and build three regression models. Three combinations of the individual models are developed and tested using a randomly split train and test data set, using the train-test split ratio of 2:1. The final combined model is selected using the Root Mean Square Error (RMSE) criterion.

2.3.6 Nature of changing winter weather severity

For trend analysis, we consider seasonally accumulated snowfall amounts and seasonal events of light, moderate, and heavy snow days and indices adopted in earlier analyses. Given the continuous and discrete types of variables, two regression approaches are adopted.

2.3.6.1 Method of Quantile regression analysis

Quantile Regression (QR) is adopted to study the long–term trends in continuous weather indices across different severity levels. Developed by Koenker and Bassett in 1978 [27], QR estimates the functional relationship between predictor variables and any user-selected quantile in the response distribution. A traditional linear regression, suited to estimate the conditional mean, has its assumptions rooted in constant variance and thus fails to acknowledge any variability across the distribution of the response variable. The linear regression assesses the symmetric changes in response variables assuming trends observed in the mean are equivalent to trends across the distribution. On the other hand, quantile regression provides estimates of any conditional quantile of a response variable without any restrictions on the distributional variance. It allows for appraising and identifying any conflicting trends in the median, and lower and upper quantiles that signify the extremes of the distribution. QR proves advantageous over conventional regression in this study because it can detect trends in statistical extremes as maintenance measures often need to be considered at different severity levels. For example, since the degree of winter severity goes hand in hand with the degree of maintenance activity carried out, any refined information on trends in the distribution of weather extremities is particularly useful in allocating and optimizing maintenance resources.

Quantile regression at 0.1, 0.2, 0.3, 0.4, 0.5 (median), 0.6, 0.7, 0.8 and 0.9 are performed using a temporal trend component ' Year ' as the predictor variable. The QR is carried out for individual indices at each of the 12 weather stations. The general form of the fitted model at any quantile, τ, at a station, S, is:

$$WSI^S = \beta_{0\tau}^S + \beta_{1\tau}^S * Year$$

2.3.6.2 Method of Poisson Regression analysis

Count indices that represent the frequency of weather events are studied for long-term patterns using Poisson regression models. The method of Poisson regression is a generalized linear model where the log conditional expected response given the covariates can be expressed as a linear combination of the covariates and a noise term, that is,

$$logE(Y|X) = \beta_0 + \sum_{k=1}^{n} \beta_k x_k + e$$

,

where Y is the response variable, X1, X2, . . . , Xn are the covariates and e is the noise term. The response is a variable of count data and is assumed to be Poisson distributed. The Poisson model is based on assumption that the mean and variance of the the response variable are equal. The equidispersion in the data were checked by using the dispersion parameter (values shown in Appendix B).

Based on the values of dispersion parameters (see Appendix A.5), the weather count data are found to be either under or over-dispersed. A quasi-Poisson regression, a special case of Poisson regression, is adopted due to the unequal mean and variance in the indices.

Multiple models of quasi-Poisson regression are performed with count indices as the response variable and time(year) as the explanatory variable. A positive coefficient estimate for the predictor variable 'year' implies increasing counts of weather events variable with time and vice versa.

Negative Binomial is another popular method for modeling over-dispersed data. While quasi-Poisson models assume a linear relationship between mean and variance of the response variable, negative binomial models the relation as quadratic. The coefficients obtained from quasi-Poisson are compared with those from negative binomial (see Appendix A.6) as a cross-check.

2.4 Results and Discussion

2.4.1 PCA and spatio-temporal variability in weather severity

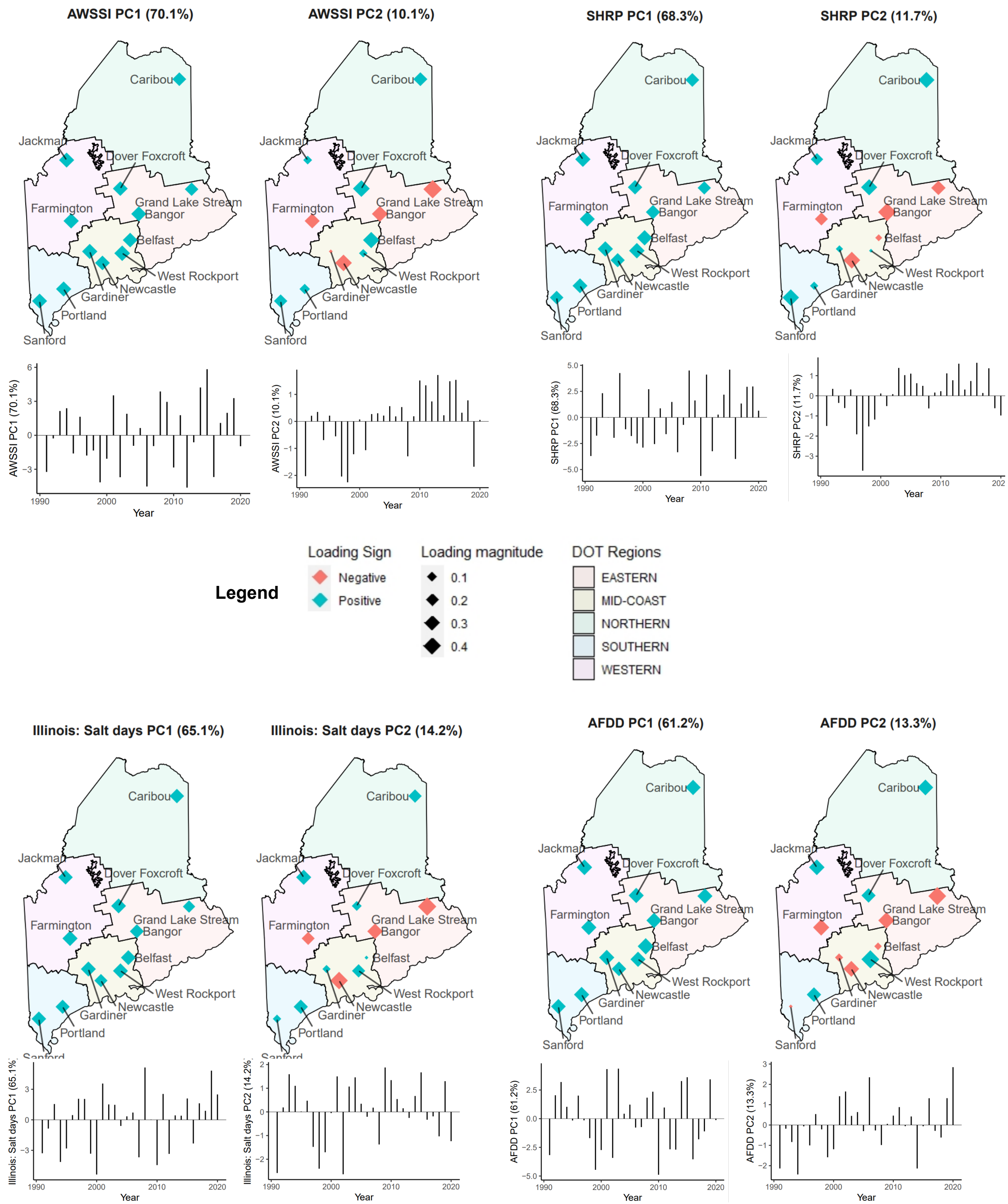
Indices/Weather events	% Var PC1	%Var PC2	%Var Total
AWSSI	70.10	10.10	80.20
SHRP	68.30	11.70	80.00
Illinois: Salt days	65.10	14.20	79.30
AFDD	61.20	13.30	74.50
Freezing rain days	46.00	13.50	59.50
Freezing snow days	43.10	12.80	55.90
Snow days above freezing temp	57.50	10.40	67.90
Frost days without precipitation	74.50	6.50	81.00

Table 2.3: Percentage variances explained by retained first two components

Table 2.3 shows the percentage of variances explained by the retained principal components. The leading two components for AWSSI, SHRP, and Salt days cumulatively explain almost 80% of variation in original data. The variance is slightly less (75%) for AFDD. The cut-off of cumulative 70% variation is common to retain in the PCs for analysis. Thus PCA solution obtained for the indices is a good representative of the original index data. Consequently, we use the PCA solution of WSIs to examine spatial and temporal patterns in weather severity. The cumulative variances are much lower (less than 70%) for three of four seasonal event counts. The lower variance implies that the components capture less information from the data.

The spatial and temporal mapping of the two leading components of severity indices highlight patterns of long-term changes and year-to-year variability in the winter weather from 1991 to 2020. Figure 2.2 presents the spatial mapping of the loading scores, both within and across the DOT maintenance regions, and time series plots of PCs for four WSIs. In all four indices, the time series of the leading component, PC1, shows oscillations every 2-3 years. The PC1 loadings from all 12 weather stations are positive and almost equal, suggesting all weather stations exhibit similar short-term variability in winter severity.

For the second component, PC2, the loadings from weather stations are unequal and opposite in signs. Three stations near the coast (Grand Lake Stream, Bangor, Newcastle) and one station in the mid-east (Farmington) show consistent negative loadings for all four indices. In addition, the time series of PC2 for AWSSI and SHRP exhibits distinct long-term trends with mostly higher values in the latter half of the analysis period. The PC2 values at the four stations seem to be decreasing, implying dissimilar weather variability and road salt burden compared to the rest stations. The exact nature of dissimilarity (increase- decrease or vice versa) between the severity at stations can be interpreted using the relations established between salt use and the components, which is explored in the section 2.4.2.



Blue and red diamond shapes represent positive and negative loadings.
The size of the diamonds represent the magnitude of loadings.

Figure 2.2: Spatio-temporal patterns in Index PCs during 1991-2020.

Correlation between index PCS

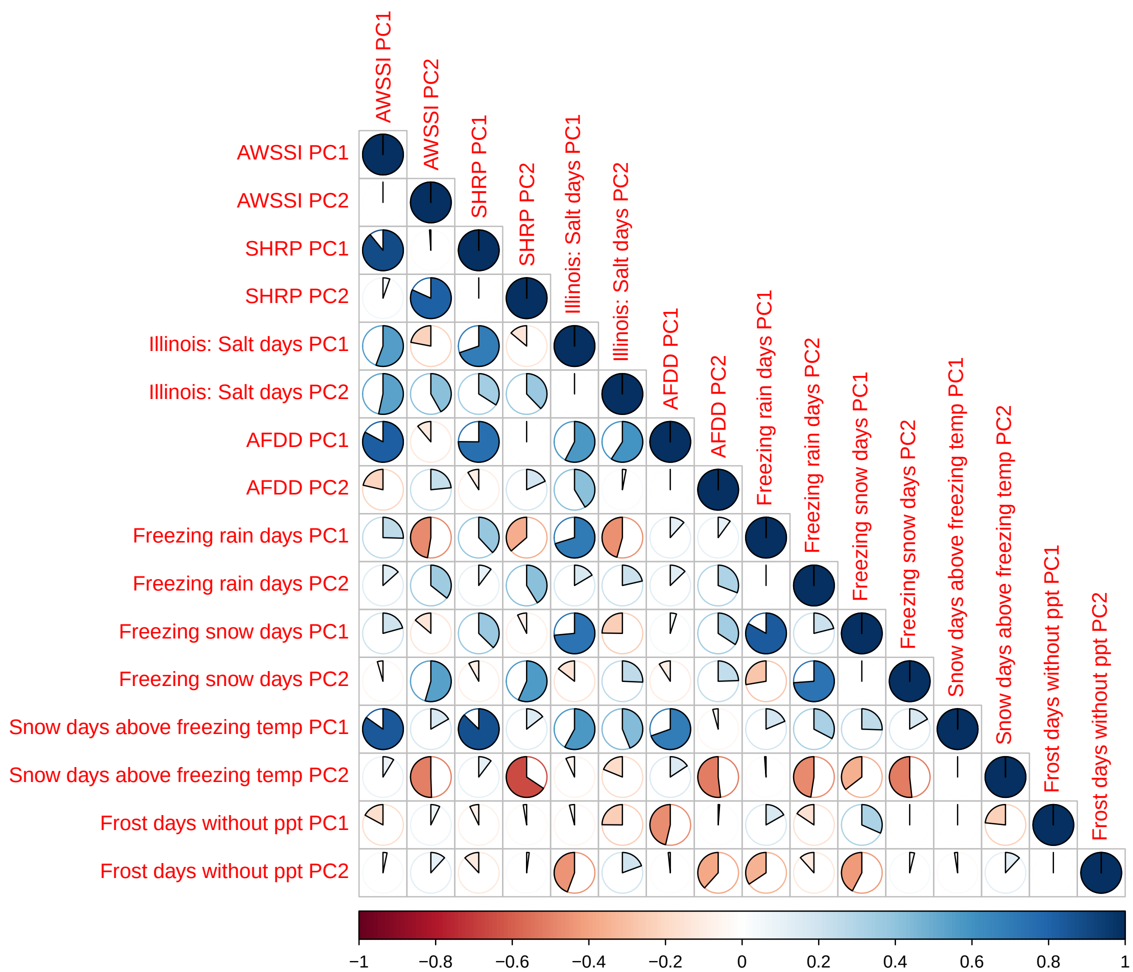


Figure 2.3: Correlogram for WSI PCs. Proportion of correlation is indicated by individual pie.

Figure 2.3 plots the correlation between the two leading components of all the indices and weather events. The PCs of AWSSI show a strong correlation with SHRP PCs (more than 75% among both PC1s and PC2s). Even though freezing rain events are not incorporated in AWSSI by design, the PCs of AWSSI and Freezing rain days show a fair correlation. The weakest correlation of AWSSI PCs is observed with those of Frost days without precipitation.

2.4.2 Road salt use, weather and non weather factors

The results from the linear regression of log-transformed road salt use are shown in Table 2.4. All four models explain at least 80% of statewide road salt use variation from 1991 to 2020. These models have both Index PCs and a temporal trend as the predictors. The trend represents changing baselines linked to deicing practices and level of service. Both the first PC and trend component significantly explain salt use variations across all models. The model based on PCs from AWSSI explains the most salt use variation of 84.5%. Both PCs and long-term trend are significant (p-value$<$0.01) for estimating salt use.

The coefficients from regression suggest that every year from 1991 to 2020, there is an almost 3% increase in road salt use if weather severity is constant. Similarly, a unit increase in PC1 results in a 2.6% increase, and that in PC2 results in a 7.5% decrease in salt use if other predictors are held constant.

Interestingly, the second principal component has a negative coefficient in the model, suggesting salt use increases with a decrease in PC2. When we look back at the spatio-temporal patterns in PCs in Figure 2.2, the four stations (New Castle, Farmington, Bangor and Grand Lake Stream), with negative loading on PC2 show increasing severity and high salt burden compared to rest stations in the latter years.

The four weather event triggers show varying degrees of relationship with salt use (see Table 2.5). The frequency of frost days without precipitation explains only 11.2% salt use variation. Higher variances (around 58%) are accounted for through snow days both below and above freezing temperatures. The relative differences in the strength of the relationship also highlight that the weather triggers, when taken together, represent the broader array of winter weather situations that require snow and ice control operations.

Model pc predictors	% Var PC1	%Var PC2	Regression Analysis 1991-2020			
			PC1 coeff.	PC2 coeff.	Year coeff.	R-squared %
AWSSI	70.10	10.10	0.026**	-0.072**	0.032***	84.50
SHRP	68.30	11.70	0.034**	-0.014	0.027***	82.10
Illinois: Salt days	65.10	14.20	0.033**	-0.016	0.026***	81.10
AFDD	61.20	13.30	0.030**	-0.032	0.030***	80.90

Table 2.4: PCA Regression results for log-transformed statewide road salt based on index pcs. Note: $p < 0.001$ (***); $0.001 < p < 0.01$ (**); $0.01 < p < 0.05$ (*); $0.05 < p < 0.1$ (+)

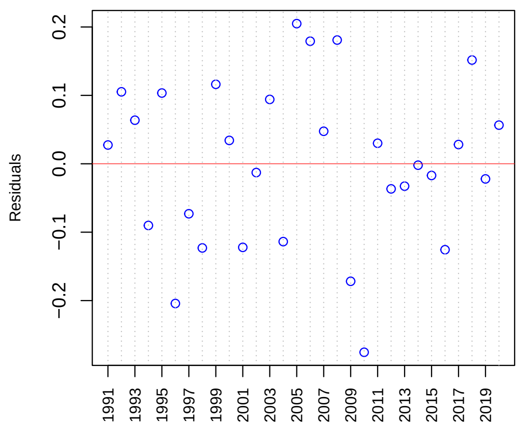
Model pc predictors	% Var PC1	%Var PC2	Regression Analysis 1991-2020		
			PC1 coeff.	PC2 coeff.	R-squared %
Freezing rain days	46.00	13.50	0.058**	0.111**	42.5
Freezing snow days	43.10	12.80	0.081***	0.109**	57.0
Snow days above freezing temp	57.50	10.40	0.068***	-0.132***	58.9
Frost days without ppt	74.50	6.50	0.032+	-0.034	11.2

Table 2.5: PCA Regression results for log-transformed statewide road salt based on weather events pcs. The significance of coefficients are as noted in Table 2.4

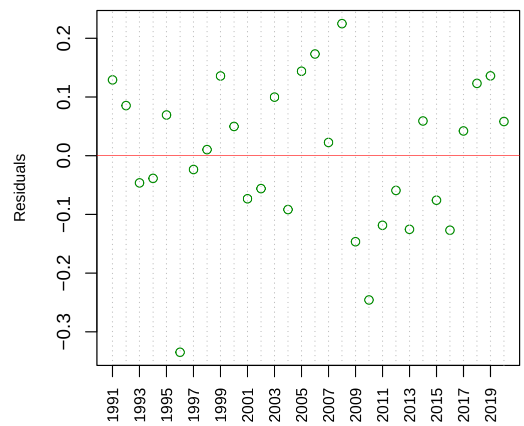
Residuals

The residual plot (Figure 2.4) highlights random nature of the WSI model residuals. The random patterns suggest that the linear models appropriately fit the data.

5

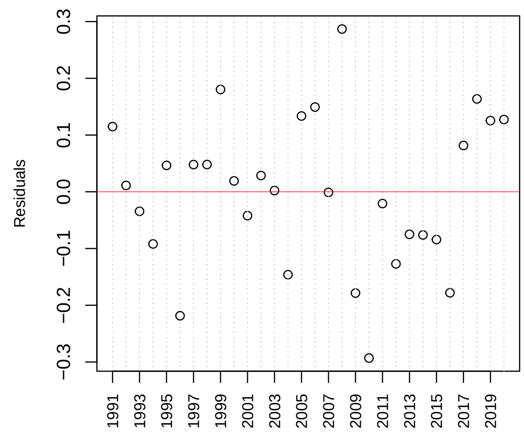


(a) Model1 (AWSSI PCs) : R^2 84.5%



(b) Model2 (SHRP PCs):R^2 82.1%

(c) Model3 (Illinois Index PCs):R^2 81.1%



(d) Model4 (AFDD PCs):R^2 80.9%

Each model also has a temporal component as predictor.

Figure 2.4: Road salt regression model residuals using PCs from four indices.

2.4.3 Combined WSI model

Models	Description
AWSSI	$log(Salt) \sim AWSSI\ PC1 + AWSSI\ PC2$
Freezing rain	$log(Salt) \sim Freezingrain\ PC1 + Freezingrain\ PC2$
Frost days	$log(Salt) \sim Frostdays\ PC1 + Frostdays\ PC2$

Table 2.6: Original regression model descriptions

Models	RMSE	Weights for		
		AWSSI	Freezing Rain	Frost days
Original				
AWSSI	0.292	1	-	-
Freezing rain	0.259	-	1	-
Frost days	0.314	-	-	1
Combined				
All three	0.247	0.2	0.7	0.1
AWSSI and Freezing rain	0.149	0.8	0.2	-
AWSSI and Frost Days	0.163	1	-	0

RMSE shown for test data.

Table 2.7: Weights and estimate errors: Individual and Combined models. Original model descriptions provided in Table 2.6

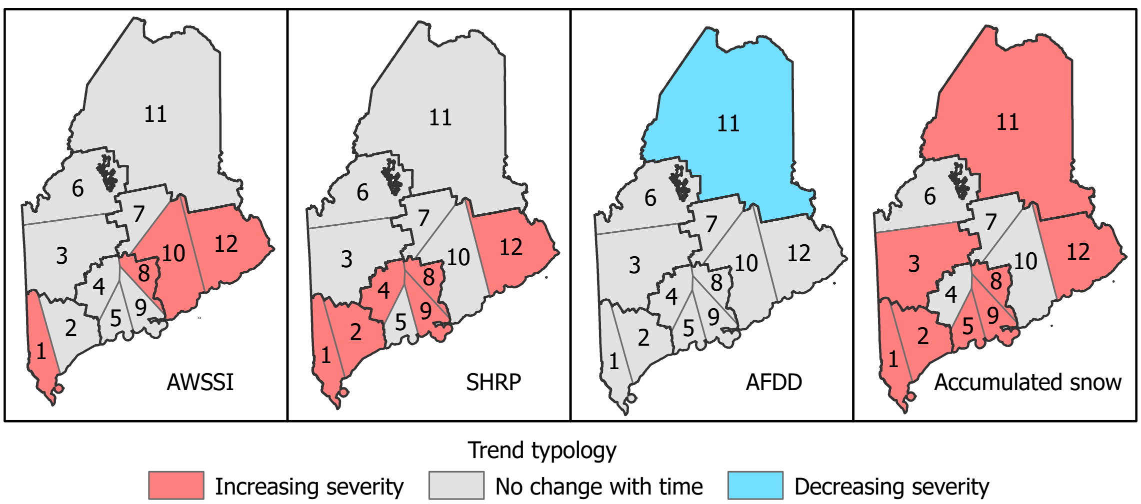
The combined model based on AWSSI model and Freezing rain days model shows much-improved accuracy over the individual forecasts (Table 2.7). There is a 48% reduction in the RMSE from original AWSSI model to the combined model. The combined model also shows the lowest RMSE among other candidate combined models. The relative weights of 0.8 and 0.2 are the percent contribution from individual models. The weighted linear average of AWSSI and counts of freezing rain days model can be beneficial to authorities in forecasting salting needs accurately and effectively planning the maintenance.

2.4.4 Quantile regression trends

The results for median quantile regression are discussed first followed by discussion on results for 0.2 and 0.8 quantile. Finally the QR results across all nine quantiles are presented.

Median trends

Figure 2.5 shows the median trend information in the Thiessen region of influence around the weather stations. Median trends in AWSSI and SHRP show increasing patterns in many coastal regions. Sanford (region 1), Belfast (8), and Grand lake stream (12) show an increase for both indices. Median AFDD has decreased over years in the northern region, but does not exhibit trend at other stations. The median seasonally accumulated snow increases broadly except for the mid-interior region.



Note: Only statistically significant trends (p value <0.1) are shown.

Figure 2.5: Trend analysis based on median quantile regression of three seasonal indices: a) AWSSI, b) SHRP, c) AFDD and d) Accumulated snow from 1991-2020 in Maine.

The positive and negative coefficients in Table 2.8 indicate an upward and downward trend in severity from 1991 to 2020. The magnitude measures the rate of change. Compared to the rest regions, Belfast shows escalating median AWSSI and SHRP over the years. Median AFDD decreases by 8.7 degrees Fahrenheit every year in the northern region. The average increase in median accumulated snow is 1.6 inches per year.

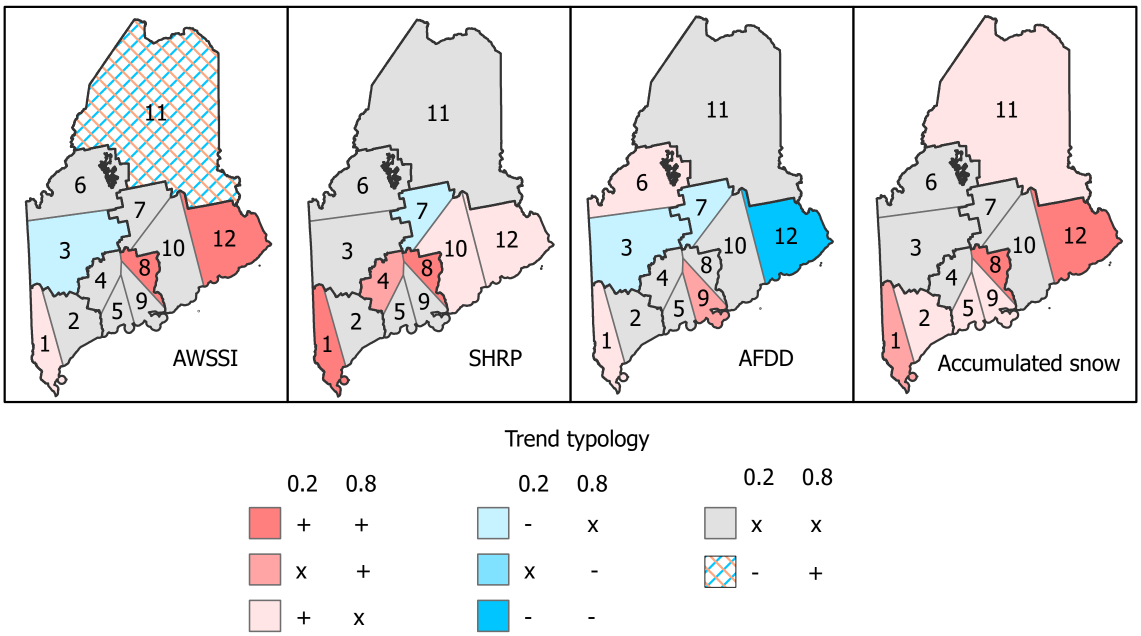
ID	Stations	AWSSI.0.5	SHRP.0.5	AFDD.0.5	Accsnow.0.5
1	Sanford	10.857 *	0.515 *	4.818	1.452 *
2	Portland	7.958	0.434 *	-0.386	1.772 *
3	Farmington	10.579	0.144	-3.375	1.322 *
4	Gardiner	3.211	0.39 *	-5.25	1.045
5	Newcastle	7.714	0.294	-7	1.787 **
6	Jackman	-2.5	0.086	-5.389	0.273
7	Dover-Foxcroft	3.143	0.191	0.467	-0.256
8	Belfast	23.556 **	0.599 **	5.238	1.9 **
9	West Rockport	0.625	0.507 *	12.827	1.819 **
10	Bangor	11.222 +	0.252	-5.773	0.621
11	Caribou	10.148	0.156	-8.711 +	1.477 **
12	Grand Lake Stream	15.056 **	0.318 *	-2.833	1.795 **

Note: $p < 0.001$ (***); $0.001 < p < 0.01$ (**); $0.01 < p < 0.05$ (*); $0.05 < p < 0.1$ (+)

Table 2.8: Median QR trends at 12 stations from 1991 to 2020. Coefficient and significance (p-value) of predictor year variable is shown.

Trends at 0.2 and 0.8 quartile

The results for upper and lower quantile regression are presented in maps in Figure 2.6. Magnitude and significance of the trends are separately presented in Table 2.9 and Table 2.10.



Note: Positive (+), negative (-) or not changing (x) trends obtained from quantile regression lower and upper quantiles of the indices are shown in the map.

Figure 2.6: Trends in lower (0.2) and upper (0.8) quantiles of seasonal indices: a) AWSSI, b) SHRP c)AFDD , and d) Accumulated snow from 1991 to 2020.

The trend typology for AWSSI index shows that the increases seen in median quantile regression are mirrored for the upper and lower quantiles for Belfast (8) and Grand Lake Stream (12). Sanford(1) shows increase in AWSSI at lower quantile (0.2). A conflicting trends in extreme quantiles is detected in Caribou. It shows increase at upper(0.8) tail and decrease for the lower(0.2) tail suggesting an increase in distributional variances of AWSSI from 1991 to 2020.

The typology for SHRP shows increase at upper quantile at Sanford, Gardiner and Belfast. SHRP trends at lower (0.2) quantile have increased at Bangor and Grand Lake stream.

The cold severity trend typology suggests incidences of lowering AFDD at 0.2 quantile at mid-interior regions (Farmington and Dover Foxcroft). This phenomenon is also reflected in decreasing lower quantile severity for AWSSI and SHRP in the two regions. Grand Lake stream shows decreased AFDD at both tails (0.2 and 0.8). AFDD is increasing at the upper tail in West Rockport and at the lower tail in Jackman.

Accumulated snow severity shows increase at both tails in Belfast and Grand lake stream. These results are consistent with trends in AWSSI. Regions Portland, Newcaslte, West Rockport, and Caribou show increase at the lower tails.

Upper quantile (0.8) trends

ID	Stations	AWSSI.0.8	SHRP.0.8	AFDD.0.8	Accsnow.0.8
1	Sanford	13.316	0.351 **	4.75	2.841 **
2	Portland	-3.941	0.239	-2.295	-0.575
3	Farmington	14.126	0.063	-1.821	0.932
4	Gardiner	-5.059	0.182 +	-1.733	-0.013
5	Newcastle	4.412	0.034	1.375	0.352
6	Jackman	5.385	0.054	-1.185	0.15
7	Dover-Foxcroft	9.105	-0.228 *	5	-0.743
8	Belfast	31.632 *	0.469 **	6.694	2.472 *
9	West Rockport	-0.318	0.141	8.433 *	0.536
10	Bangor	9	-0.221	3.757	0.8
11	Caribou	13.478 +	0.001	-8.159	0.73
12	Grand Lake Stream	28.958 *	0.259	-6.214 +	1.729 *

Note: $p < 0.001$ (***); $0.001 < p < 0.01$ (**); $0.01 < p < 0.05$ (*); $0.05 < p < 0.1$ (+)

Table 2.9: Upper(0.8) QR trends at 12 stations. Coefficient and significance (p-value) of predictor year variable is shown.

The upper tail trends in AWSSI, SHRP and Accumulated snow are all positive and upwards. Grand Lake stream showed negative trend in upper tails of AFDD. The highest increase for AWSSI and SHRP are observed in Belfast. West Rock shows highest increase for AFDD. The highest rate of accumulated snow, equal to 2.8 inches/year, is observed in Sanford.

Lower quantile (0.2) trends

Both upwards and downwards trend are observed at lower tails of AWSSI. Caribou (11) and Farmington (3), which do not exhibit trends at other quantiles, show downwards trend. Farmington shows steepest decline and Belfast show steepest rise in 0.2 quantile of AWSSI. The maximum rise SHRP is observed in Sanford. All trends in lower tails of AFDD are negative with steepest at Grand Lake stream. Accumulated snow is all up-trending with maximum of 1.396 inches/year at Grand lake stream.

ID	Stations	AWSSI.0.2	SHRP.0.2	AFDD.0.2	Accsnow.0.2
1	Sanford	4.375 *	0.646 *	9.912 *	1.55
2	Portland	6.667	-0.138	6.795	0.925 *
3	Farmington	-17.867 +	0.028	-9.857 +	-0.535
4	Gardiner	-5.68	0.025	-8.135	0.664
5	Newcastle	6.517	0.035	1.208	1.093 **
6	Jackman	-5.75	-0.085	-8.324 *	0.6
7	Dover-Foxcroft	-16.938	0.024	-7.75 +	-0.758
8	Belfast	11.875 **	0.354 +	8.636	0.861 +
9	West Rockport	0.333	0.223	-1.712	0.71 +
10	Bangor	7.917	0.191 +	-0.25	0.244
11	Caribou	-12.353 +	0.172	-7.5	1.037 *
12	Grand Lake Stream	8.25 +	0.422 *	-11.625 *	1.316 +

Note: $p < 0.001$ (***); $0.001 < p < 0.01$ (**); $0.01 < p < 0.05$ (*); $0.05 < p < 0.1$ (+)

Table 2.10: Lower(0.2) QR trends at 12 stations. Coefficient and significance (p-value) of predictor year variable is shown.

Comparing across the quantiles, Caribou shows decreasing AWSSI at lower tail but increasing AWSSI at upper tail. Thus, the variance in the severity as measured by AWSSI appears to increase at Caribou. While such significant and conflicting trends across the three quantiles are not observed elsewhere, the variances, in general, are observed to be increasing during the period. More detail on the distributional variances is provided by QR results across all quantiles which is presented in the next page.

QR results across all quantiles : AWSSI

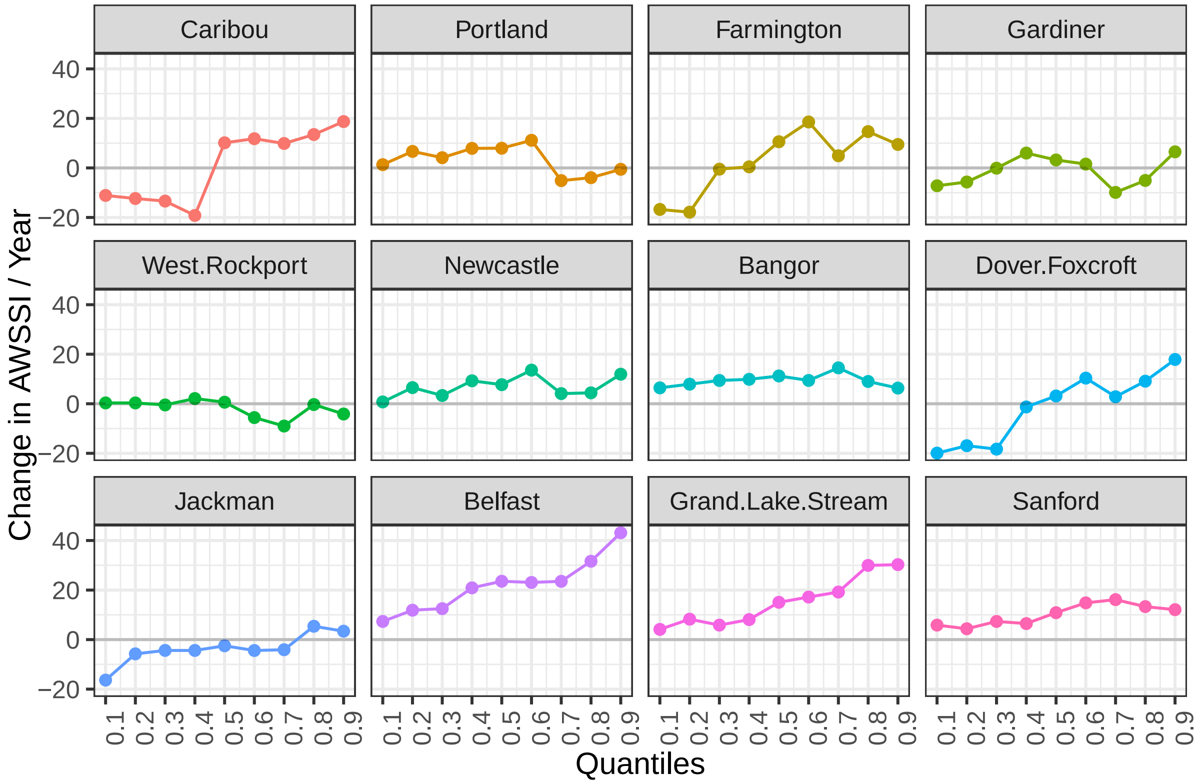


Figure 2.7: Quantile regression for AWSSI from 1991 to 2020. Slopes of quantile regression lines are shown.

Figure 2.7 presents a concise summary of the quantile regression for AWSSI at 12 locations. Each point represents the coefficient (slope of regression) obtained from particular quantile regression model. Values above 0 represent increasing trend and below 0 denote decreasing trend. As suggested by key quantiles, Caribou indeed shows diverse trends across distribution, negative for lower half quantiles and positive for upper half. Similarly diverse trends are observed for AWSSI at Farmington and Dover-Foxcroft. Bangor, Belfast, Grand Lake Stream and Sanford show upwards trends across all quantiles. Jackman has mostly negative trends across the distribution.

The results for SHRP, AFDD and Accumulated snow are presented in Appendix A.2. In addition to trends in seasonal indices, trend analysis are performed for monthly values of severity for months of November, December, January, February, March and April during

1991 to 2020. The results for monthly AWSSI, AFDD and Accumulated snow are presented in Appendix A.3 and A.4.

The asymmetric trends in the extreme ends of the weather index distribution underscore an important concern for planning and decision making, in that the trends in extreme have disproportionately large impact and careful consideration of the trends may allow for better planning and adaptation approaches.

2.4.5 Trends in frequency of selected weather triggers

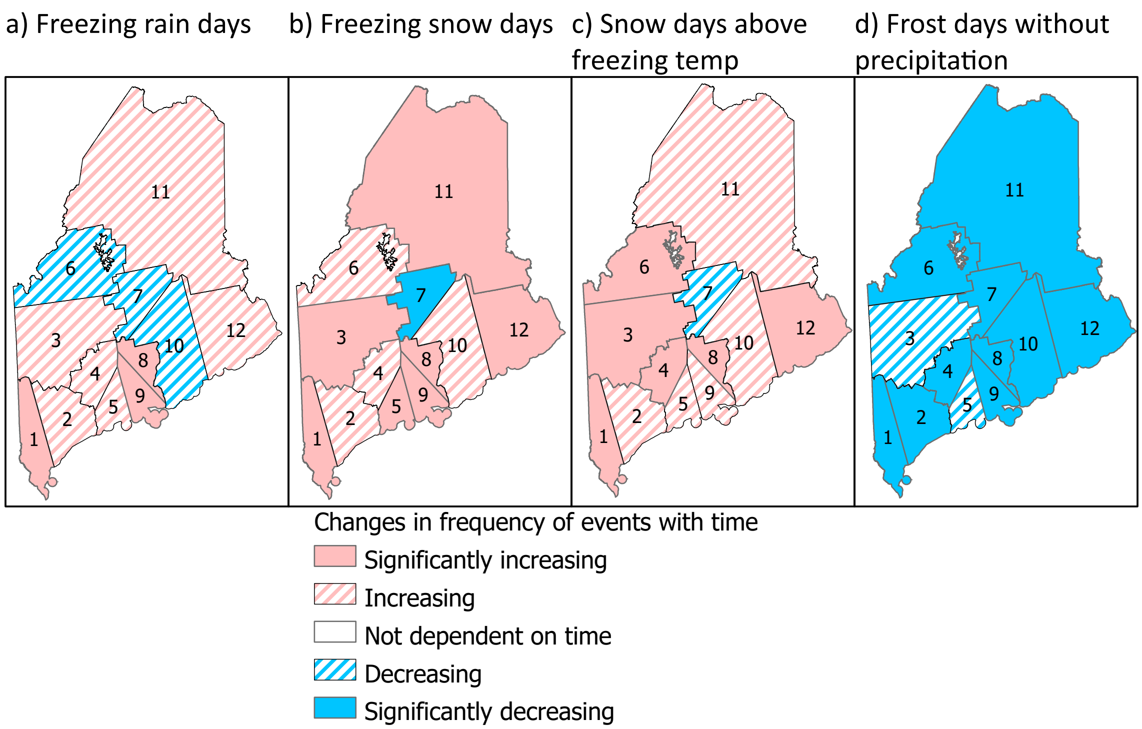


Figure 2.8: Trends in the seasonal frequency of extreme winter weather events over winters from 1991 to 2020 for indices: a) Frost days without any precipitation, b) Freezing rain days, c) Snow days with freezing temperatures and d) Snow days above freezing temperatures.

The incidence of increase in snow days during both days with freezing and non-freezing mean air temperature, is observed at most regions. However, the central region (Dover Foxcroft) shows decrease in the snow days. Similarly, incidence of frost days without precipitation shows broad scale decrease. Freezing rain days appears to increase significantly at regions Sanford (1), Belfast (8) and West Rockport (9).

ID	Stations	Freez rain days	Freez snow days	Snow days above frez temp	Frost days without ppt
1	Sanford	0.015 +	0.042 **	0.044 ***	-0.003 *
2	Portland	0.005	0.002	0.005	-0.003 *
3	Farmington	0.003	0.022 **	0.013 +	-0.001
4	Gardiner	0.004	0.012	0.019 *	-0.004 *
5	Newcastle	0.011	0.014 +	0.002	-0.002
6	Jackman	-0.008	0.008	0.016 **	-0.006 **
7	Dover.Foxcroft	-0.007	-0.016 *	-0.006	-0.002 +
8	Belfast	0.023 **	0.037 ***	0.04 ***	-0.003 *
9	West Rockport	0.014 *	0.027 **	0.013	-0.005 **
10	Bangor	-0.005	0.004	0.007	-0.004 *
11	Caribou	0.005	0.01 +	0.002	-0.005 ***
12	Grand Lake Stream	0.008	0.057 ***	0.029 **	-0.004 **

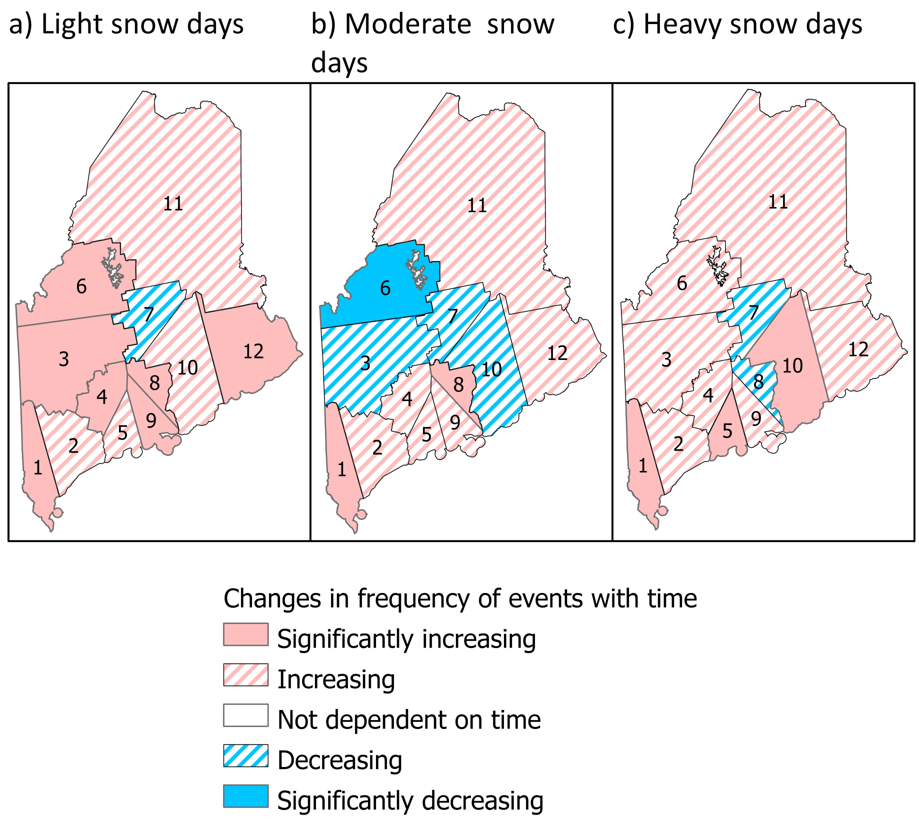
Note: $p < 0.001$ (***); $0.001 < p < 0.01$ (**); $0.01 < p < 0.05$ (*); $0.05 < p < 0.1$ (+)

Table 2.11: Quasi-Poisson Regression Results for four weather events. Coefficients and significance (p-value) of time variable are presented.

Table 2.11 details the estimated coefficients of the predictor variable 'year'. The coefficients measure change in log mean values of count with every year. Positive denote increased incidences and negative denote decreased incidences of weather events.

2.4.6 Trends in seasonal frequency of light, moderate and heavy snowfall

The results from Quasi-Poisson regression for three classes of snowfall days are discussed in this section.



Signs and statistical significance of the coefficient of time variable in each regression model is plotted in one of four categories (increasing, significantly increasing, decreasing and significantly decreasing).

Figure 2.9: Trends in the seasonal frequency of extreme winter weather events over winters from 1991 to 2020 for indices: a) Light snowfall (less than 4 inches) days, b) Moderate snow days (between 4 to 12 inches), and c) Heavy snow days (greater than 12 inches).

The trend typology in Figure 2.9 highlights many regions receive increasing days of light snowfall days. Moderate snow fall showed mixed trends across locations. While such moderate snow days are increasing at Sanford and Belfast, the eastern regions seemed to receive less incidence of such days. The increasing incidence of heavy snowfall seemed to be more apparent in coastal regions. The diverse patterns in spatial trends in different levels of snowfall can help authorities in managing maintenance materials resourcefully.

ID	Stations	Light snow days	Moderate snow days	Heavy snow days
1	Sanford	0.047 ***	0.045 ***	0.067 +
2	Portland	0.002	0.005	0.04
3	Farmington	0.017 **	-0.004	0.008
4	Gardiner	0.018 **	0.007	0.019
5	Newcastle	0.005	0.012	0.111 **
6	Jackman	0.018 **	-0.016 +	0.008
7	Dover Foxcroft	-0.008	-0.01	-0.006
8	Belfast	0.043 ***	0.021 +	-0.01
9	West Rockport	0.016 *	0.017	0.032
10	Bangor	0.006	-0.012	0.067 *
11	Caribou	0.003	0.009	0.041
12	Grand.Lake.Stream	0.04 ***	0.016	0.024

Note: $p < 0.001$ (***); $0.001 < p < 0.01$ (**); $0.01 < p < 0.05$ (*); $0.05 < p < 0.1$ (+)

Table 2.12: Quasi-Poisson Regression Results for three classes of snow days. Coefficients and significance (p-value) of time variable are presented. Light snow : less than 4 inches snow; Moderate snow: between 4 to 12 inches of snow; and Heavy snow: greater than 12 inches of snow.

Quasi Poisson regression results for the seasonal snow events are provided in Table 2.12. Sanford is the only station that shows increase in seasonal incidence of all three classes of snow days. A statistically significant(p-value <0.1) negative trend is observed for moderate snow days in Jackman.

CHAPTER 3
GROUNDWATER WELL CONTAMINATION DUE TO ROAD SALT IN MAINE

3.1 Introduction

Rock Salt (NaCl) is the most common deicing agent in winter road maintenance. The rock salt dissociates into sodium and chloride ions as the snow melts. While the sodium ions tend to bind in soil layers, the chlorides ions do not get involved in any biological processes nor get adsorbed in soil layers. The chloride ions are not involved in any biological processes, nor are they adsorbed in soil layers. They percolate through the subsurface and accumulate in groundwater sources. In public water systems, excess chloride can show secondary effects such as a salty taste in water and corrosion of plumbings and fixtures. Moreover, rock salts can contain up to 5% of trace minerals and possible contaminants such as lead, and arsenic [9], adding in the environmental and health concerns.

Groundwater contamination from the road salt contaminants is a significant concern because these effects are long-term, and it can take up to decades for recovery [35]. In Maine, a state where over half the population relies on private wells for drinking water, the concern of road salt contamination of wells is strengthened.

There are two types of groundwater wells in Maine: Shallow dug wells that are mostly built in sand and gravel aquifer, and bedrock wells that are drilled deep into bedrock aquifers. Shallow wells can easily capture the overland dissolved saltwater due to less overburden thickness. However, the deicing salt intrusion in bedrock wells is hard to characterize. Maine's bedrock geology primarily consists of igneous and metamorphic rocks, which are less permeable but allow infiltration through cracks, fractures, and faults in the bedrock layers. In addition, local hydro-geological conditions, well location and distance from road salt loads, roadside slopes, and hydraulic gradient can influence road salt transport into the wells.

A good understanding of chloride contamination in wells is essential for identifying elevated chloride risk zones and implementing additional caution in winter road salt application. This study presents a preliminary investigation of chloride contamination in Maine wells based on well sampling data from 2001-to 2020. Important hydro-geological and topographical fractures that influence the transport of road salt contaminants into groundwater sources and wells will be discussed.

The main objectives of the study are:

1. To investigate the status of sodium and chloride contamination of groundwater wells in Maine
2. To assess changing chlorides in wells with well types and well depth.
3. To provide estimates of local contamination risk for surrounding wells based on incidence of contaminated wells

3.2 Data and Methods

The well sampling data used in the study is obtained form Maine DOT [10]. The data contains sampling records from investigative sampling tests conducted in private wells and pre-construction sampling tests conducted along public roads. Hence the data is not representative of drinking water wells in Maine. There are 5387 sample test records and 44 fields for each test record. These fields contain information on street/ geographical address for well households or sampling locations, sampling date, well type and well depth, and water quality parameters. The sampling date for the tests ranges from 2001 to 2020. In addition to chloride, concentration levels were also recorded for sodium and arsenic.

We screened the data based on the completeness of the record for chloride concentrations. The remaining 4740 wells are used in the data visualization and risk computation. Additionally, where wells do not have information on geographical coordinates, approximate well locations are obtained by geocoding from available street addresses information.

The contaminant levels thresholds for chloride are adopted from US National Secondary Drinking Water Standards set by Environmental Protection Agency (EPA). Maine CDC follows EPA's regulations for Chloride in Maine public water systems. The Secondary Maximum Contaminant Level (SMCL) for Chloride, as recommended by the EPA's secondary drinking water standard, is 250 milligrams per liter (mg/L). Since high amounts of chloride give a salty taste to water and corrode pipes, pumping, and plumbing fixtures, SMCL for Chloride is set to indicate water quality problems. The secondary standard is not enforceable but is recommended as a reasonable goal.

Chloride contamination risk

We estimate the risk for wells in regions around the sampling locations. For this, we create circular buffer zones around individual sampled wells and count incidences of total sampled and contaminated wells (wells exceeding SMCL for chlorides). Local risk within an area is calculated by dividing the number contaminated by the total number of wells. We compute the risk for study regions of varying radius ranging from 250 meters to 5000 meters.

Chloride and Arsenic in wells

Arsenic is a naturally occurring chemical found in soil and rocks. High arsenic water is more common for drilled wells, but even shallow dug wells can show elevated arsenic [5]. Both Maine CDC's Maximum Exposure Guideline(MEG) and US EPA's MCL for arsenic is 10 ppb. Potential health effects from long-term exposure to Arsenic above MCL include skin damage, problems with the circulatory system, and increased risk of getting cancer. Recent research have focused on the effect of road salt has on mobilizing heavy metals from bedrocks including arsenic [42, 24, 23, 39]. Moreover, traces of arsenic and other metals have been found in deicers [9].

In this study, arsenic contamination status is also investigated using the sample well data. Joint contamination of chloride and arsenic are estimated for study areas of radius 5000 meters. The joint risk is calculated by dividing the number of wells within the study area exceeding thresholds of both chloride and arsenic with the total number of wells sampled within the area.

3.3 Results and Discussion

3.3.1 Chloride contamination in wells

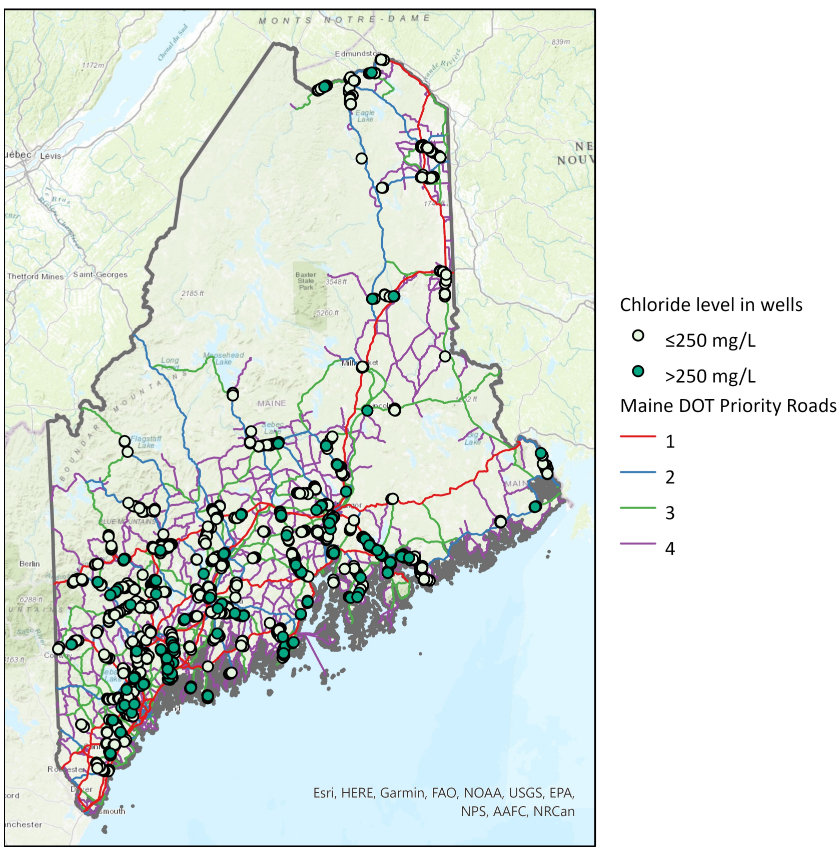


Figure 3.1: Chloride concentrations (mg/L) in Maine. Data is from Maine DOT groundwater samplings conducted from 2001 to 2020.

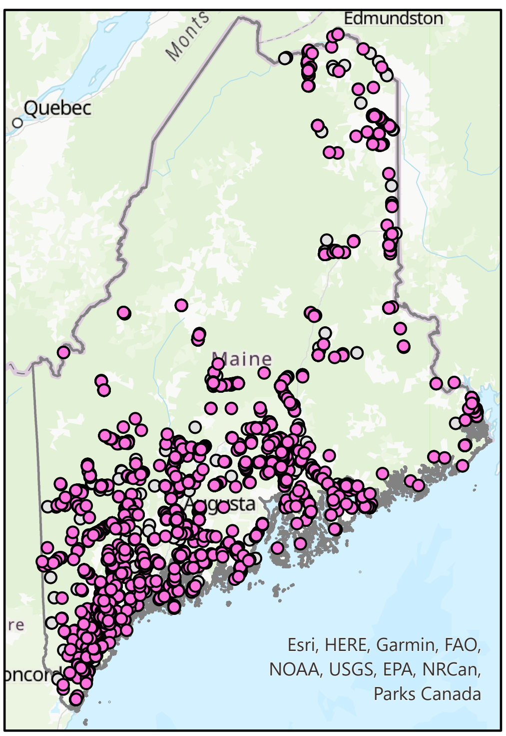
We found 182 wells, out of 4740, that exceed chloride levels above US EPA's SMCL (250 mg/L). Figure 3.1 presents the location of tested and contaminated wells. The cases of chloride contamination are concentrated in southern, mid-coast, and some eastern parts.

Moreover, a majority of tests were conducted during the 2000-2006 period, wherein the annual average exceeded 400 samples. Relatedly, three-fourths of the identified cases of chloride contamination were identified during 2000-2006.

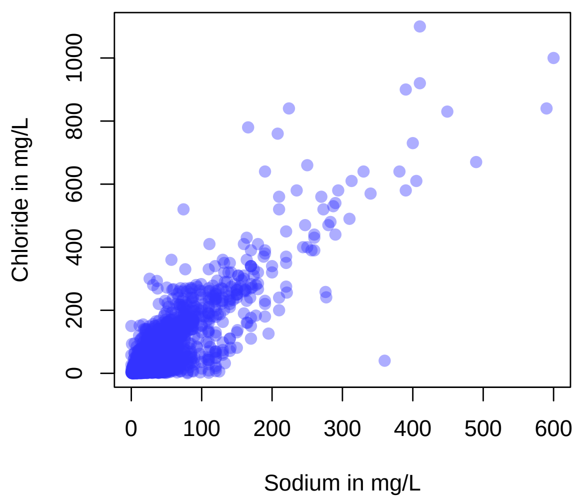
It is important to note that wells shown are a combination of private wells as wells as pre-construction sampling tests. As such, analyses presented in this report require careful interpretation and not to be construed as representing the spatial patterns of statewide well contamination. The latter would require a systematically designed sampling approach.

Sodium contamination status

For most healthy people, a sodium level up to 100 milligrams per liter of water will not substantially increase risk [6]. But in view of individuals on low-sodium diet, Maine CDC recommends 20 mg/L of sodium as a drinking water standard [6]. Excess sodium from salt in the diet increases the risk of high blood pressure and cardiovascular disease [6].



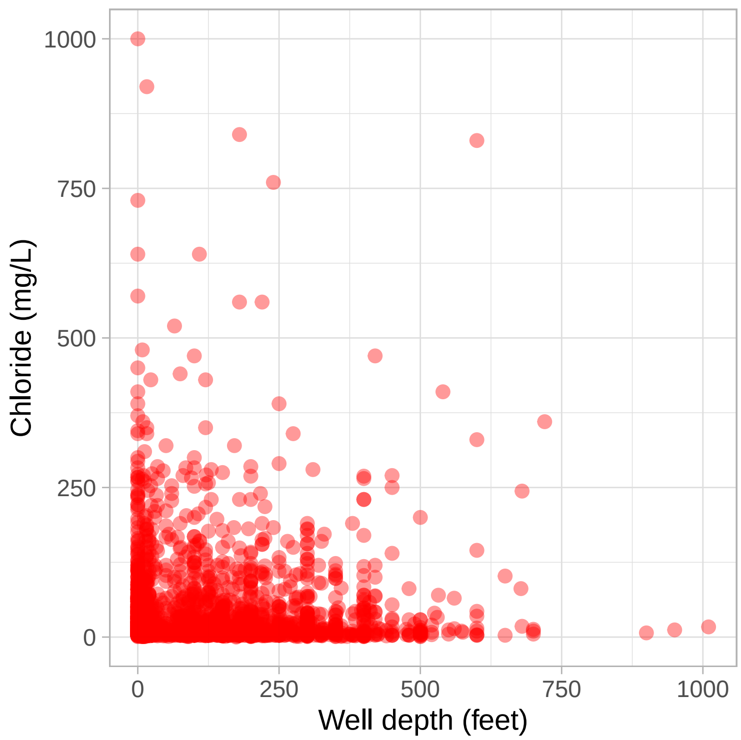
(a) 2349 Wells with sodium exceeding recommended low sodium diet value (10 mg/L).



(b) Chloride and sodium in test wells. Three well tests with highest sodium concentration (990 mg/L , 1160 mg/L and 2000 mg/L) not shown for better data visualization.

Approximately 50% (2349 out of 4740) wells exceed the recommended sodium level for low Sodium diet. The well locations are shown as in Figure 3.2a. 203 wells have Sodium exceeding 100 mg/L. In addition, the data suggests common incidence of elevated concentrations of sodium and chloride in test wells shown in Figure 3.2b. Both chloride and sodium can occur naturally in groundwater; however, coinciding elevated levels suggest a possible salt-water intrusion.

Well depth and Chloride levels

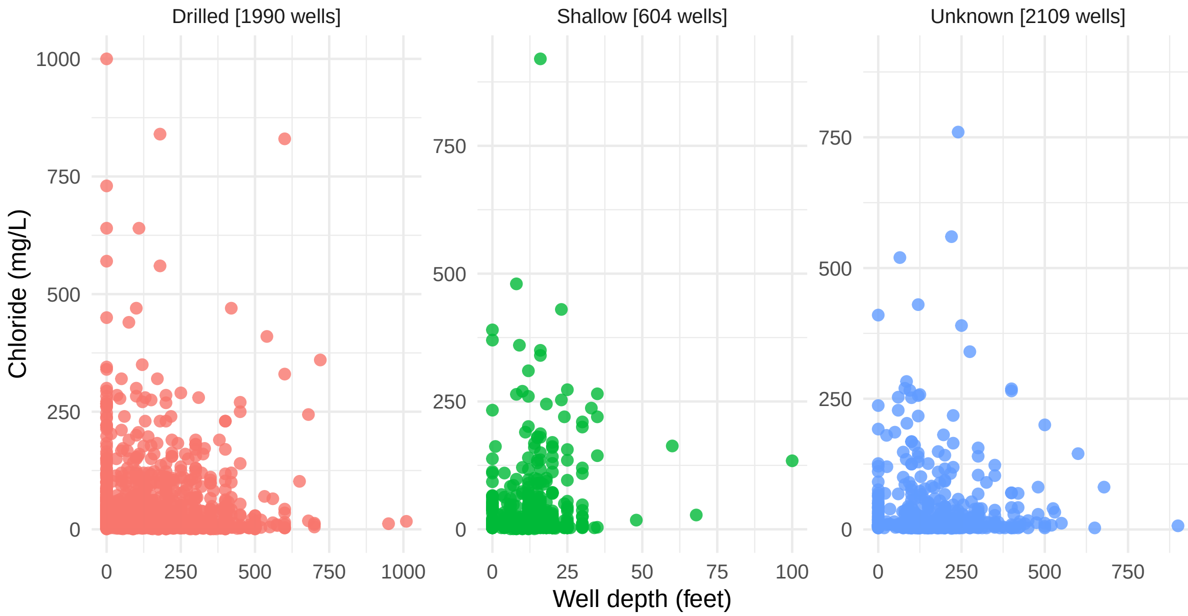


Wells with chloride levels more than 1000 mg/L not plotted for better data visualization.

Figure 3.3: Chloride concentrations decreasing with well depths based on 2061 wells with well depth information.

The plot 3.3 shows a general pattern of decreasing chloride levels with increasing well depths. The reason can be shorter infiltration path and time in shallower wells that tend to capture salt water melt more readily.

We further study this phenomenon in both shallow and drilled bedrock wells. The pattern of higher chloride in shallower wells seemed to be consistent across the well types



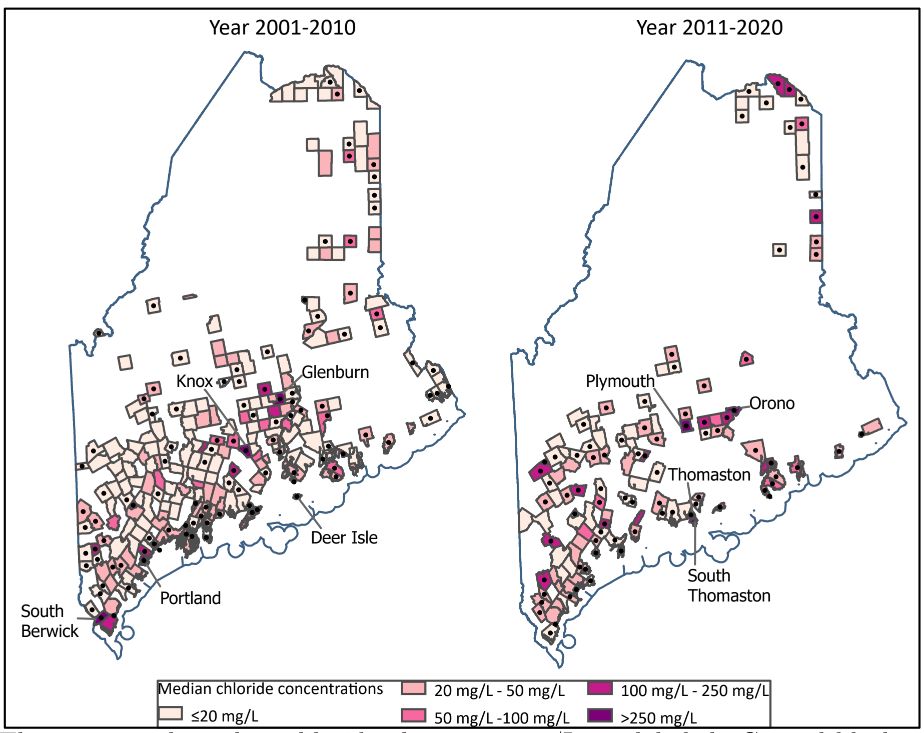
Wells with chloride levels more than 1000 mg/L not plotted for better data visualization.

Figure 3.4: Chloride concentration and well depths by well type.

(see Figure 3.4). The result further strengthens overland flows as a possible contamination source. However, this offers partial view of the well vulnerability as other local hydro-geological factors also control the transport of road salt to wells. These factors are studied more on section 3.3.5.

3.3.2 Sodium and chloride levels across Maine towns

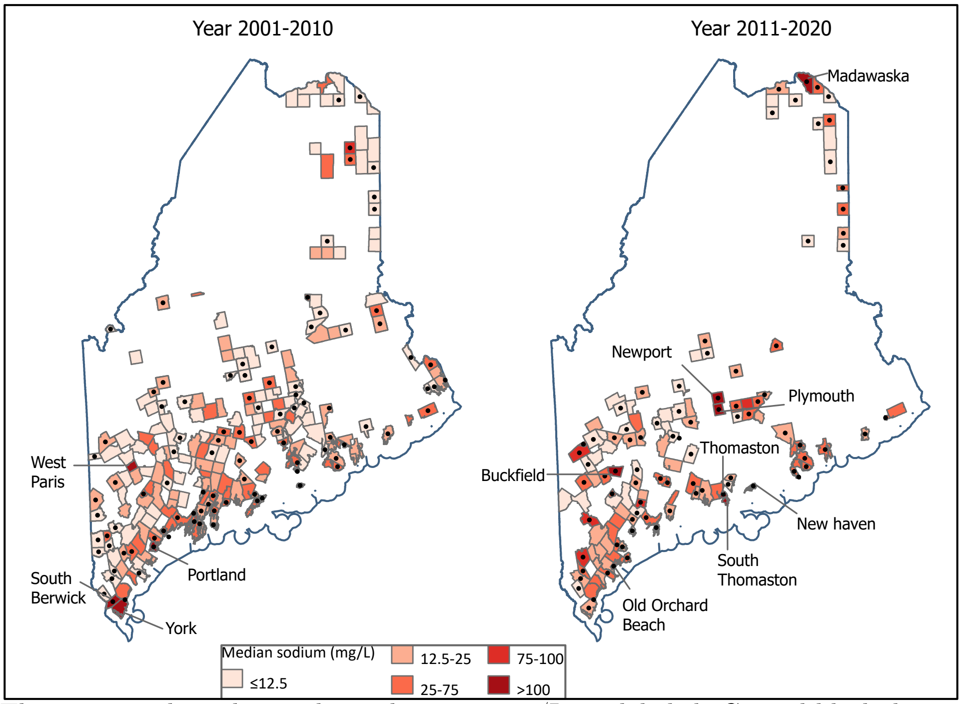
Maine's winter road maintenance responsibility is shared by Maine DOT, towns, and counties. The municipalities maintain 81% of the state's total winter maintained miles, sidewalks, and parking lots. In this section, we use the sampling test data to assess the presence of sodium and chlorides in Maine towns from 2001 to 2020. The median chloride concentration in towns over two periods (2001-2010) and (2010-2020) are presented in Figure 3.5. Towns with median chloride concentrations above 250 mg/L are labeled. During 2011-2020, 15 towns have at least one sampling test with chloride concentration above the SMCL. The town of Durham in Androscoggin shows the maximum number of contamination cases of 13 for this period. South Thomaston in Knox county shows the highest number of contaminated cases of 4.



The towns with median chloride above 250 mg/L are labeled. Central black dots denote towns with less than 5 sampling tests.

Figure 3.5: Median chloride concentration in Maine towns over two periods.

Similarly, the median sodium levels in towns for the two periods are presented in Figure 3.6. Three towns during 2001-2010 and six town during 2011-2020 are found to



The towns with median sodium above 100 mg/L are labeled. Central black dots denote towns with less than 5 sampling tests.

Figure 3.6: Median sodium concentration in Maine towns over two periods.

exceed the threshold of 100 mg/L. Towns Plymouth, Orono, Thomatson and South Thomaston show excess of both sodium and chloride levels during 2011-2020.

The following graph 3.7 details the contaminated sample tests accumulated over cities and towns by Maine DOT maintenance regions. The information can help assess risk for the population at large. The highest incidence of chloride contaminated sample tests are detected for second class cities (population range of 1501-10,000). While the wells sampled did not totally represent the drinking water wells, chloride contamination patterns can be suggestive of undetected contamination or rising chloride levels for the proximal wells.

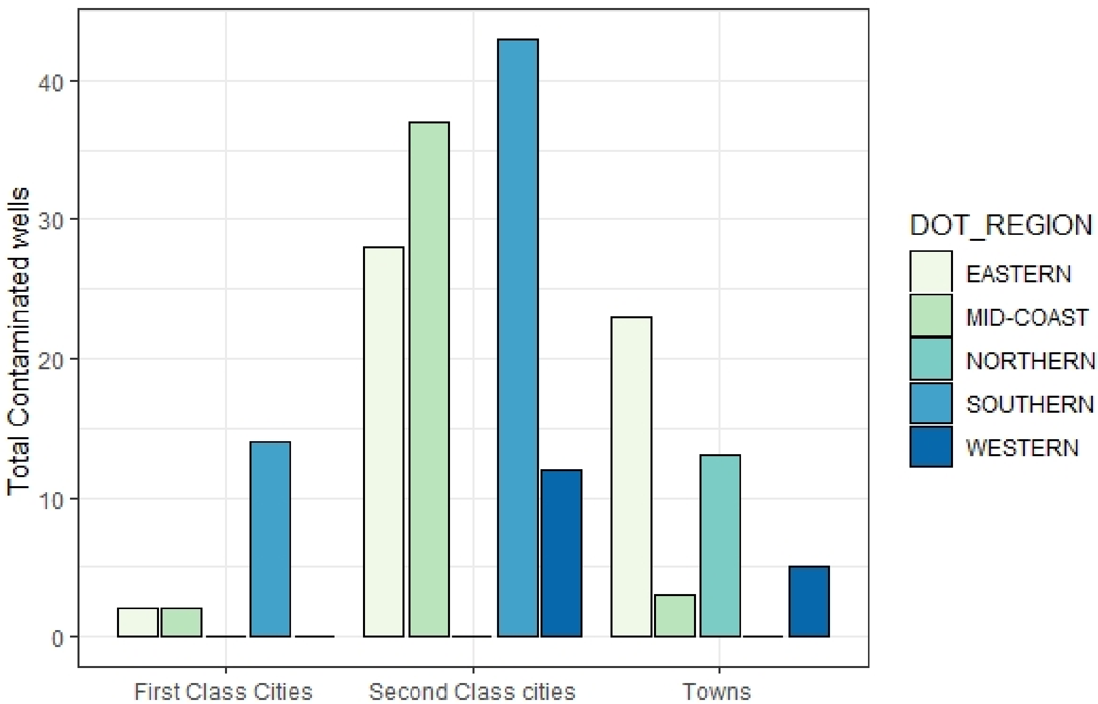


Figure 3.7: Sum of Chloride Contaminated wells recorded in First and Second Class cities, Towns across the Maine DOT regions.

Description of City and Town Class:

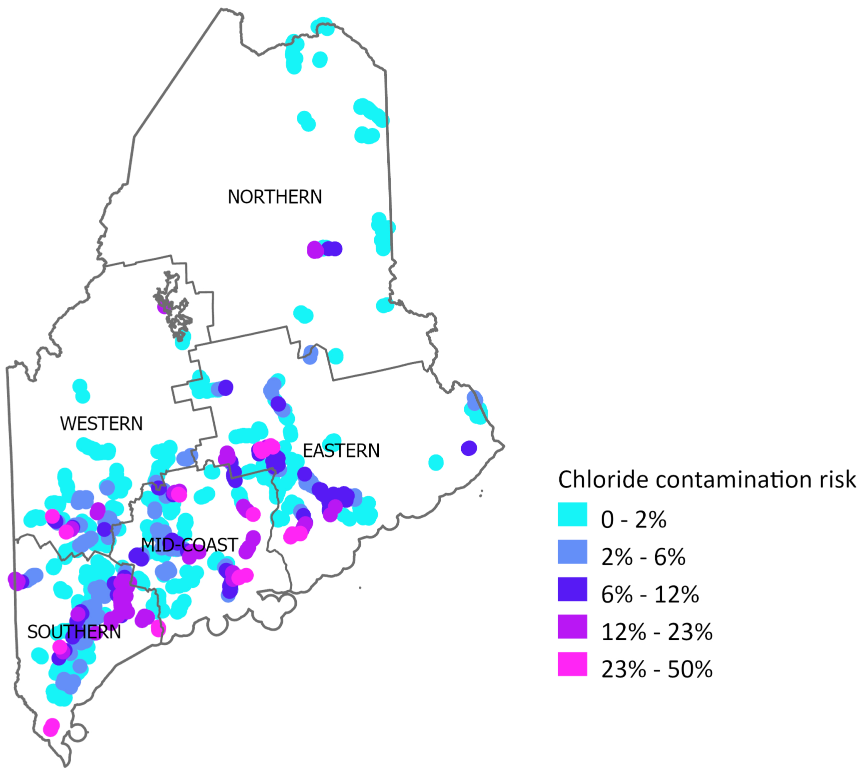
Towns, A: $<$ 1,500

Second Class Cities, B: 1,501 – 10,000

First Class Cities, C: $>$ 10,000

3.3.3 Chloride contamination risk around well locations

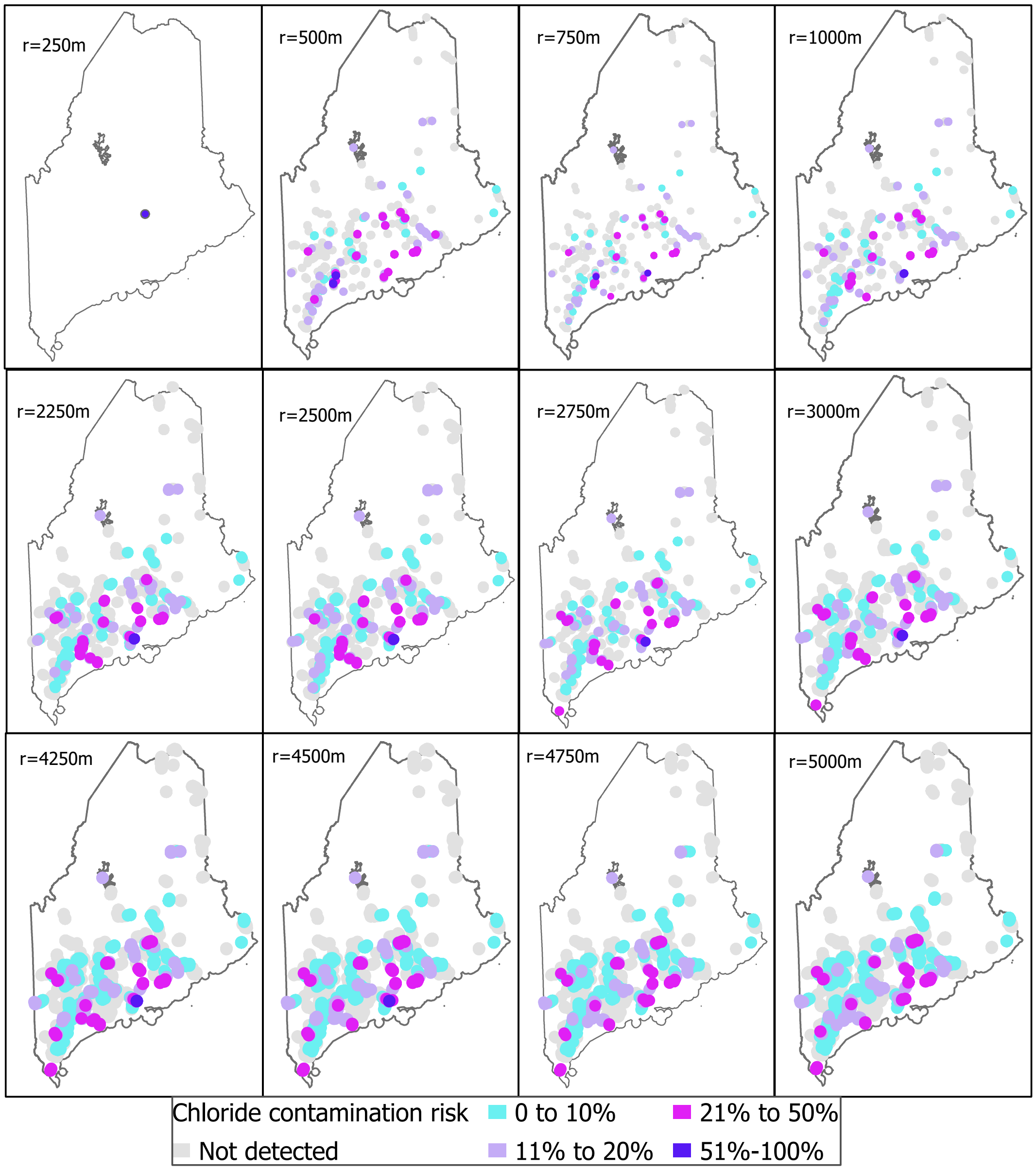
The estimates of chloride contamination risk obtained for circular areas of radius 5000 meters are shown in Figure 3.8. The local estimates highlight potential risk zones mainly in mid-coast and southwestern Maine. Important to note is that the risk estimates for regions are based on the number of total wells within the regions and are not constant.



Risk estimates are provided only for areas with more than 5 test wells.

Figure 3.8: Estimated chloride contamination risk in study areas of radius 5000 meters around sampled wells.

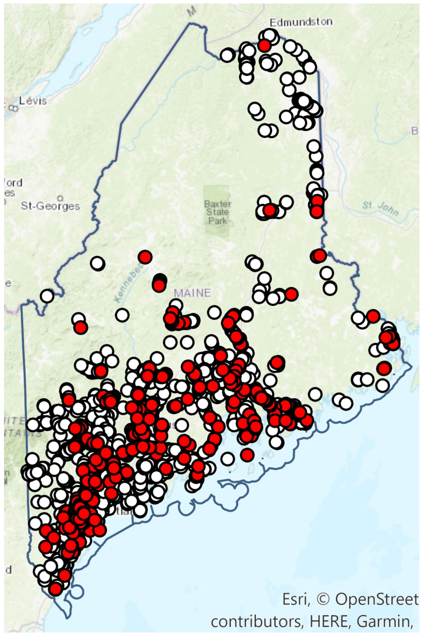
Similar risk estimates are obtained for circular areas of smaller radii (see Figure 3.9). Distribution of number of wells for the sets of buffer radii is presented in Figure B.1 in Appendix B. The quantified risk offers a limited view of the relative likelihood of spatially proximate sites with high contamination levels. While limited by the nature of sampling, a foreknowledge of local risk can be useful for estimating remediation strategies and guidance to local communities.



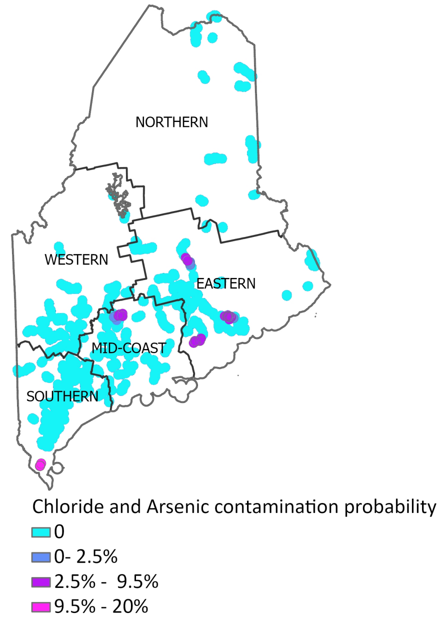
Note: Risk estimates are provided only for areas with more than 5 wells. Only one study buffer with radius 250 meters have at least 5 wells.

Figure 3.9: Local estimates of chloride contamination risk around sample locations for varying radii.

3.3.4 Arsenic incidence in Maine



(a) Well sampling locations and Arsenic contamination. At the locations marked in red, the Arsenic levels were found to exceed the MCL.



(b) Well Contamination probability due to chloride and Arsenic in circular study regions of radius 5000 meters around test wells.

Similarly, 603 wells out of the 4527 complete well test records on Arsenic levels show arsenic concentration above MCL of 10 parts per billion (ppb). The map on 3.10a shows the location of well tests where the arsenic concentrations exceed the MCL. Moreover, joint local estimates, as mapped in Figure 3.10b, show distinct clusters of non-zero risk of contamination due to both arsenic and chloride at four locations. Maine's bedrock geology is characterized by high levels of arsenic. Therefore, the phenomenon of arsenic mobilization due to road salts should be investigated in depth at the identified locations.

3.3.5 Chloride levels and influencing factors

The rate of transport of dissolved road salt within the soil layers is largely influenced by hydraulic properties of the layers. Hydraulic conductivity is a property of soil that describes the ease with which a fluid can move through pore spaces. Ideally, higher conductivity of subsurface layers implies higher infiltration rate. However topographical factors, such as presence of bedrock fractures, distance to nearest salted roads, come into play and significantly alter the course and rate of infiltration.

In this section, we study the variation of chlorides with three hydro-geological factors: distance to nearest sources (high salt burden roads and salt piles), distance to nearest faults and soil hydraulic property. Part of well location information logged in the sampling data referred to the street address or post office boxes rather than the actual location of wells. As such, for this section, only 1744 wells with recorded geographical coordinates are selected.Spatial location of the wells exceeding SMCL for chloride in relative to distances to roads, and fault lines is presented in Map 3.11.

The values of saturated hydraulic conductivity (Ksat) for Maine are obtained from the global Ksat map at 1 km resolution at depths of 0 cm, 30 cm, 60 cm and 100 cm [15]. Equivalent vertical saturated conductivity is estimated over the depth of 100 cm. The bedrock fault lines data are obtained from Maine Geological Survey [43]. Location information from road salt stockpiles are obtained from Maine DOT [11]. The estimates of distances from approximate well location to the nearest high priority roads (Priority 1,2 and 3), salt stock piles and faults are obtained using nearest distance analysis tool available in ArcGIS Pro 2.6.

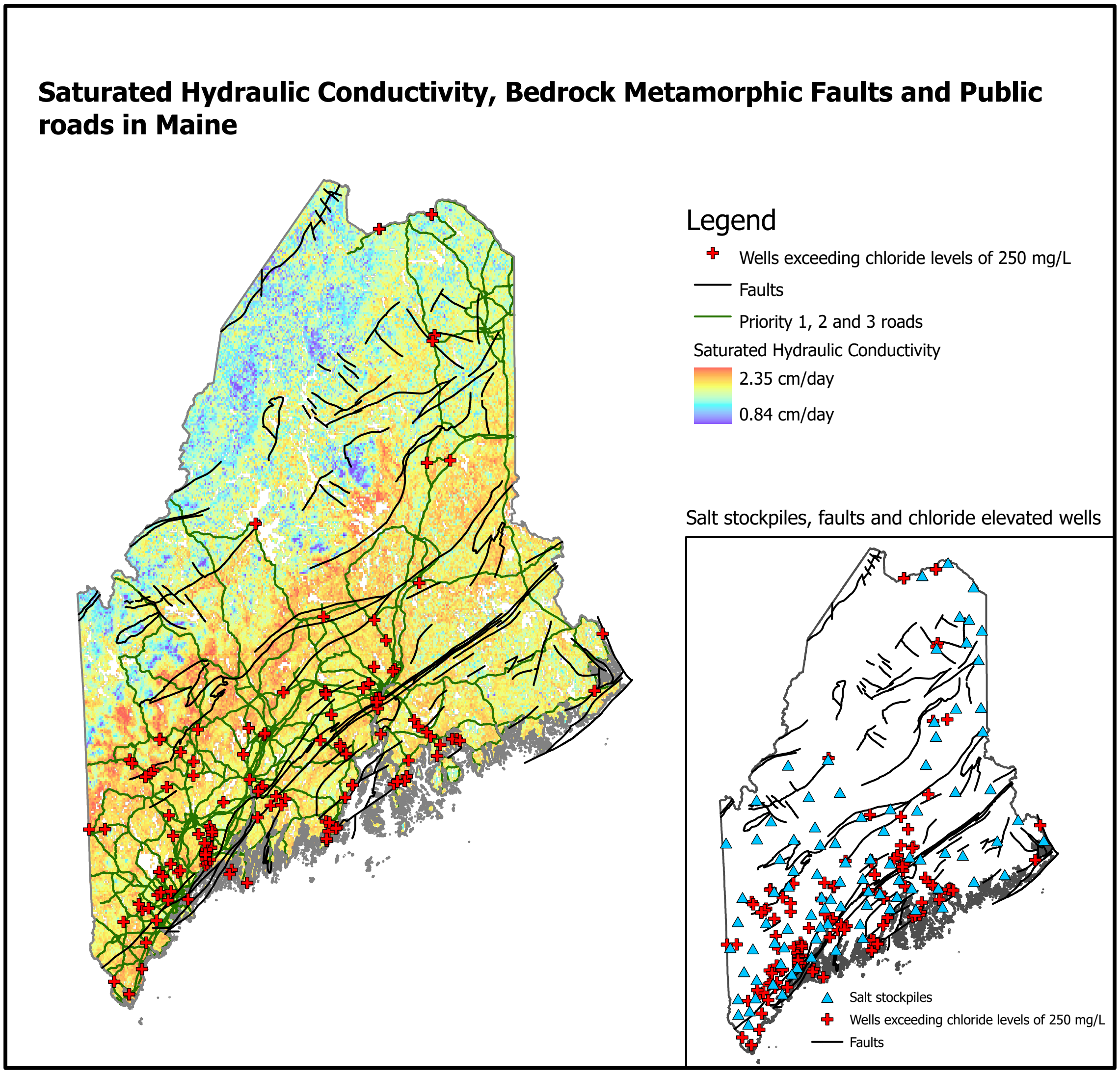


Figure 3.11: Locations of chloride contaminated wells with respect to faults, public roads (Priority 1,2 and 3), saturated hydraulic conductivity and salt stockpiles in Maine.

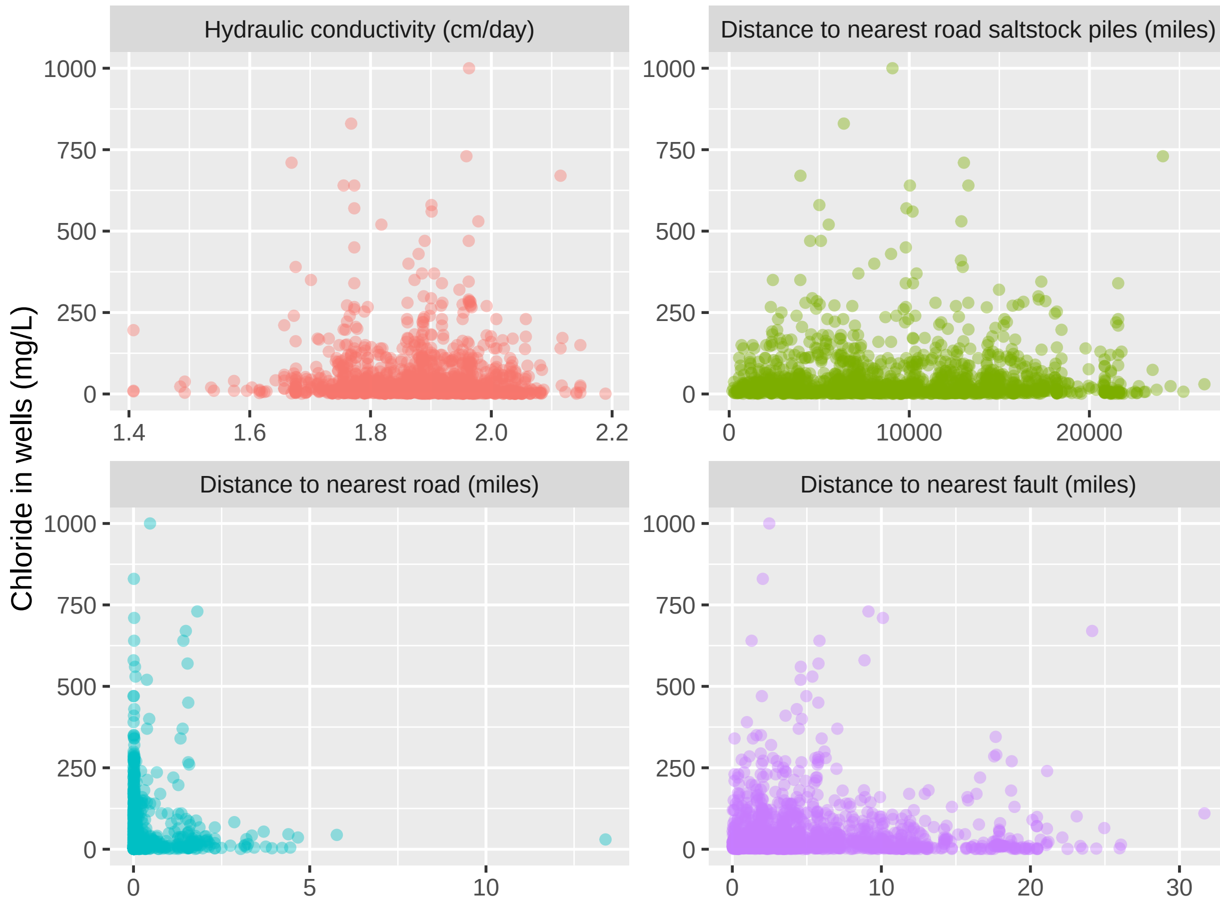


Figure 3.12: Effect of saturated hydraulic conductivity, nearest distance to roads, salt piles and faults on chloride concentrations in 1744 wells for which the exact location information were available.

The bottom left plot in Figure 3.12 highlights increase in well chloride levels with decreasing distance to nearest roads. This preliminary study is unable to show any patterns of elevated chlorides with distance to nearest faults, salt piles or with hydraulic conductivity. However, few other studies have conducted in-depth studies and confirmed effects of these factors in drinking water wells in Maine.

In 2012, USGS investigated relations among water levels, chloride concentration and depth of bedrock fractures in four road salt contaminated wells in Maine [40]. They used dissolved oxygen data and borehole logs data to understand the interaction of fractures and groundwater flow. The results indicate that the bedrock fractures have a substantial influence of transport of chlorides to the groundwater wells.

A closer study by Maine DEP in 2021 studied chloride contamination risk in private wells in Maine [21]. They compared well chloride levels for varying roadside slopes, soil hydraulic property, surface and bedrock geology, and presence and orientation of bedrock fractures. Results indicate the mean values of chloride levels are highest in wells where the well capture zone (based on 75 foot well pump radial capture zone) is located in downslope and lowest where the zone is located in distal upslope from the centerline of road.

In addition, shallow wells with the capture zone in downslope from road are found more likely to get contaminated compared to deeper drilled wells. In case of deep wells drilled into bedrocks, more optimal alignment between dominant bedrock fracture direction and direction from road to well was found to increase the soil hydraulic conductivity in groundwater in downslope compared to upslope. These effect of decreasing chlorides in deeper wells is also apparent in our results.

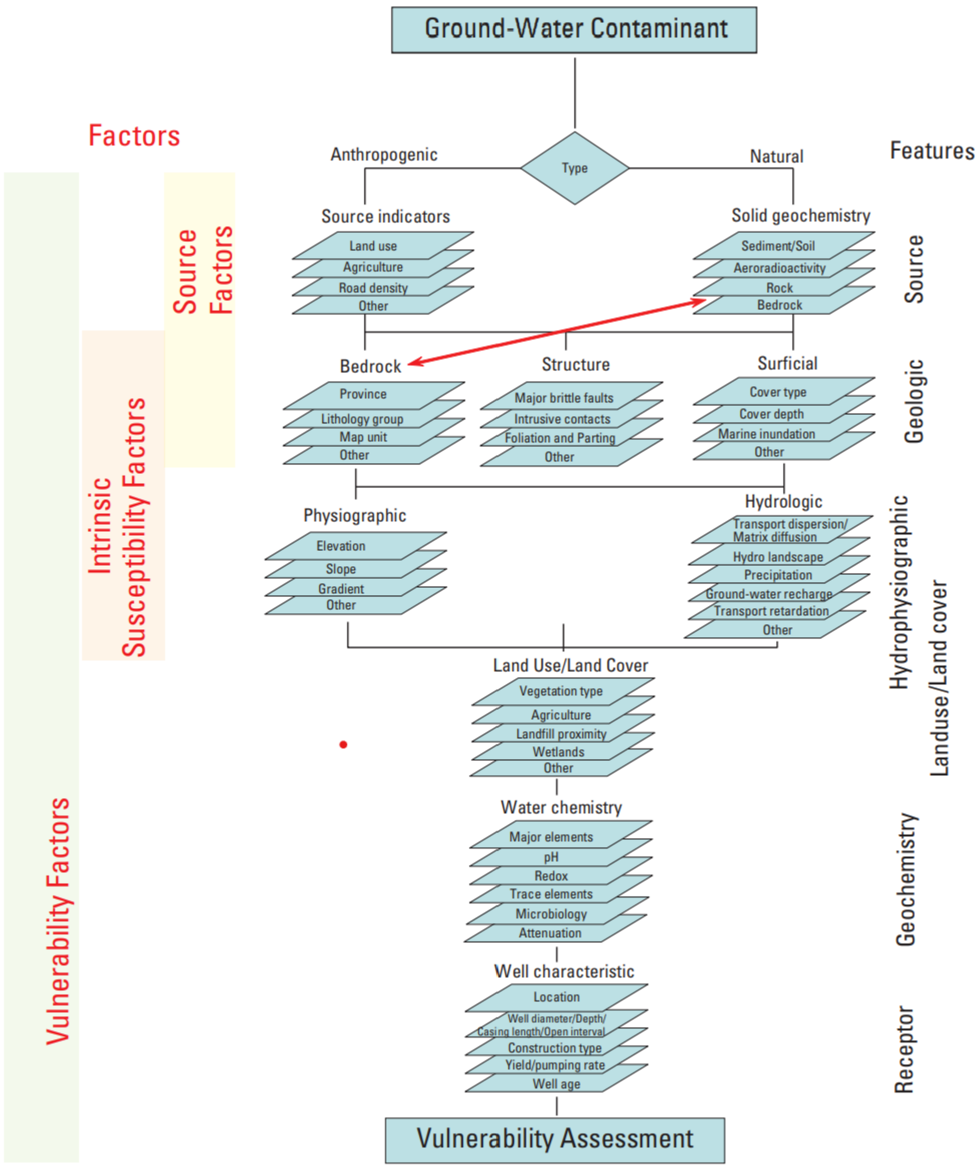
When all the factors; geology, overburden soil property, varying road side slopes, and well types are considered, the three highest risk well categories obtained from the study are: Volcanic bedrock wells , Dug shallow wells and Wells lying in 5 to 7 degrees soil slope (well to road). The high risk denotes the greater likelihood of chloride contamination in downslope wells from road and lower chloride concentration for upslope wells.

The comprehensive studies highlight the vulnerability of groundwater wells in context of hydro-geological factors. The estimated local contamination risk from our study can be studied along with well vulnerabilities to assess risk to individual wells.

Existing framework for vulnerability assessment

In 2008, USGS developed a framework for evaluating water quality of the New England crystalline rock aquifers [18]. The framework consists of four categories of spatial variables: (1) geologic, (2) hydrophysiographic, (3) land-use land-cover, and (4) geochemical. On a regional scale, these variables represent indicators of natural and anthropogenic sources of contaminants, as well as generalized physical and chemical characteristics of the aquifer system that influence ground-water chemistry and flow. These factors can be combined along with groundwater well vulnerability factors as well depth, well location, etc. to assess the water quality. The framework is presented in Figure 3.13.

This comprehensive framework can be a guidance tool for future works aimed to establish relation between road salt and groundwater contamination and associated vulnerability assessment.



Reprinted from "Harte, Philip T., et al. Framework for evaluating water quality of the New England crystalline rock aquifers. 2008."

Figure 3.13: Preliminary framework approach for the evaluation of regional ground-water quality in the New England crystalline rock aquifers proposed by USGS (2008).

CHAPTER 4
CONCLUSIONS

The work presented here focuses on studying the causal factors and effects of historical road salt use in Maine. The literature review details established indices, development approaches, and existing relations to winter road maintenance. An appropriate WSI suited to closely representing Maine's climate will help in strategic road salt application. This study uses four existing winter severity indices: AWSSI, SHRP, Illinois Salt Day Index, and AFDD, to characterize Maine's climate and study their applicability to road salt usage. The selected weather indices estimate changing weather severity and influence on road salt application. In addition, trends in winter weather conditions and their relation to salt use are investigated since road salt application occurs with severe weather conditions. Finally, impact assessment of road salt on groundwater wells is performed to facilitate informed salt use decisions. The research provides assessment based on analysis of water quality test data.

4.1 Road Salt and Winter Weather

The leading components of WSI, obtained from PCA, suggest the presence of both shorter and long-term winter weather variability in Maine. In general, stations at Farmington, New Castle, Bangor, and Grand Lake Stream show increasing long-term severity patterns. The subsequent analysis using PCA regression relates weather indices and events to salt use. The existing indices and long-term baselines for changing practice help explain most variation in statewide salt use data from Maine DOT. The models provide an appropriate fit for salt use data with R^2 greater than 80%, with the AWSSI model performing the best (R^2=84.5%). Both snow days and freezing rain days show moderate influence on road salt (R^2 around 50%). The frost days without precipitation that represent the risk of road ice formation due to moisture present at roadsides show less influence (R^2=11.2%). Moreover, trend analysis shows such frost days are declining from 1991 to 2020.

A method of model combination is suggested as a better alternative when the intent is to achieve accuracy rather than to explain variability. A combined model based on 80% weights for AWSSI estimates and 20% weights for Freezing rain day estimates shows improved accuracy. There is a 48% reduction in Root Mean Squared Error compared to the error from the model-based solely on AWSSI.

The investigation of changing nature of winter severity and incidence of weather events is achieved using Quantile Regression and quasi-Poisson Regression. We investigate trends across quantiles to identify any the asymmetric trends in winter severity. Results show that many regions are characterized by changing distributional variances in winter severity from 1991 to 2020. The station in Caribou shows decreasing trend at the lower tails of AWSSI distribution and an increasing trend at the upper tail, suggesting an incidence of highly varied winter at the location. While other stations do not show such conflicting trends, broad-scale increased variability is observed from quantile regression. Mainly increasing severity is observed along the coastal regions. Decreasing trends for AWSSI are observed at Caribou and Farmington at a lower tail (0.2 quantiles). Similar decreasing trends are observed in cold severity as measured by AFDD. The accumulated snow amounts show broad-scale increases across the state.

Trend information on episodic indices is obtained from quasi-Poisson regression. Results highlight diverse spatial patterns of incidence and the need for region-specific plans for maintenance and resources planning. The incidence of freezing rain days is increasing at three stations along the coast. Similarly, the incidence of snow days is rising in most regions. Within the different classes of snowfall, we find broad-scale increasing trends in the incidence of light snow (snow less than 4 inches) days.

The information on regional disparity in winter severity and incidence of severe conditions is essential for anticipating variability in winter road maintenance, including road salt application. Future studies focused on regional salt data can estimate the influence of weather conditions and severity on regional salt use patterns.

4.2 Groundwater Contamination

The water quality test data provide the current status of groundwater contamination due to chlorides in Maine. Although not wholly representative of drinking water wells, the test wells' chloride levels suggest elevated levels in the proximity of high priority roads. Local risk of well contamination due to excess chloride or excess of both chloride and arsenic are estimated. The risk estimates for chloride contamination show the contamination prevalent across the high population density locations. Since most winter road maintenance duties lie with local municipalities, the spatial assessment of local risk is critical in planning for reducing road salt application. The presence of joint chloride and arsenic contamination at four locations provides ground for further investigation of arsenic mobilization from bedrocks at the sites. The potential health implication of the finding is a strong justification for further study of this phenomenon. Established frameworks can guide future works on vulnerability assessment of drinking water wells and risk to the population.

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APPENDIX A

A.1 Winter season length at 12 stations

The index AWSSI accumulates daily severity scores based on estimated winter onset and cessation day. The criteria for the start and end dates are:

Winter starts with the earliest occurrence of three conditions:

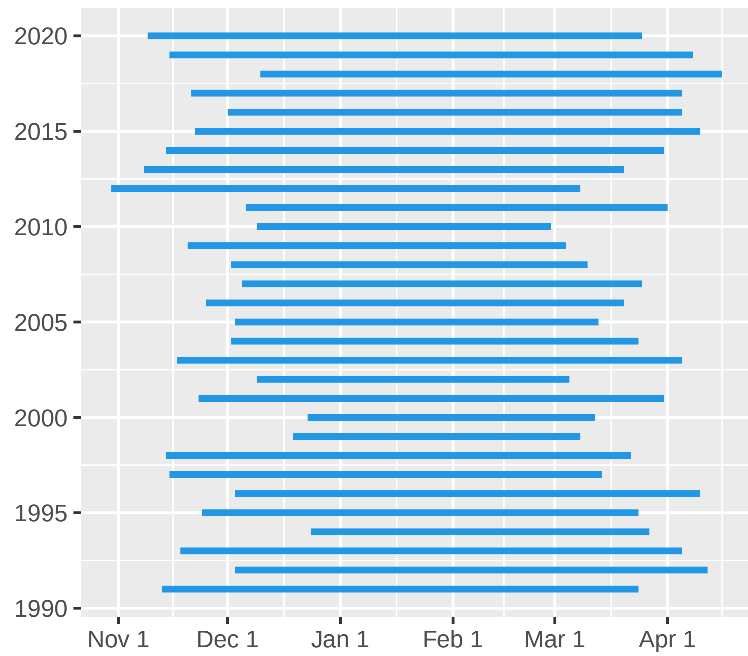
- First measurable snowfall ($>=$ 0.1 inch)
- Maximum temperature at or below 32°F
- December 1

The end day is the last occurrence of:

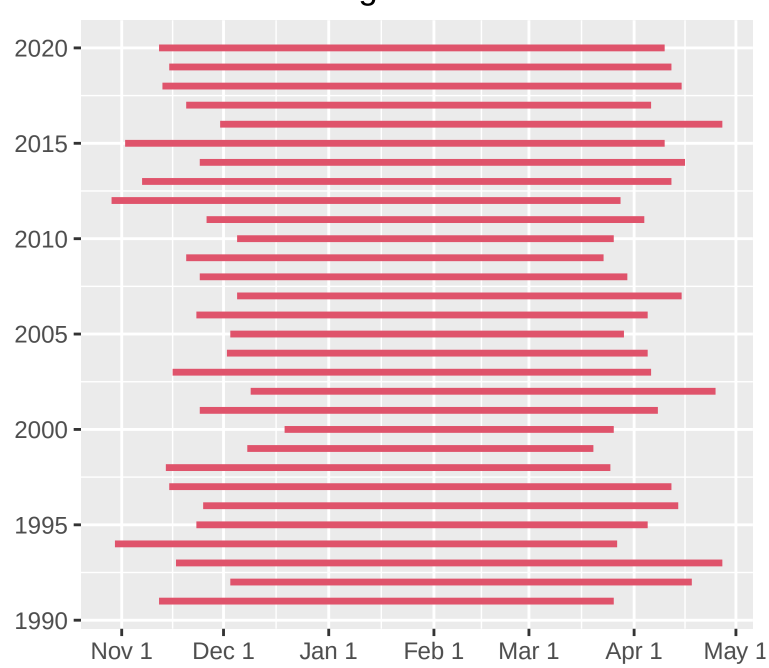
- Last measurable snowfall ($>=$ 0.1 inch)
- Last day with 1 inch of snow on the ground
- Last day with a maximum temperature of 32°F or lower
- February 28/29

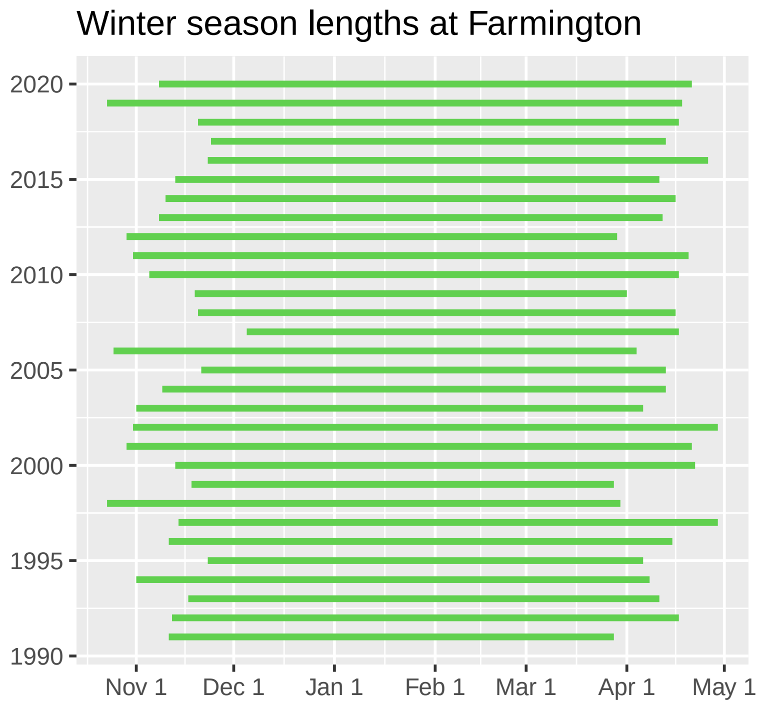
The varying season length obtained for 12 stations are plotted below.

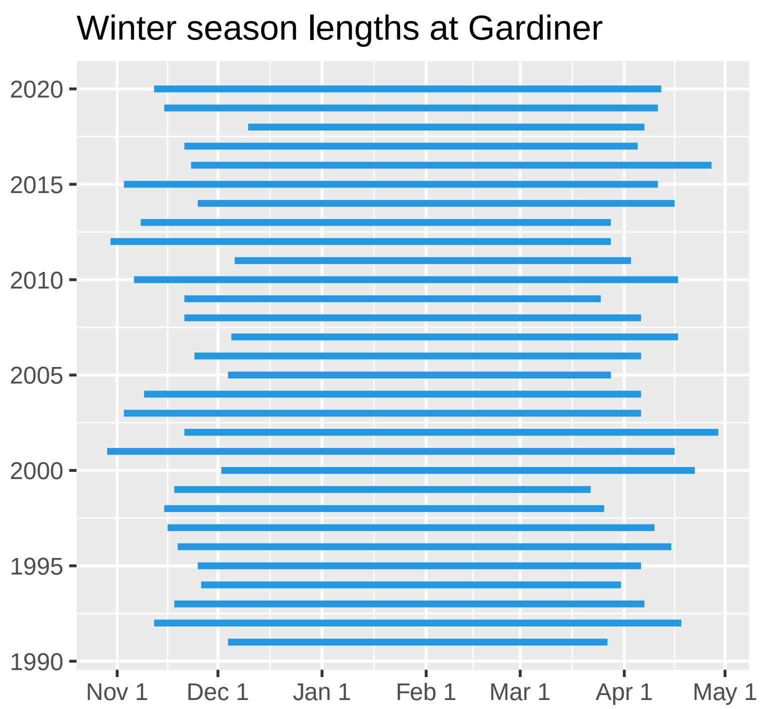
Winter season lengths at Sanford



Winter season lengths at Portland

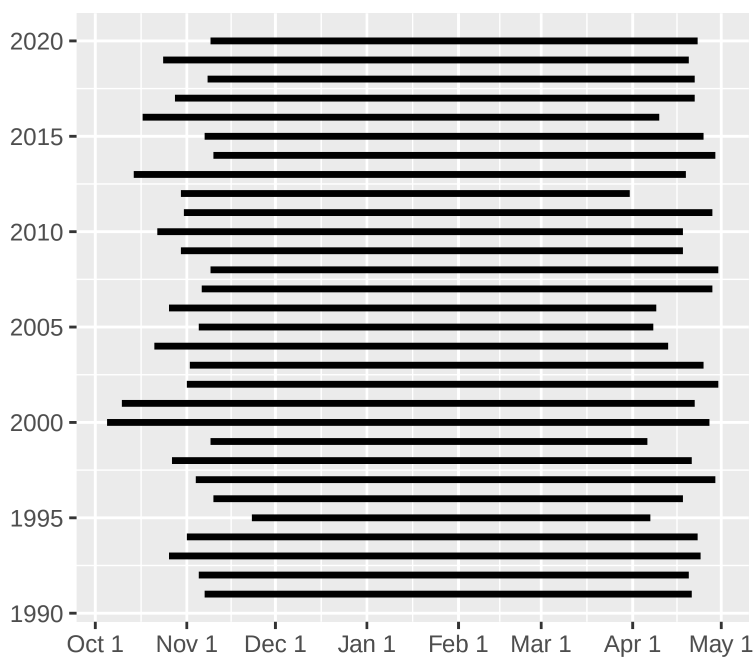


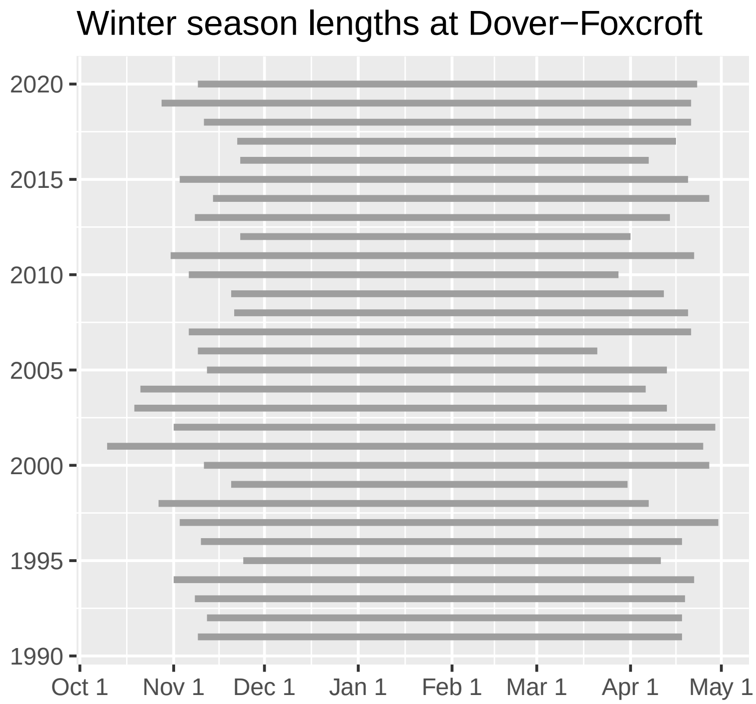

Winter season lengths at Farmington
2020
2015
2010
2005
2000
1995
1990
Nov 1
Dec 1
Jan 1
Feb 1
Mar 1
Apr 1
May 1

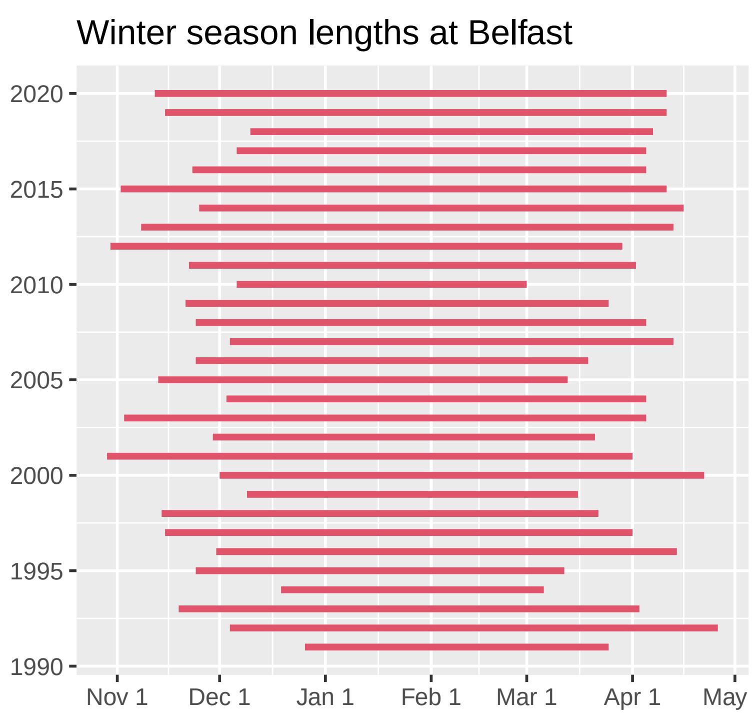

Winter season lengths at Gardiner
2020
2015
2010
2005
2000
1995
1990
Nov 1
Dec 1
Jan 1
Feb 1
Mar 1
Apr 1
May 1

Winter season lengths at Newcastle

Winter season lengths at Jackman




Winter season lengths at Dover−Foxcroft
2020
2015
2010
2005
2000
1995
1990
Oct 1
Nov 1
Dec 1
Jan 1
Feb 1
Mar 1
Apr 1
May 1


Winter season lengths at Belfast
2020
2015
2010
2005
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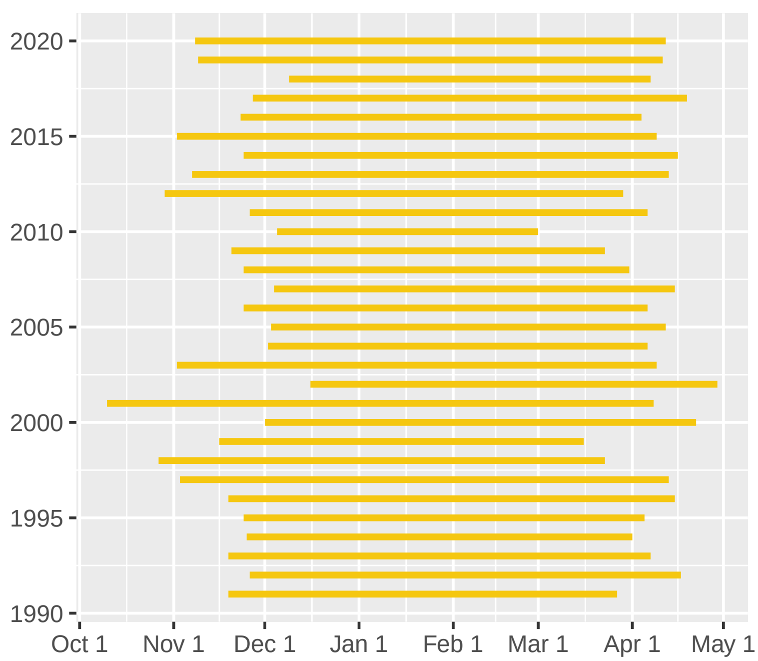
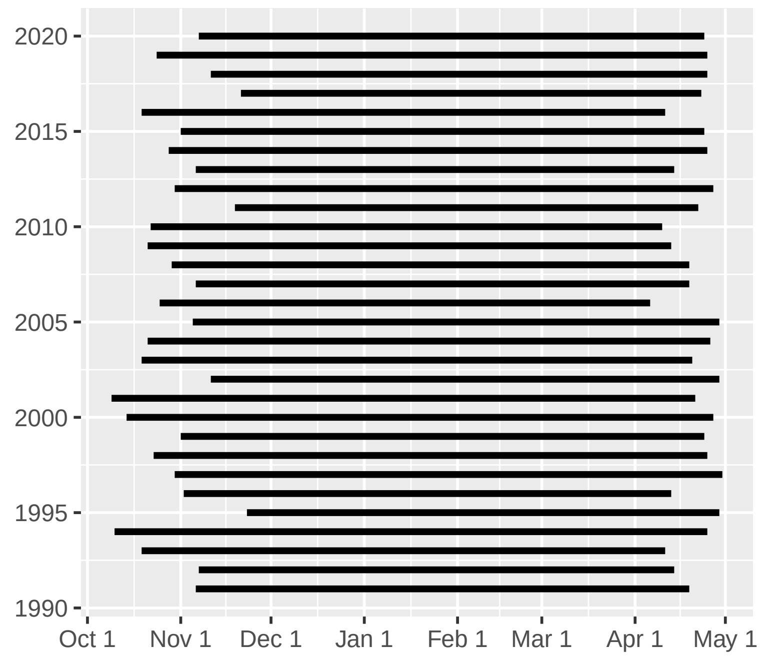
1990
Nov 1
Dec 1
Jan 1
Feb 1
Mar 1
Apr 1
May 1

Winter season lengths at West Rockport

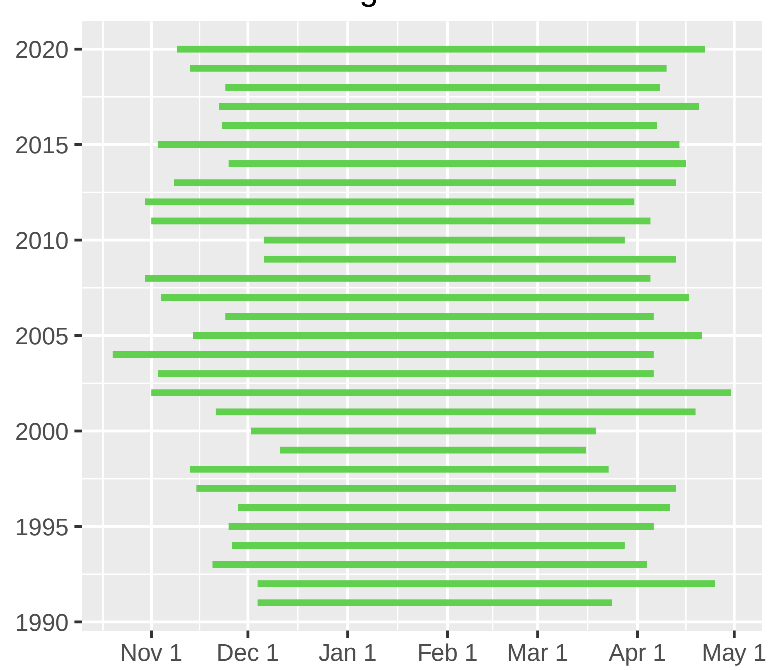
Winter season lengths at Bangor



Winter season lengths at Caribou



Winter season lengths at Grand Lake Stream



A.2 QR results across all quantiles for SHRP, AFDD and Accumulated Snow

The figures below present a concise summary of the quantile regression for other three indices: SHRP, AFDD and Accumulated snow at 12 locations. Each point represents the coefficient (slope of regression) obtained from particular quantile regression model. Values above 0 represent increasing trend and below 0 denote decreasing trend.

SHRP

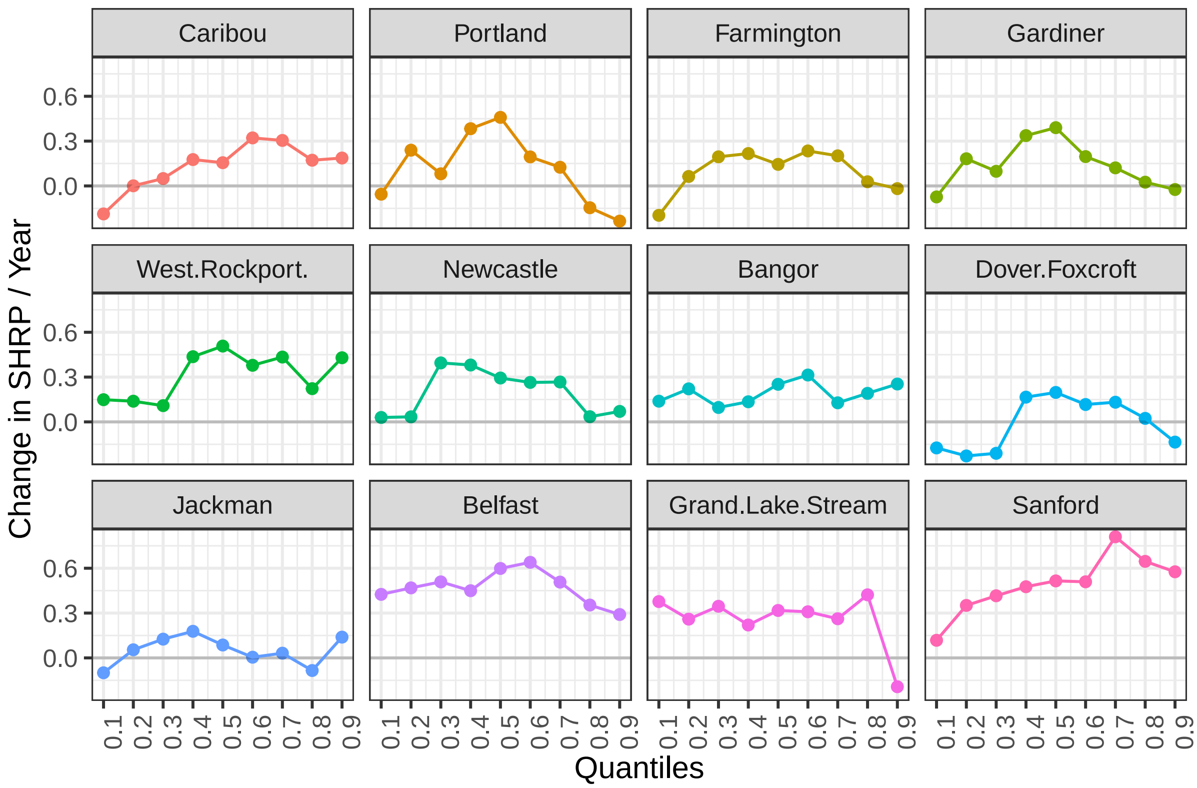


Figure A.1: Quantile regression for SHRP during 1991 to 2020.

AFDD

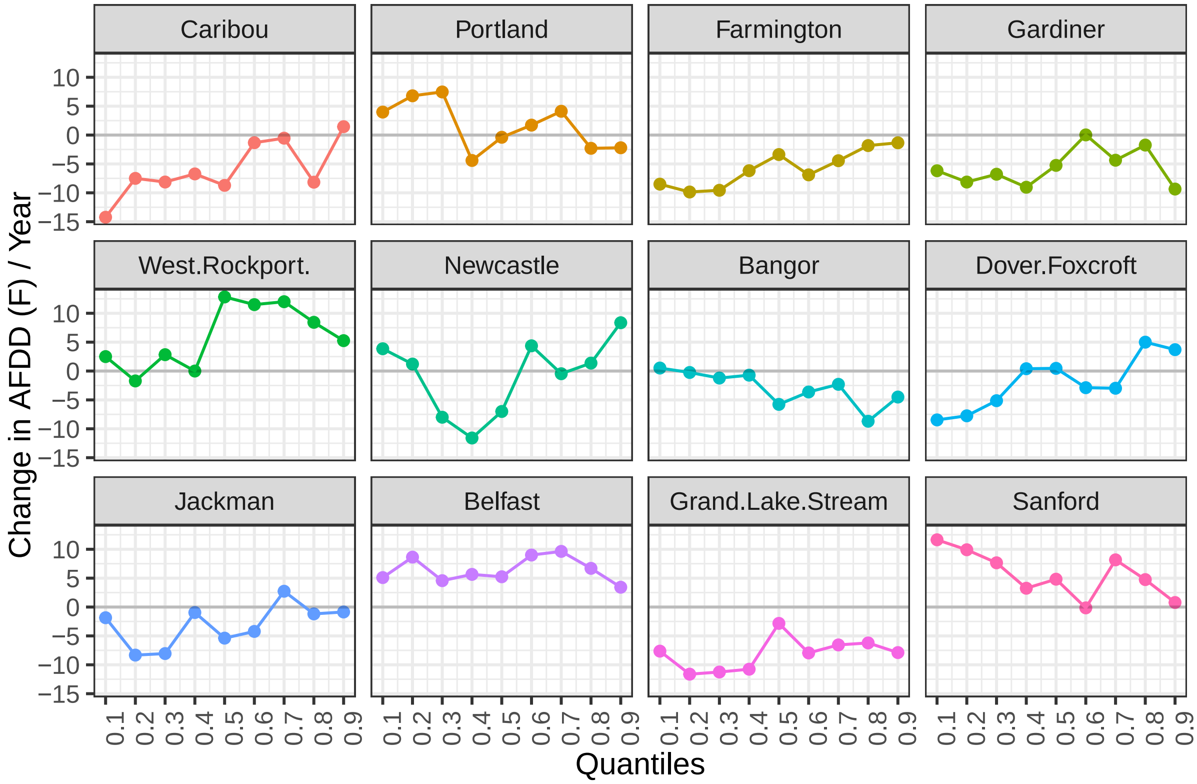


Figure A.2: Quantile regression for AFDD during 1991 to 2020.

Accumulated snow

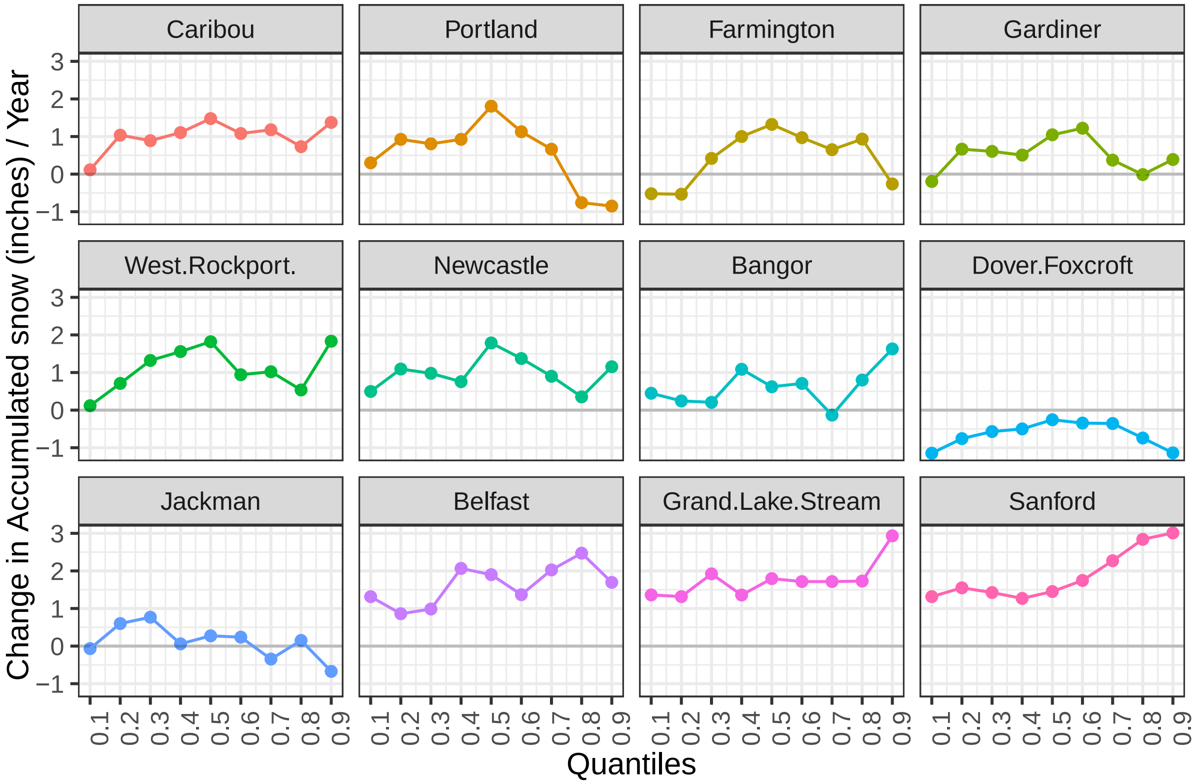


Figure A.3: Quantile regression for Accumulated snow during 1991 to 2020.

A.3 Trends in monthly AWSSI using quantile regression

In addition to QR of seasonal AWSSI, we performed the regression for monthly values of AWSSI. The results are shown in following three tables.

Stations	Nov	Dec	Jan	Feb	Mar	Apr
1	-0.113	1.941	6.75 **	2.857 *	3.444 **	-0.304
2	0	1	7.516 *	8.1 +	-2.964	0
3	-0.232	7.278	-1.061	3.143	1.5	0.88
4	0	2.71	1	-0.923	-1.611	0
5	0.455 *	1.154	4.333	1.24	-2.31	0.211
6	-0.577	0.792	-4.733 +	3.476 +	-3.36	-0.972
7	0	7.88	-8.381	4.632	-2.966	-3.571
8	0.308 *	3.76 *	10.571	11.706	3.762 *	0.853 +
9	0	4.833 *	-2.063	-4.773	-1.222	0
10	0.333 +	6.727 *	7.2 *	9.533 +	-1	1.2 *
11	-3 +	4.304	-2.3	3.654	0.517	-3.6
12	0.246 *	7.429 **	10.471 **	11.158 **	6.429 **	1.556 **

Note: $p < 0.001$ (***); $0.001 < p < 0.01$ (**); $0.01 < p < 0.05$ (*); $0.05 < p < 0.1$ (+)

Table A.1: Lower (0.2) QR results for monthly AWSSI

Station	Nov	Dec	Jan	Feb	Mar	Apr
1	0.2	3.5 **	10.143 **	10.2 **	3 +	0
2	0.444	9.071 *	3.957	1.333	0.067	1.25
3	-0.647	6.929 +	-6.81 +	5.593 *	1.412	1.231
4	0.632	11 **	0.214	1.765	1.833	1.143
5	1.783 +	3.818	1.259	2.13	4.875	2.84 +
6	-3.882 +	2.231	-1.333	1	-1.5	0
7	0.625	1.493	-6.833 *	-1.818	0.231	-0.385
8	0.636 +	6.95 *	14.083 **	12 **	6.125 **	2.2 **
9	0.448	6.167 *	-2.167	-0.6	-2.414	1.333 +
10	2 +	9.714 **	2.286	5.321	2.154	2
11	1.067	2.133	-0.5	-0.923	0.267	3.188
12	1.333 *	9.056	14.444	13.588	11.611	2.261 *

Note: $p < 0.001$ (***); $0.001 < p < 0.01$ (**); $0.01 < p < 0.05$ (*); $0.05 < p < 0.1$ (+)

Table A.2: Median (0.5) QR results for monthly AWSSI

Stations	Nov	Dec	Jan	Feb	Mar	Apr
1	1.45	13.667 **	8.68 **	10.45 *	6.571 +	0.5
2	-0.176	10.545 *	-6.143	4.765	1	-0.25
3	2.05	-0.259	-3.28	7.235 *	-8.038 +	2.571
4	3.7	-0.684	-3.7 +	0	-3.682	-1.333
5	3	-4	-2.609	6.684 +	-4.435	-2.714
6	2.533	1.417	1.238	-2.095	-5.462	4.92 +
7	1.441	0.84	-7.65 **	-2.333	-1.071	-0.852
8	3.75 *	9.381 +	13.545 *	12.2 *	8.5 +	2.133 +
9	0.4	-5.105	6.548	-0.913	-0.167	-0.654
10	1.933	13.28 *	7.375	-2.5	0.727	1.3
11	6.531 +	-1.55	-2.6	-1.071	0	-0.15
12	5.429	10.75 +	12.538	10.706 **	9.786 **	4 *

Note: $p < 0.001$ (***); $0.001 < p < 0.01$ (**); $0.01 < p < 0.05$ (*); $0.05 < p < 0.1$ (+)

Table A.3: Upper (0.8) QR results for monthly AWSSI

A.4 Trends in monthly AFDD and accumulated snow using quantile regression

Table A.4 presents both monthly and seasonal trends in the accumulated snow at upper quantile for all stations. At location Sanford, the seasonal increase appears to be apparent in months of November, December and February. Similarly, locations Belfast and Grand lake stream also exhibit increased snow severity for early winter months. Additionally, monthly severity trends can be identified for those locations that did not pick up trend in seasonal scale. For example the location Bangor shows increased severity for February and decreased severity for March, even though no seasonal trend was observed. Most locations show increasing trends during months of November, December, January and February but decreasing trends for March and April.

ID	Stations	Nov	Dec	Jan	Feb	Mar	Apr	Seasonal
1	Sanford	0.115 +	0.788 *	0.305	1.182 *	0.452	0.08	2.841 **
2	Portland	0.005	0.131	-0.783 +	0.889 *	-0.604	-0.204	-0.575
3	Farmington	0.182	0.410	0.046	0.367	-0.420	-0.152	0.932
4	Gardiner	0.271	0.421	0.28	0.484	-0.568 +	-0.023	-0.013
5	NewCaslte	0.335 +	0.065	-0.108	0.85 +	-0.571	-0.038	0.352
6	Jackman	-0.333	0.056	-0.6 *	0.11	-0.1	0.045	0.15
7	Dover.Foxcroft	0.231	-0.017	-0.468 +	-0.197	-0.808 *	-0.205	-0.743
8	Belfast	0.333 **	0.667 *	0.467	0.659	0.167	0.196	2.472 *
9	West.Rockport	0.1	0.518	0.2	0.437	-0.776 **	0	0.536
10	Bangor	0.173	0.159	0.089	0.662 *	-0.85 *	-0.014	0.8
11	Caribou	0.481	0.875 *	-0.187	-0.2	-0.089	0.076	0.73
12	Grand.Lake.stream	0.5 +	0.532 +	0.639 *	0.367	0.241	0.194	1.729 *

Note: $p < 0.001$ (***); $0.001 < p < 0.01$ (**); $0.01 < p < 0.05$ (*); $0.05 < p < 0.1$ (+)

Table A.4: Upper(0.8) QR trend in Monthly accumulated snow at 12 stations. Coefficient and significance (p-value) of predictor year variable is shown.

ID	Stations	Nov	Dec	Jan	Feb	Mar	Apr	Seasonal
1	Sanford	-0.008	-0.116	-0.032	-0.076	-0.06		-0.055
2	Portland	0.048	-0.015	0.211 +	0.04	0.061	0.092 +	0.008
3	Farmington	0.04	0.013	0.164	0.086	0.083	0.073	0.12 +
4	Gardiner	0.056	0	0.237 *	0.095	0.079	0.097	0.053
5	NewCaslte	-0.016	-0.062	0.098	0.015	-0.019	0.068	-0.02
6	Jackman	0.023	-0.033	0.171	0.057	0.013	0.068	0.055
7	Dover.Foxcroft	0.073	-0.003	0.101	0.014	0.029	0.1	0.108 *
8	Belfast	-0.003	-0.181 +	0.019	0.009	-0.064		-0.038
9	West.Rockport	0.001	-0.1	0.091	-0.041	-0.074	-0.006	-0.056
10	Bangor	0.012	-0.063	0.079	0.006	-0.039	0.095	0.041
11	Caribou	0.131	0.082	0.219 +	0.121 +	0.087	0.063	0.111 +
12	Grand.Lake.stream	0.112	0.206 *	0.33	0.117	0.124 +	0.105 +	0.197 *

Note: $p < 0.001$ (***); $0.001 < p < 0.01$ (**); $0.01 < p < 0.05$ (*); $0.05 < p < 0.1$ (+)

Table A.5: Upper(0.8) QR trend in Monthly mean temperature at 12 stations. Coefficient and significance (p-value) of predictor year variable is shown.

Mean air temperature trends at lower and upper quantile highlight scattered but increasing trends specific in months of January, February and March. Referring to table A.5 for mean air temperature, sporadic increase patterns are observed seasonally as well as monthly. In seasonal scale, locations Farmington, Dover Foxcroft, Caribou and Grand Lake stream show increase but with less statistical significance. At monthly scale, a decrease mean temperature is observed for month of December in Belfast. Scattered increase is found in all months except for November.

The lower quantile(0.8) for mean air temperature does not exhibit significant seasonal trends. While at monthly scale, incidence of increasing trends, however, scattered, are common in months of January, February and March.

ID	Stations	Nov	Dec	Jan	Feb	Mar	Apr	Seasonal
1	Sanford	-0.01	-0.057	-0.124	0.093	-0.268 *		-0.06
2	Portland	-0.025	0.071	0.201 +	0.237	-0.012	0.028	0.073
3	Farmington	0.025	-0.001	0.118	0.243	0.032	0.062	0.031
4	Gardiner	-0.003	0.108	0.232	0.264	-0.1 +	0.078	0.045
5	NewCaslte	0.014	0.086	0.254 +	0.203	-0.12 +	-0.03	0.037
6	Jackman	-0.031	-0.109	-0.079	0.322 +	-0.032	-0.041	-0.038
7	Dover Foxcroft	0.007	0.051	0.172	0.125	-0.055	0.085 *	0.017
8	Belfast	-0.072	-0.011	0.166	0.099	-0.055		-0.06
9	West.Rockport	-0.071 +	-0.173 *	0.282 +	0.111	-0.107 +	-0.012	-0.014
10	Bangor	-0.075	-0.046	0.332 *	0.193	-0.015	-0.005	0.035
11	Caribou	-0.009	0.002	0.272 +	0.251 +	-0.068	-0.021	0.015
12	Grand.Lake.stream	-0.011	0.047	0.454 **	0.342 *	0.016	0.086	0.068 +

Note: $p < 0.001$ (***); $0.001 < p < 0.01$ (**); $0.01 < p < 0.05$ (*); $0.05 < p < 0.1$ (+)

Table A.6: Lower (0.2) QR trend in Monthly mean temperature at 12 stations. Coefficient and significance (p-value) of predictor year variable is shown.

A.5 Dispersion parameters for weather count data

The values of dispersion parameter obtained from Poisson regression of seasonal frequency of winter events are provided in tables below:

Stations ID	Freezing rain	Freezing snow	Snow days above freez temp	Frost days without precipitation
1	1.34	1.38	2.00	0.42
2	1.36	1.00	3.06	0.44
3	1.18	1.14	1.95	0.57
4	1.71	1.76	1.71	0.45
5	1.39	1.57	2.41	0.44
6	0.69	0.91	1.66	0.99
7	0.82	0.81	2.11	0.38
8	1.13	0.97	1.69	0.48
9	0.92	1.01	3.06	0.53
10	1.08	1.84	1.85	0.53
11	0.81	1.01	1.56	0.42
12	0.65	1.26	3.59	0.45

Table A.7: Dispersion parameters for four weather events at 12 weather stations.

Stations	Light snow	Moderate snow	Heavy snow
Sanford	2.05	0.47	0.88
Portland	1.92	1.84	0.81
Farmington	1.65	1.16	1.14
Augusta	1.35	1.13	0.70
Newcastle	1.48	1.54	0.52
Jackman	1.91	1.19	0.82
Dover Foxcroft	1.44	0.86	1.47
Belfast	1.28	1.83	1.03
West Rockport	1.40	1.75	0.76
Bangor	1.53	1.20	0.93
Caribou	0.90	1.35	0.95
Grand.Lake.Stream	4.03	1.48	1.05

Table A.8: Dispersion parameters for light, snow and heavy snow days at 12 weather stations.

A.6 Negative binomial regression results

The coefficients obtained from Negative binomial regression for weather event count data are presented in tables below. The results conform with the results from quasi-Poisson regression analysis.

	Freezing rain days	Freezing snow days	Snow days above freezing temp	Frost days without ppt
Sanford	0.015 +	0.042 ***	0.041 ***	-0.003
Portland	0.005	0.002	0.004	-0.003
Farmington	0.003	0.022 **	0.012 *	-0.001
Augusta	0.004	0.012	0.018 **	-0.004 +
Newcastle	0.011	0.014 *	0.002	-0.002
Jackman	-0.008	0.008	0.016 **	-0.006 **
Dover.Foxcroft	-0.007	-0.016 *	-0.006	-0.002
Belfast	0.023 **	0.037 ***	0.04 ***	-0.003
West.Rockport.	0.014 *	0.027 **	0.013	-0.005 *
Bangor	-0.005	0.004	0.007	-0.004 +
Caribou	0.005	0.01 +	0.002	-0.005 *
Grand Lake Stream	0.008	0.058 ***	0.032 **	-0.004 *

Note: $p < 0.001$ (***); $0.001 < p < 0.01$ (**); $0.01 < p < 0.05$ (*); $0.05 < p < 0.1$ (+)

Table A.9: Negative binomial regression results for four weather event counts.

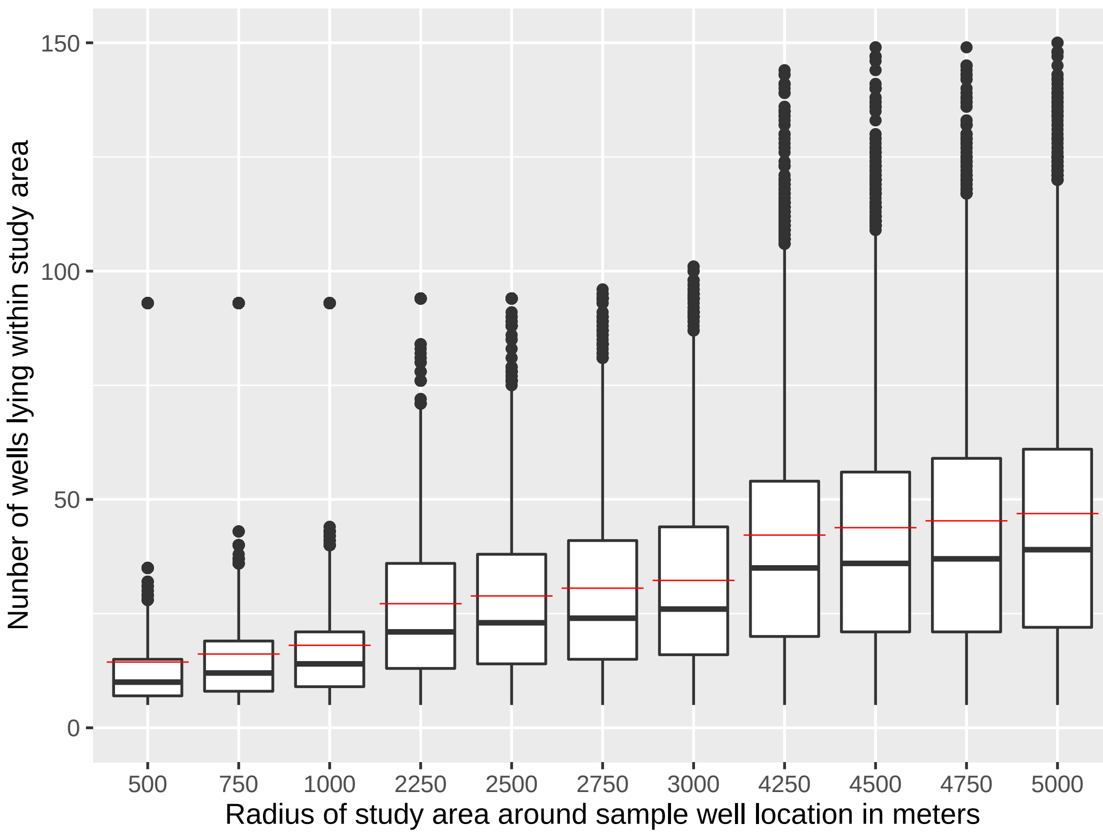
	Light snow days	Moderate snow days	Heavy snow days
Sanford	0.043 ***	0.045 ***	0.067 +
Portland	0.002	0.005	0.04
Farmington	0.017 **	-0.004	0.008
Augusta	0.018 **	0.007	0.019
Newcastle	0.005	0.012	0.111 *
Jackman	0.018 ***	-0.016 *	0.008
Dover.Foxcroft	-0.008	-0.01	-0.006
Belfast	0.042 ***	0.022 +	-0.01
West Rockport	0.015 *	0.017	0.032
Bangor	0.006	-0.012	0.068 *
Caribou	0.003	0.009	0.041
Grand Lake Stream	0.046 ***	0.016	0.024

Note: $p < 0.001$ (***); $0.001 < p < 0.01$ (**); $0.01 < p < 0.05$ (*); $0.05 < p < 0.1$ (+)

Table A.10: Negative Binomial regression results for three classes of snow days. Coefficients and significance (p-value) of time variable are presented. Light snow : less than 4 inches snow; Moderate snow: between 4 to 12 inches of snow; and Heavy snow: greater than 12 inches of snow.

APPENDIX B

The plot below shows the distribution of number of wells used in local risk computation for varying buffer radius.



Note: Any regions with less than 5 well tests are not included in all sets. The horizontal red line denotes mean of the distribution.

Figure B.1: Distribution of well sampling cases in study regions for eleven values of buffer radius.

BIOGRAPHY OF THE AUTHOR

Dikshya Parajuli was born in Pokhara, Nepal on April 10, 1994. She attended the Institute of Engineering at Tribhuvan University and graduated in 2017 with a Bachelor's degree in Civil Engineering. She started her Masters in Civil Engineering graduate program at The University of Maine in the fall of 2019. Dikshya Parajuli is a candidate for the Master of Science degree in Civil Engineering from the University of Maine in May 2022.