Temporal and Spatial Impacts of Extreme Weather Events on Winter Wheat and Milling Oat Yields in Southern Ontario

by

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Abstract

This is a comprehensive study of extreme weather events in southern Ontario from 1950 to 2017, and their impacts on winter wheat and oat yields. Trends in temperature and precipitation were evaluated annually and seasonally. There were significant shifts toward increased warming, growing season length, and the frequency of precipitation events. Warm and precipitation extremes are increasing in intensity, duration, and magnitude. Random Forest regression was used to investigate how different extreme weather indices were related to winter wheat crop yield, across crop pheno-phases and controlling for soil texture. Crop-specific indices were important indicators, explaining 40% of yield variance. Winter Warming Index was the most important index in the RF model, linked to a 72% increase in mean square error when removed. Changing extreme weather distributions in southern Ontario seems to be increasing potential negative impacts on farming winter wheat and milling oats, so adaptive plans should be considered.

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Chapter 1. Introduction and Literature Review

1.1 Introduction

Global warming has been progressing steadily since 1850, with an increase of about 1ºC in global average temperature (IPCC, 2014). As of the fifth report of the Intergovernmental Panel on Climate Change (IPCC), between 1983 and 2012, the Earth's surface faced its warmest 30-year period since 1880, (IPCC, 2014). In Canada, the average annual temperature has increased by 1.7 ºC since 1948 and this increase is reported to be twice the global average, with a major increase in the northern regions (Bush et al., 2019a). In Ontario the increase in average annual temperature was not uniform across the area (Expert Panel on Climate Change Adaptation, 2009). For instance, the average annual temperature has increased by 1.3 ºC in the south-west part of Ontario during the last 60 years, with a less significant increase in the southeast (Expert Panel on Climate Change Adaptation, 2009). However, Ontario is predicted to experience an increase in annual average temperature of about 2.5 ºC to 3.7 ºC by 2050 (Bush et al., 2019a).

Several studies have examined trends in weather indices based on daily temperature and precipitation in Canada, and noted a change in warm conditions across Ontario (Vincent et al., 2018; Bush et al., 2019a; Vincent et al., 2015a). High numbers of hot days and nights are not very common north of 60°N, but a significant increase by 1-3 days in the frequency of hot summer days and nights has been noticed in the southern regions of Ontario (Bush et al., 2019a; Vincent et al., 2018). Additionally, warmer winters and springs have resulted in a decrease in the number of frost days and ice days, an increase in the length of growing seasons, and an increase in the number of growing degree days (Vincent et al., 2018; Bush et al., 2019a). From an agricultural perspective, these conditions could be promising for Ontario agriculture and could provide the potential for northward expansion and opportunities for new crop varieties across Ontario (Comer et al., 2017).

Nevertheless, the increase in annual mean temperature, especially in the southern regions, has been associated with an increase in hot extremes, a decrease in cold extremes, and an increase in the number of freeze-thaw cycles (Bush et al., 2019a). As well, extreme weather events are projected to increase in intensity, duration, and frequency across Ontario, affecting crop growth and yields (Comer et al., 2017; Bush et al., 2019a; Iizumi and Ramankutty., 2016; He et al., 2018).

The relationship between climate extremes and variations in crop yields has been the subject of many studies (Leng and Huang, 2017; Lesk et al., 2016; Iizumi and Ramankutty, 2016). It has been shown, using many different statistical approaches, that extreme weather stressors such as heatwaves, excessive rain, and droughts have significant impacts on crop yields worldwide (Tao et al., 2009; Konduri et al., 2020). Cereal crops are a vital part of the cropping system in Ontario, cultivated on approximately 25% of the arable land (OMAFRA, 2016a). In 2016, Ontario ranked fourth among Canadian provinces for total field crop area (Statistics Canada, 2017a), with winter wheat being the most commonly grown cereal, followed by spring barley, spring wheat, and oats (OMAFRA, 2016a). According to the Census of Agriculture of 2016, winter wheat is the third largest crop and it held third place in terms of area, despite a decline in the area seeded between 2011 and 2016, at 1,100,003 and 1,080,378 acres, respectively (Statistics Canada, 2017a); however, Canada's year-to-year wheat and oats yields fluctuate due to regional weather patterns and other factors (Logan, 2015).

Recently, winter wheat and oat yield losses have been documented in Ontario due to extreme weather events. In 2018 and 2019, for instance, the increase in freeze-thaw cycles during the period from January to February impacted fields where winter wheat had been shallowly planted in many counties, particularly in fields with heavy clay soils, resulting in heaving of winter wheat (frost goes into the ground underneath the crown and lifts it out of the ground), which affects the crop's

survival (OMAFRA, 2018a; OMAFRA, 2019a). About 500 damage reports from many counties' fields across the area were issued in 2018 (OMAFRA, 2018). The damage was even more significant in 2019, since the extent of the freeze-thaw cycle events affected winter wheat yields in a greater number of counties across Ontario. This winterkill was the most significant event in the history of the winter wheat plan with Agricorp (a provincial government agency that provides crop production insurance), with the counties harvesting less than 70% of the acres seeded the previous fall (OMAFRA, 2019). Accordingly, $46 million was provided to Ontario producers, with $28 million going towards replanting payments and $18 million going towards yield shortfalls (OMAFRA, 2019a). Similarly, over the past several decades, oat production and yields have shown variability across Ontario due to many factors, such as droughts, and delays in seeding dates. Many oat varieties are seeded in late-July or early-August following wheat and spring cereal for an early-October harvest (Bagg, 2013). The delay in the harvest of the early crops leads to a delay in planting oats, which could contribute to yield decreases and fluctuations. Milling oats also could be significantly impacted by the delay in seeding date since dry and hot conditions in June and July affect the crop in certain growth stages such as pollination and grain fill periods (OMAFRA, 2019; OMAFRA, 2017a; OMAFRA, 2016b).

Studies investigating the impacts of extreme weather events on winter wheat and milling oats yields in Ontario are needed to ensure sustainable yields for both crops since these crops are vital in the Ontarian agricultural system (OMAFRA, 2016a). These investigations help better assess the relationship between extreme weather events and the crops' yield variability and help farmers to understand when and where extreme events are expected to have major risk on winter wheat and oat crops, which could improve agricultural practices and support in the region. Research conducted so far has analyzed crop genotypes and their interactions with environmental factors

(Haji and Hunt, 2011; Yan and Hunt, 2001). Other studies analyzed climatic and non climatic factors to predict winter wheat survival and yield variance (Hayhoe et al., 2003a; Cabas et al., 2010; Weersink et al., 2010). However, those latter studies did not analyze the impacts of weather variables on crop growth in different pheno-phases, and to our knowledge, there are no studies in the literature that have examined the effects of extreme weather events on winter wheat and milling oat yields in the region, particularly at regional scales such as townships.

In the past decades in Canada, many studies have modeled the impacts of weather variables on winter wheat cultivars (Hayhoe et al., 2003a; Qian et al., 2010; He et al., 2018a); locally, some studies in a controlled environment investigated the crops' genotype sensitivity toward specific environmental conditions such as temperature, soil moisture, cold hardiness, and ice encasement tolerance (Andrews and Gudleifsson, 1983). Other studies focused on investigating the vulnerability of certain cultivars to certain environmental stressors at specific locations (Reid et al., 2007a; Cabas et al., 2010).

Yet in Ontario, the impacts of extreme weather events considering both temperature and precipitation variables and the spatial variations of these variables across the region on winter wheat and milling oats are not very well understood. There is scarcity in research that studies this relationship, therefore we need to investigate yield variability across these crops as a function of extreme weather. We can determine climate indices that are strongly associated with yield variability across the region. Moreover, we know that site conditions such as soil quality (soil texture, soil water retention capacity, etc.) can also impact crop responses. However, a lot of these qualities are difficult to obtain or estimate across large spatial extents and through time. Soil texture is one important variable of concern, since it determines soil water thresholds (SWT), and it is relatively stable in time. Studying the variations in soil texture in southern Ontario, represents one

readily-available (in terms of data) component of important soil-plant interactions. For instance, soil texture determines soil water content and thresholds, which determine the quantity of water available for the plant consumption, and when and how much water is needed for the plants (Datta et al., 2017). Integrating soil texture in the study can help to assess the potential for soil qualities to moderate the impacts of weather on crop yield.

Therefore, the purpose of this research is to study the impacts of extreme weather events on crop growth at different growth stages and project these impacts on crop yields. This can be broken down into the following aims:

- Understand the changes in the frequency, intensity, and patterns of extreme weather events that could potentially impact cereal cropping systems in southern Ontario between 1950 and 2017, and downscale these changes from regional (southern Ontario) to township levels;
- Develop and design sets of crop-specific phenological and agroclimatic indices (an indicator of an aspect of weather variable that has a significant impact on crop growth) for milling oat and winter wheat, which will help in understanding the influence of extreme weather events on crop growth. These crop-specific indices will permit the investigation of the crops' thresholds and their tolerance to extreme temperatures and precipitation events during the period from 1950 to 2017;
- Study the variation in soil texture in the area and its potential role in modifying the impacts of weather on crop yields;
- Estimate the relationship between winter wheat-specific extreme weather indices and average residual yields using crop yield data from 1987 to 2019, which will help in comprehending how extreme weather events in southern Ontario could explain winter

wheat yield variance, and determine which of the designed indices are particularly valuable in indicating conditions leading to low or high yields, controlling for soil texture.

1.2 Literature review

1.2.1 Regional trends in weather variables and extremes

Some studies have provided in-depth analyses of temperature and precipitation trends in Canada (Bush et al., 2019; Zhang et al., 2010; Vincent et al., 2015; Wazneh et al., 2017). Historical observations of annual mean temperatures in Canada from 1960 to 2020 show that the Canadian warming rate is twice the global average rate of warming (Figure 1) (Vincent et al., 2015; Bush et al., 2019).

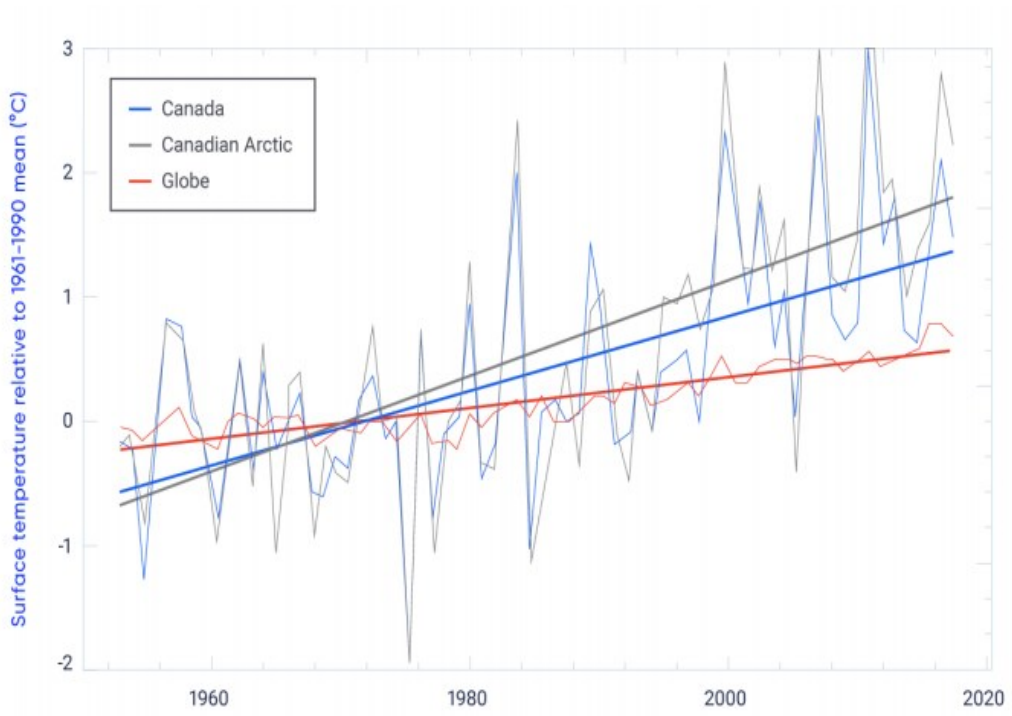


Figure 1: Rates of warming in Canada compared with the global rate. Source: (Bush et al., 2019).

Weather trend analysis in the 20th century (1900–1998) showed an increase in the mean annual temperature by about 1 ℃, and increases in the annual total precipitation of about 5 to 35% for the same period (Zhang et al., 2000). Most of these studies gave particular attention to the national scale; for example, Bush et al. (2019) and Vincent and Mekis (2006) showed fewer cold nights, cold days, and frost days, and increasing trends in warm nights, warm days, and summer days across Canada. Other downscaled studies at regional scales showed increasing trends in both lowest and highest percentiles of daily maximum and minimum temperatures for southern Canada (south of 60˚N) (Bonsal et al., 2001). Similarly, Wazneh et al. (2017) examined and evaluated the trends in historical climate and extreme weather events for southern Ontario using a suite of observed and simulated climate indices at local or small regional scales, and showed an increasing trend in annual total precipitation with a wide range of 5 to 35% in different regions.

In Ontario, there has been an increase of 1.3 ºC in the mean annual temperature over the region (Bush et al., 2019a; Vincent et al., 2018). In addition to the changes in annual mean temperature, Ontario has also experienced changes in seasonal mean temperature during the period from 1948 to 2016 with the major trend in winter indicating an increase of 2.0 ºC, while a smaller increase of 1.0 ºC has been noticed on autumn temperatures (Figure 2) (Bush et al., 2019; Vincent et al., 2015b; Vincent et al., 2018).

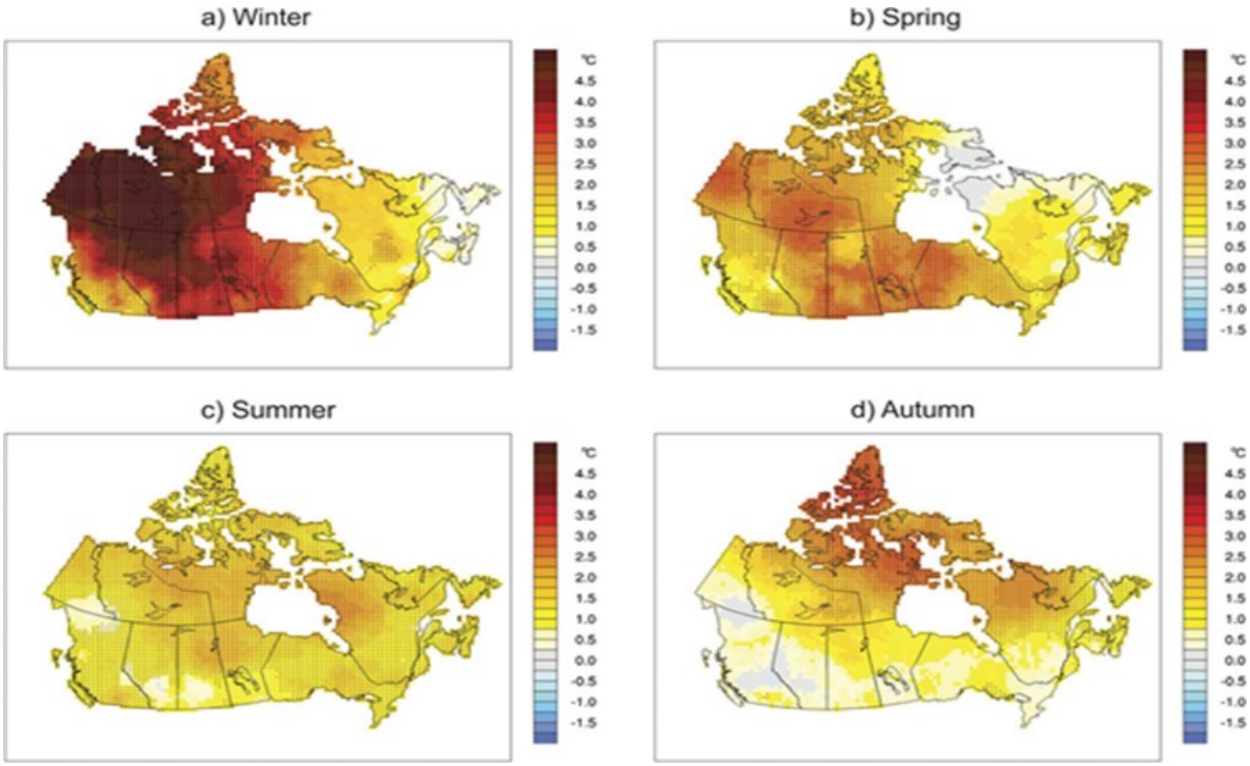


Figure 2: Trends in seasonal mean temperatures (°C/65 years) across Canada. Source: Vincent et al. (2015b). Grid squares with trends statistically significant at the 5% level are marked with a dot.

Normalized precipitation anomalies (normalized by dividing the anomalies by the 1961- 1990 averages) over Canada also increased of about 19% from 1948 to 2012, with the most statistically significant increase being observed in southern regions, including southern Ontario (Vincent et al., 2015b). Similar to the temperature trends, mean annual precipitation increased about 10% during the period from 1948 to 2012, while seasonal trends in precipitation ranged from increases of 5% in winter to 18% in fall (Bush et al., 2019; Vincent et al., 2015) (Figure 3 and 4).

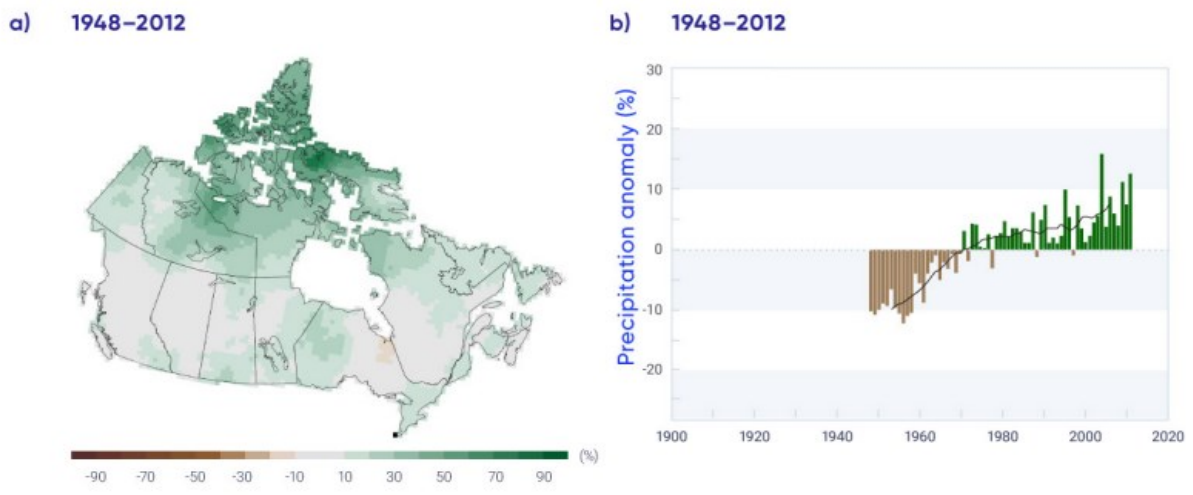


Figure 3: Changes in annual precipitation, 1948 to 2012. Source: Bush et al. (2019)

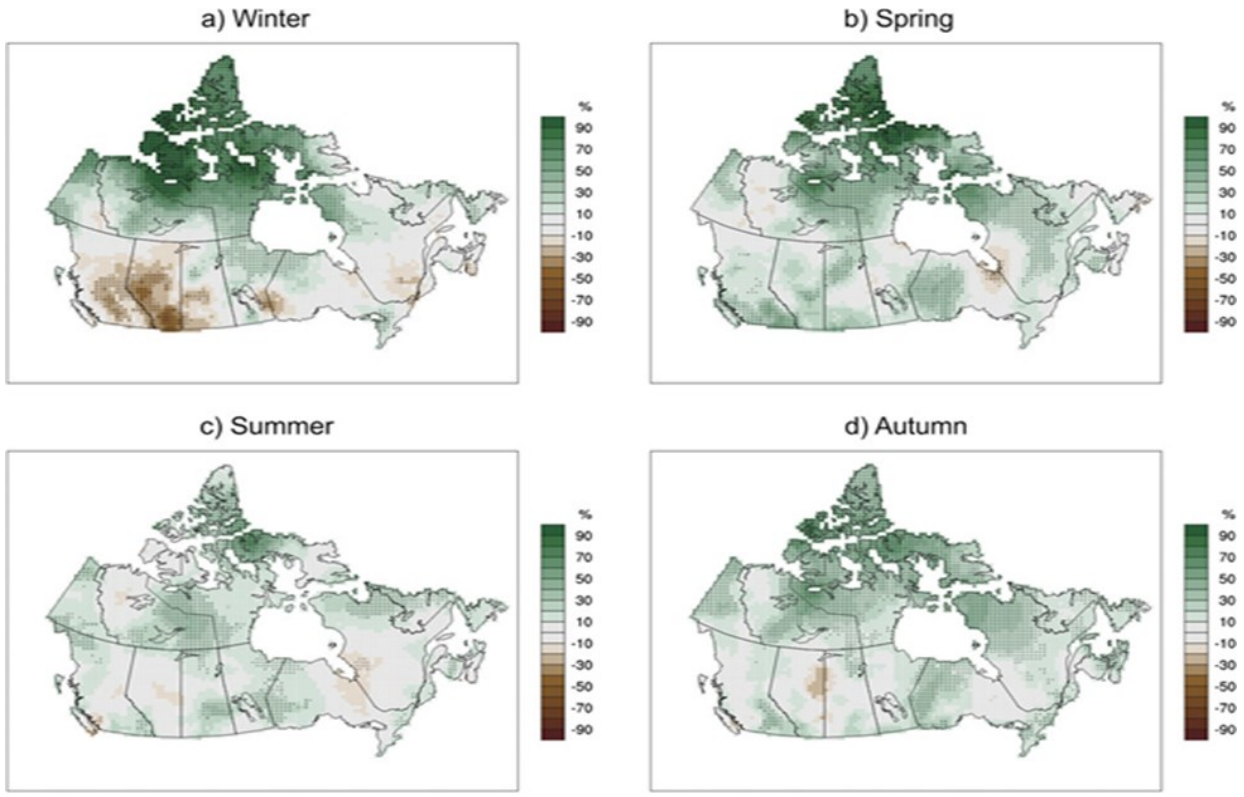


Figure 4: Observed changes in normalized seasonal precipitation (%) between 1948 and 2012. Source: Vincent et al. (2015).

Within Ontario, in the last few decades there has been an increase in annual air temperature accompanied by milder and shorter winters, prolonged freeze-free periods, and a decrease in the number of ice days (Number of days with maximum temperature ≤ 0°C from July to June). While summers have become warmer, the growing seasons have become longer, and annual precipitation has also increased (Reid et al., 2007; Waldick et al., 2017; Bush et al., 2019; Vincent et al., 2015; Vincent et al., 2018).

In terms of extreme weather events, Ontario has experienced more prolonged dry spells and increases in annual heavy precipitation days, very heavy precipitation days, and very wet days (Deng et al., 2016; Bush et al., 2019). During the last 60 years, the average temperature increase has varied from about 1.3 °C in the west to a little increase in the southeast (Expert Panel on Climate Change Adaptation, 2009). Although annual temperatures in northwestern and eastern Ontario were below the baseline average across Canada (defined as the mean over the 1961–1990 reference period) (Government of Canada, 2020), the warmer conditions, especially in winter and spring, have caused increases in some extreme weather events such as heatwaves, droughts, and floods resulting from earlier peak spring streamflows (Bush et al., 2019a).

Some regions in Ontario are expected to receive approximately 6% more precipitation than the mean annual precipitation observed in the latter half of the twentieth century in all seasons (Waldick et al., 2017; Bush et al., 2019). Still, climate models predict that precipitation in large areas such as southern Ontario is projected to decrease under high emission scenarios, mainly in summer periods (Bush et al., 2019a). Furthermore, the region is projected to have more extreme heat events and fewer extreme cold events, longer growing seasons, shorter snow and ice cover seasons, and earlier peak spring streamflows (Bush et al., 2019a). While warmer conditions leading to prolonged growing season lengths are expected to benefit crop growth in the region, intensified

and localized extreme events such as hailstorms, droughts, and floods are expected to increase in frequency, intensity, and duration (Bush et al., 2019; Deng et al., 2016). Consequently, this could have harmful impacts on the yields of vital crops in the Ontario agricultural system (Waldick et al., 2017), such as winter wheat.

1.2.2 Crop-specific indices and historical view on cereal crops in Ontario

Zaytseva (2016) presented crop-specific indices to describe the relationships and interactions between crops and climate conditions in eastern Ontario. That work used weather indices to describe trends in climate extremes in eastern Ontario for agriculturally-based periods, based on temperature and precipitation variables and extreme weather event indices. The work showed an increase in warmer and wetter conditions in most parts of the region. The most notable changes in both temperature and precipitation extremes were observed in the eastern-most part of this region and along the St. Lawrence River, where most of the agricultural lands in the eastern region are located (Zaytseva, 2016). Overall, a decrease in the frequency of cold temperature extremes and an increase in the frequency of warm temperature extremes in the study region were found, and the annual total precipitation and frequency of extreme precipitation events increased (Zaytseva, 2016). That study also developed phenological and agroclimatic indices specifically applied to corn and soybeans. These crop-specific indices demonstrated the potential impacts of extreme events on crop yields, depending on the sensitivity and the response of the crops to extreme weather in their different phenological stages. Although increases in the length of growing seasons and crop heat units could benefit some crops, including corn and soy which dominate eastern Ontario, these crops are susceptible to drought, which significantly limits their development (Zaytseva, 2016).

Since cereal crops are vital for the cropping system in Ontario, the present study focuses particularly on winter wheat and milling oats. Globally, wheat (*Triticum aestivum L*) was one of the first plants cultivated by humankind (Bélanger et al., 2002), and now it is the second most cultured cereal crop, after rice, with a production of about 765 million tonnes annually (Bélanger et al., 2002; Hyles et al., 2020). Canada is one of the biggest producers of wheat (Hyles et al., 2020), and according to Statistics Canada (2017), wheat is the third most abundant crop in terms of area seeded. Ontario contributes most to the production of winter wheat, whereas in the prairies spring wheat dominates (Statistics Canada, 2017a). Since 1980, the number of cereal market classes has expanded considerably (OMAFRA, 2017a); for example, the demand for milled oat products has increased significantly, and oat-milling capacity is estimated to be approximately 100,000 tonnes per year (OMAFRA, 2020a). Since oats and winter wheat are vital parts of the socio-economic system in Ontario, investigations of the sensitivity of these two crops would be beneficial, to estimate the risks posed to these crops by extreme weather events.

Cereals such as winter wheat and oats grow in cool weather and because they demand adequate moisture (McLeod, 1982), they are also vulnerable to overly high temperatures (Stokopf, 1985). In contrast to winter wheat, oats can grow in marginal environments with limited nutrients (McLeod, 1982), but they require more moisture (Saskatchewan Ministry of Agriculture, 2009) and are less tolerant to frost (Ziesman et al., 2010).

Winter wheat can tolerate extremely cold temperatures, down to -23°C (OMAFRA, 2017a), and therefore Ontario's winter temperatures rarely cause damage to winter wheat yields, in contrast to oats, which are sensitive to low temperatures (Brown and Blackburn, 1987). Despite this tolerance, it has recently been noted that the increasing frequency and intensity of extreme weather events such as frosts, floods, and droughts in Ontario are likely causing a decline in winter wheat yields

(Tan and Reynolds, 2003). On the other hand, the increases in daily temperatures and warm springs and summers, and the prolongation of growing seasons, are likely favorable for oat production (McLeod, 1982). In other words, climate change creates both risks and opportunities for Ontario's agriculture system (OMAFRA, 2020b). Although the growing seasons are becoming longer and warmer, which likely creates new cropping opportunities (Weber and Hauer, 2003), warming extreme weather events such as droughts and intensive rainfalls can significantly damage Canadian food production systems (Council of Canadian Academies, 2019).

1.2.3 Extreme weather events

Since the release of the fifth report on climate change by the IPCC in 2014, studies of extreme weather events have been growing in the literature (IPCC, 2014; IPCC, 2021). An extreme weather event is considered to be the occurrence of a value of a weather variable above or below a threshold value near the upper or the lower ends of the range of observed values of the variable (IPCC, 2021). The sixth report of the IPCC defines an extreme weather event as "an event that is rare at a particular place and time of year" (IPCC, 2021). These commonly- adopted thresholds are subjective at local and regional scales due to drivers such as location and topography, and they are strongly influenced by

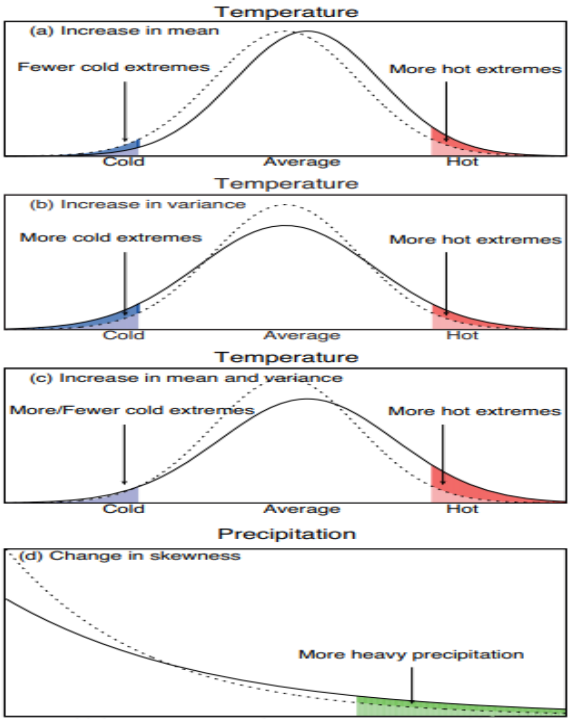


Figure 5: Probability density function. Dashed lines represent a previous distribution, and solid lines a changed distribution. The probability of occurrence, or frequency of extremes, is denoted by the shaded areas. Source: IPCC (2013)

large-scale weather patterns and phenomena. By consequence, the definition of an extreme weather event may vary from place to place in an absolute sense (IPCC, 2021). Notwithstanding shifts in the distribution of weather or climate variables in a region, an extreme event is considered a rare occurrence. A rare event could be evaluated differently from place to place and depending on the timing of its occurrence. In this research, IPCC definition was adopted, that an extreme event is considered to be an event that is "rare as or rarer than the 10th or 90th percentile of a probability density function estimated from observations" (IPCC, 2013). Probability density functions were used to show the relative chances of the occurrence of different outcomes of a variable, as shown in (Figure 5).

Upward trends in annual and seasonal temperature extremes in the lower and higher percentiles of daily minimum and maximum temperature distributions in Canada have been observed over the past several decades in many studies (Bonsal et al., 2001; Bush et al., 2019a; Vincent et al., 2018). Seasonally, a decrease in days with extremely low temperatures and an increase in days with extremely high temperatures has been observed (Bush et al., 2019a). In Canada, the frequency of extreme weather events such as storms, freezing rain, and heatwaves has increased considerably in the past few decades (Bush et al., 2019a). Cao (2008) confirmed a robust upward trend in the frequency of hailstorm events in Ontario (Cao, 2008; Seneviratne et al., 2012), while Cheng et al. (2012) suggested that daily ice-storm or freezing rain events for the three coldest months from December to February are projected to increase in eastern Ontario by 50%–70% by 2050, and by 80%–110% for 2081 to 2100 (Cheng et al., 2012).

In recent years, a variety of extreme weather events has been recorded in different parts of Ontario; for instance, a series of flood events has been noted, particularly in 2017 and 2019 (Government of Canada, 2020). The most damaging event was in 2019 when tropical storm Olga hit the region

with up to 50 mm of rain, raising water levels. Spring 2019 was the coldest in 22 years and had serious flooding events. These events caused severe agricultural losses across the region (Government of Canada, 2020). In that same spring, planting was delayed, resulting in the failure of about 5% of Ontario's crops (Government of Canada, 2020). Additionally, there was an increase in hail frequency over the region, such as the hailstorm in the last week of June 2017 which resulted in damage to many crop fields (Field et al., 2012; OMAFRA, 2017).

1.2.4 Extreme weather indices and cereal crops

Global warming is increasing rapidly, causing more frequent and intense extreme weather events, and in the Canadian context, the pace of warming may surpass the adaptive capacity of many vital systems (Council of Canadian Academies, 2019). Agricultural production in Canada is subject to significant yield reductions due to climate extreme events. These yield reductions were demonstrated by the 2001 and 2002 drought periods on the Canadian prairies (Wheaton et al. 2005), which resulted in a 30% reduction of the spring wheat yield relative to the 1976–2005 30-yr mean (Qian et al. 2009). Hence, to ensure sustainable agricultural yields for winter wheat and milling oats, it is important to understand historical patterns of the frequency and intensity of extreme weather events and to monitor the crops' agroclimatic conditions (Qian et al., 2010).

In the past few decades, Ontario has experienced more frequent spring flooding, summer drought periods, and winter storms. In 2011, farmers in Ontario suffered from water deficits around mid-July, where long periods of hot and dry weather affected wheat production, while in September and October, there was an excessive amount of rain, which significantly delayed the harvest season (Environment and Climate Change Canada, 2011). The spring of 2018 brought cool and wet conditions followed by hot and dry weather during the critical grain-filling period (grain formation stage), which caused negative impacts on yields for many farmers (OMAFRA, 2018). Ontario's

weather conditions pose a high risk for fusarium, migration of insect pest, and plant disease due to the warming weather and the wet conditions in summer (Reid et al., 2007a). Furthermore, decreased snow cover and rapid snowmelt leave the soil without protection for long periods, increasing the risk of erosion (Reid et al., 2007b).

According to Anton et al. (2011), droughts in 2001 and 2002 cost the industry $6.14 billion, while droughts in 2003 contributed to net farm losses in income of $13 million. Within individual provinces, crop insurance claims have been significantly increasing (Anton et al., 2011), and in Ontario, insurance payments totaled approximately $1 billion from 1966 to 2000 but increased by about $640 million between 2000 and 2004 (Anton et al., 2011). These economic effects have contributed to an increased interest in proactively addressing the negative impacts associated with changes in climate and weather conditions (Helfrich and Prasad, 2011).

Studying and understanding the relationships between extreme weather events and cereal yields is a complex process for multiple reasons. First, extreme weather events show non-uniform variations in temporal and spatial patterns, as is the case with precipitation (Wazneh et al., 2017, AghaKouchak et al., 2012). Second, the perception of extreme weather varies geographically depending on how well the area and its farmers are prepared to tolerate these events (IPCC, 2012). Third, besides the spatial factors, extreme weather events also have critical impacts that depend on the timing and the phenological stage of the crop. For instance, a rainstorm that lasts several days could be problematic for crops such as spring wheat and oats in springtime, when the soil is already moist (Rosenzweig et al., 2001). Therefore, given the spatial and temporal variability in both extreme weather events and crop phenology, it is important to take a regional and crop specific approach when investigating the effects of extreme weather events.

There is a scarcity of all-inclusive information on factors contributing to poor winter wheat and milling oat survival, particularly at a local scale (township level) and considering growth stages; the assessments of the relationships between weather and field-site information such as topography, winter rainfall, and air temperature extremes are required (Hayhoe et al., 2003). This research, therefore, provides a comprehensive regional study that helps understand the pattern, frequency, and intensity of extreme weather events in the southern Ontario. Then, I analyze the implications of these extreme events on winter wheat and milling oat yields depending on their growth stages. Moreover, the study provides later analyses of the soil textures in the region and how soil texture and extreme weather events could influence crop yields across southern Ontario.

Climatic indices were selected, defined, and computed based on a set of 27 indices for extreme climate variables set out by the Expert Team on Climate Change Detection and Indices (ETCCDI, 2020) in addition to a set of indices developed by Environment and Climate Change Canada for eastern Canada consisting of 12 indices for temperature and 6 for precipitation (Canadian Centre for Climate Modelling and Analysis, 2012; Zaytseva, 2016). To better understand and describe extreme weather events and to make this information usable for farmers and policymakers, these climatic indices will be calculated locally and adapted for the agricultural system of southern Ontario. For the purpose of analyzing and determining the relationships between extreme weather events and crop yields, a crop-specific set of phenological and agroclimatic indices was calculated according to the tolerance of the two crops and their responses to extreme conditions such as floods, frost, drought, and snow thaw during winter.

Chapter 2. Study region and phenology of winter wheat and milling oats

2.1 Study region

Ontario is the second-largest province in Canada (Baldwin et al., 2007). It has more than half of the highest quality (Class 1) agricultural land in the country (Chapagain, 2017), supporting about 49,600 farms (Statistics Canada, 2017b; Chapagain, 2017). Most farms and cash crop production enterprises are concentrated in the southern Ontario region, which has the most diversified and productive agricultural system in Canada, producing around one-quarter of all farm revenue in the country (Chapagain, 2017). The study area covers about 140,000 km2 and extends approximately from 83°W, 42°N in the south to 74°W, 46°N in the north (Figure 6). Southern Ontario does not have a universally recognized spatial extent so a regional map from Land Information Ontario was used to select townships to be included in the study area as shown in Figure 6.

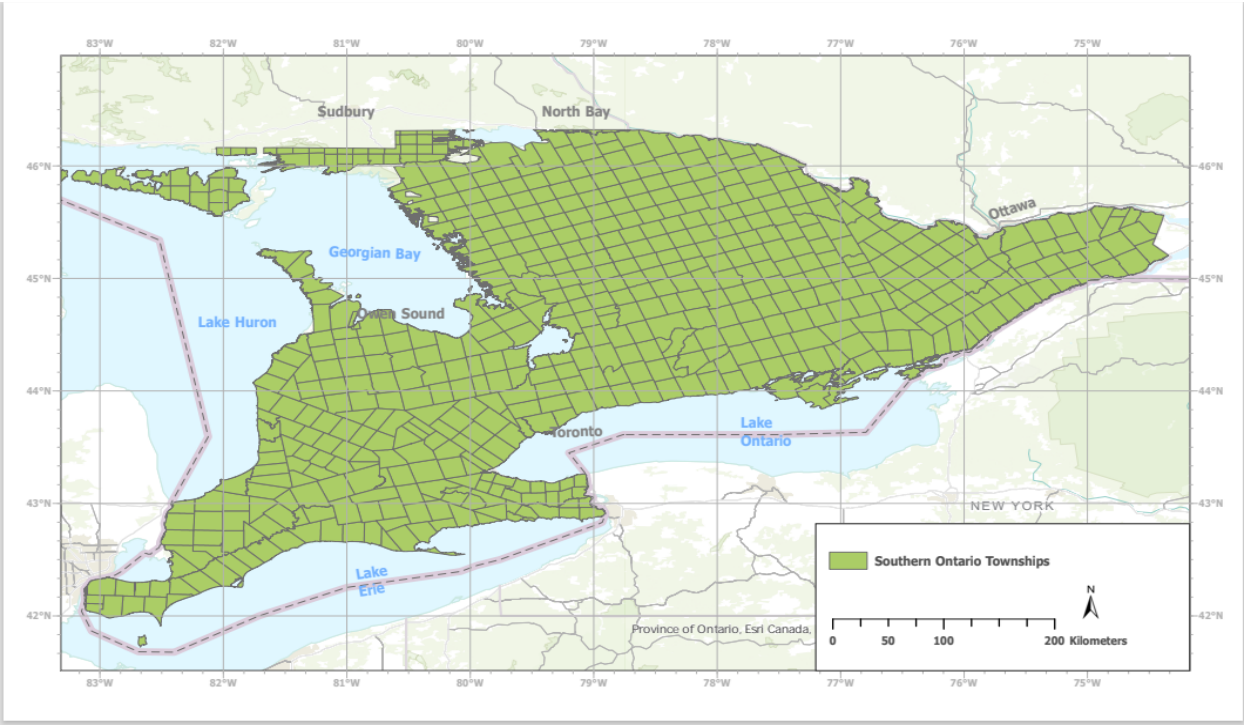


Figure 6: Map of the study area representing the southern Ontario region. The 614 polygons represent township divisions.

The region's climate is described as humid continental, with the exception of areas under the influence of Hudson Bay (Bowman, 1967; Baldwin et al., 2007). Three important air sources influence the region's climate: cold, dry polar air from the north, which dominates during the winter; moist, Pacific polar air passing over the western prairies; and warm, moist, sub-tropical air from the Atlantic Ocean and the Gulf of Mexico (Baldwin et al., 2007).

Large water bodies, such as the Great Lakes, and local relief modify the area's winter temperature. Lake Huron, for instance, moderates the temperatures during the winter season, whereas local relief influences the temperature gradients in areas of increased elevation, such as the highlands near Caledon in southern Ontario and the northern areas of the study region near Algonquin Park. Pockets of lower temperature are evident in each of these higher elevations, and these locations have fewer growing-degree days than the areas surrounding them (Bowman, 1967; Baldwin et al., 2007). January is usually the coldest month in southern Ontario, and the southern part is milder compared to the northern regions. The mean minimum temperature ranges from -6 ºC in the south to -17 ºC in the north (Bowman, 1967).

Precipitation is also significantly modified by the Great Lakes as well as other topographic features, particularly in areas near Georgian Bay and Lake Huron (Bowman, 1967). The southern and eastern parts of the study region are influenced by moister air from low-pressure areas. Winds associated with the low-pressure conditions collect moisture and sweep it from west to east across the Great Lakes, then drop precipitation on the colder landmasses at the eastern ends of Georgian Bay and Lake Huron, in areas called "snow belts" (Baldwin et al., 2007). The rise in elevation over the Algonquin highlands causes considerably greater snowfall in the areas of Huntsville and Dorset than along the upper Ottawa Valley, 100 km to the east. Summer precipitation patterns are more

related to continentality than to the lake effect, with precipitation being greatest away from the lakes, where air masses cause storm cells to build over land. The greatest summer precipitation occurs in the central portions of the province and the upper Ottawa Valley, and deficit values are particularly high in the areas of southern Ontario just outside the lake-effect precipitation zones. These areas have relatively low precipitation, high summer temperatures, and well-drained soils (Baldwin et al., 2007).

2.2 Winter Wheat Phenology and tolerance to extreme weather events

In Canada, about 700,000 ha of winter wheat were seeded in 2016 (Agriculture and Agri-Food Canada, 2019). In central and eastern regions of Canada, winter wheat is grown as part of a corn-soybean-winter wheat rotation and is most commonly seeded after a soybean crop (Agriculture and Agri-Food Canada, 2019; OMAFRA, 2017a). Knowing the growth stages of winter wheat is essential for precisely scheduling management inputs and control measures (OMAFRA, 2017a). The impacts of weather extremes on wheat yields can vary greatly across the different months of the growing season (Tack et al., 2014).

As a crop's development stages have an important influence on winter survival, yield potential, maturity, and infection with diseases such as rust and fusarium head blight (Acevedo et al., 2002), it is very important to analyze each crop’s growth stages and investigate their tolerance to extreme weather events in each of these stages. Therefore, Zadok's growth scale was used to examine the stages of crop growth and the responses to different stresses (Zadoks et al., 1974). Zadok's growth scale is a 0-99 scale for development and is based on the 10 principal cereal growth stages, which are: germination, seedling, tillering, stem elongation or jointing, booting, heading, flowering anthesis, milk and dough development, and ripening, as shown in Figure 7 (Zadoks et al., 1974; AWWPC, 2011).

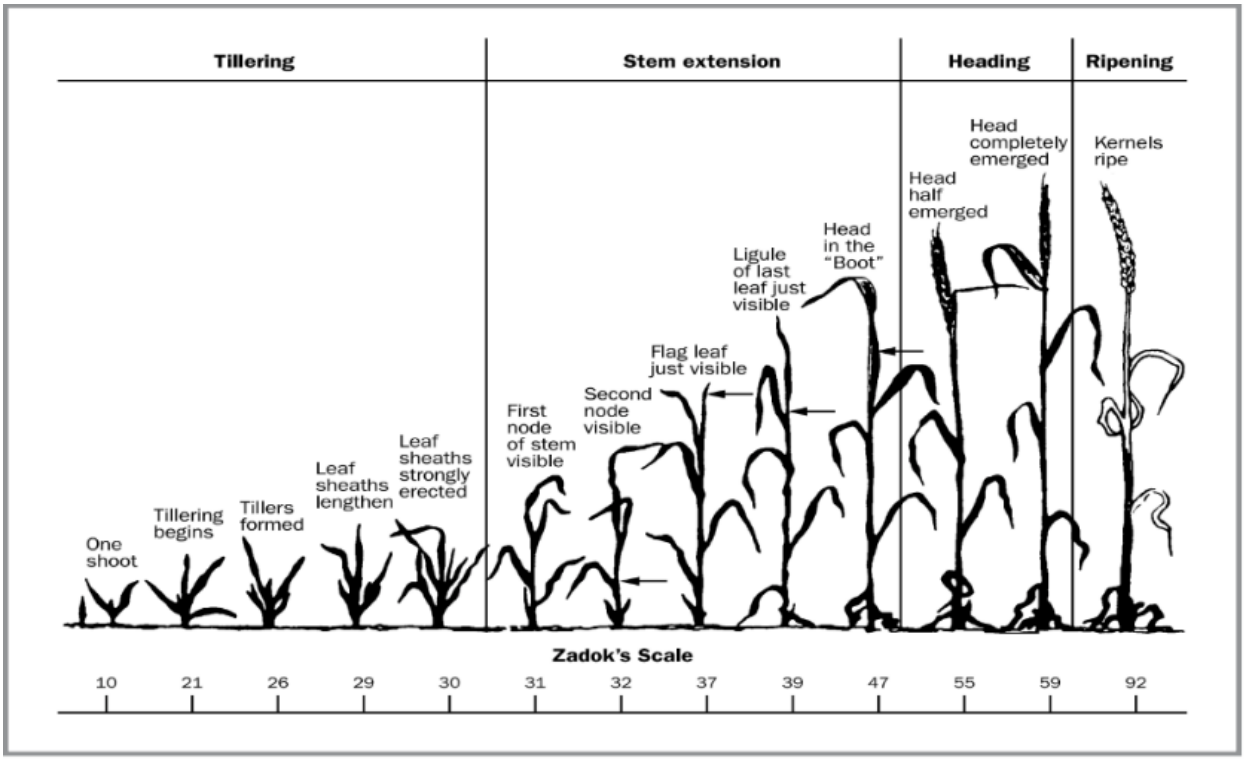


Figure 7: Cereal growth stages (Zadok's scale). Source: Ministry of Agriculture, Food and R Affairs (2017).

This scale is widely used in cereal crop management since it provides a good description for both vegetative and reproductive stages; it is recognised for both research purposes and farm practices, especially for knowing good timing for the application of chemicals and fertilisers (Acevedo et al., 2002). Since it describes all stages of the cereal growth cycle it was used to investigate cereal crops' ability to tolerate different climatic stressors and diseases in each of these growth stages.

Ontario's weather conditions rarely cause crop death (OMAFRA, 2017a), however, the impacts of the variability in temperature and precipitation on winter wheat yields in the study area are not very well understood, particularly for agriculture-based periods and at relatively local scales (e.g., townships).

Winter wheat is sown in late August and harvested in mid-to-late July of the following year. The duration of its growth stages varies depending on the sowing date and genotype (Acevedo et al., 2002). In late fall, winter wheat experiences a natural hardening process requiring acclimation to the cold and a series of biophysical and biochemical alterations to increase hardiness over the winter and boost the ability to survive during the ice-freeze period (Qian et al., 2010). Winter wheat hardening is a process that happens in the early stages of the plant's growth when carbohydrates concentrate in crowns and taproots, which can help the crop tolerate very low temperatures (e.g., -24°C). The early-stage development (autumn conditions) of winter wheat is critical for its winter survival (Skinner et al., 2008; Fowler, 2018).

Variations in planting dates have been proven to have influences on winter wheat yields. For example, Andrews et al. (2011) studied the impacts of delaying planting of soft white winter wheat (*Triticum aestivum L.)* on the crop survival and grain yields in eastern Ontario and confirmed that delayed planting was associated with reduced survival at Ottawa in 1987 and in all years at Douglas (Andrews et al., 2011). Other research has shown that planting season delay resulted in a 1.1 bu/acre/day decrease in yield for each day that planting was delayed beyond the optimum date (OMAFRA, 2018b).

Andrews et al. (2011) indicated that changes in the fall planting date can also affect the overall tolerance of overwintering wheat plants to harmful weather events. The sensitivity of delayed planting to injury from ice encasement increases in northern areas when planting is delayed by the late harvest of preceding crops (Andrews et al., 2011). As well, seeding depth can have a significant impact on cereal development. Cereals should be planted uniformly at a depth of 2.5 cm (1 in.), therefore careful attention to the seeding dates and depth improve winter survival and

ensures higher yields (OMAFRA, 2017a). The development of cereal seedlings can be determined by certain growing degree day (GDD) accumulations (OMAFRA, 2019b). Any development more or less than three to five tillers, the plant has a low chance of surviving winter conditions (Andrews et al., 2011; Allard et al., 2019). Generally, for each inch of planting depth, cereals require 80 GDDs at 5°C as base temperature for the seeds to germinate and 50 more GDDs for emergence. If the planting date and depth are not respected, winter cereals can be destroyed during the winter and early spring period (i.e., winterkill) by frost-heaving, ice, low temperatures, and snow mold (OMAFRA, 2017a). As a result, the fewer the total GDDs resulting from later planting, the higher the moisture content in the crop leaves, which increases the crop's sensitivity to freezing events and potentially diminishes the crop's survival (Andrews et al., 2011). In addition, tolerance to ice encasement decreases with delayed planting dates, and demonstrates significant correlations with specific winter wheat genotype survival (Andrews et al., 2011). Bergjord et al. (2008) adapted the Canadian model that simulates the course of frost tolerance of winter wheat under continental climatic conditions to be used in regions under oceanic climate conditions, and they concluded that ice encasement and snow mold are the major causes of winter damage in the two cultivars studied in central Norway (Bergjord et al., 2008).

Most winter wheat damage occurs in late fall and early spring. In early spring, the crop experiences a de-hardening process, which is a physiological preparation for new growth in the coming growing season (Qian et al., 2010). Due to warmer winters and when there is an increase in temperature followed by freezing conditions (freeze and thaw cycles), ponds of water can form in fields due to floods and heavy rainfall. These ponds will freeze and form ice cover, which is one of the most significant causes of winter wheat die-off, as ice cover prevents the plants from getting enough oxygen (Hayhoe, 2002).

Even though winter wheat can tolerate very low temperatures, this tolerance is completely lost when the average daily soil temperature at the depth of the crown rises above 9°C, which is the minimum temperature that the plants are usually hardened to in the early stages. In addition, during the dormancy season, if the crown of the crop is exposed to warmer temperatures than their minimum survival temperature (which is between -18 and -24 °C depending on cultivars) for about 50 hours, the cold hardiness of the plant can decrease considerably (Fowler, 1982).

Regarding crop tolerance to high temperatures, winter wheat is very sensitive to drought and high temperature extremes (Ihsan et al., 2016). Winter wheat usually requires temperatures between 0° and 7°C for 30 to 60 days during the first growth stages (Acevedo et al., 2002), and if the temperature exceeds 30°C during floret formation, significant damage occurs to the crop (Acevedo et al., 2002). High temperatures severely limit wheat yields since they accelerate plant development, and specifically affect the floral organs, fruit formation, and functioning of the photosynthetic apparatus (Acevedo et al., 2002; Hyles et al., 2020). Also, high temperatures in the stages of grain formation and filling can reduce the period from the ear emergence to the maturation stage, and which could affect the grain filling (Djukić et al., 2019). Similarly, temperatures greater than 30 °C during the grain filling period are known to reduce kernel mass in wheat (Djukić et al., 2019). Additionally, these high temperatures could affect the availability of water from rainfall or irrigation (Antle et al., 2013). Since less than 1% of Ontario farm area is irrigated, as reflected in the 2011 Agricultural Census (Statistic Canada, 2011), precipitation is generally the only source of water, hence winter wheat is very sensitive to drought events (Tack et al., 2014).

Tack et al. (2014) studied the impacts of warming and drought on ten wheat verities in different locations in Kansas, USA, and they confirmed that exposure to warming and drought lead to reductions in mean yields, leaving the yields more susceptible to other risks. Weather scenarios were simulated for a baseline period, with the simulations being done by using an increased temperature (one-degree Celsius warming) scenario, a decreased precipitation scenario (tenth-percentile rainfall outcome), and a combination of warming and drought scenario. From these scenarios, warming resulted in an 11% yield reduction, drought a 22% reduction, and warming and drought a cumulative 33% reduction (Tack et al., 2014).

Overall, investigating crop tolerance thresholds is essential for determining the most appropriate phenological indices to incorporate into our analyses. This literature review finds that for winter wheat poor seeding conditions, early floods, early or late frosts, winter thaws, minimum fall temperatures, and fall hardening are important variables to consider. Analyses of winter wheat phenology and crop tolerance were therefore investigated to define a comprehensive list of crop-specific indices (Table 2).

2.3 Oat (Avena sativa) phenology and tolerance to extreme weather events

Cereal crops such as winter wheat and milling oats have similar characteristics and similar growth stages, except that winter wheat is an overwinter crop while milling oats are a spring crop, altering their tolerances to weather variability. Oat tolerances have been reported in the literature and compared with winter wheat, depending on the pheno-phases and tolerance thresholds. Since these cereals have very similar phenology and development patterns, Zadok's growth scale can be used to investigate their growth stages and responses to different stressors (Ministry of Agriculture, Food and Rural Affairs, 2017) (Figure 7).

Milling oats are seeded as spring cereal in early spring between April 10 to May 10 (OMAFRA, 2019c) and are usually harvested in mid summer to early October of the same year depending on the planting dates. They require 100-103 days to mature (MAFRI, 2010). Normally, they flower and mature quickly in short-season conditions (Ziesman et al., 2010) Milling oats are very responsive to planting dates, and early spring planting increases oat yields (May et al., 2004).

Milling oats are less tolerant to frost than winter wheat (Ziesman et al., 2010), and early frost decreases oat seed quality at harvest time (Saskatchewan Ministry of Agriculture, 2008a). For instance, a temperature of -1°C persisting for 3 to 4 hours can cause damage to the crop, and when the temperature drops below -2 to -3 °C, the crop can be significantly affected by killing frosts (Ziesman et al., 2010). Regarding hot temperatures and drought stresses, oats are more sensitive than winter wheat (Miller, 1984), and hence late planting reduces the quality of the harvested crop. Moreover, drought periods and high temperatures impact the reproductive stages of oats (Martin et al., 2012; Stokopf, 1985). For example, warm temperatures between 20°C–28°C in the daytime and 16°C–22°C at night favor diseases at the flag leaf stage (Zadok's 37) to flowering stages (Zadok's 61–71) (Ziesman et al., 2010). In addition, warming shortens the developmental duration of oats by increasing their development rate (Y. Zhang et al., 2019). While the changes in temperature and rainfall patterns reduce crop growth rate, these changes contribute to a reduction in crop yield (Y. Zhang et al., 2019)

In contrast to winter wheat, oats tolerate poor drainage (Ministry of Agriculture, Food and Rural Affairs, 2017), and are less sensitive to moisture than winter wheat; however, excess precipitation causes stress on oat plots during the growing season (May et al., 2004; McLeod, 1982). At the

tillering stage, for instance, the crop is more sensitive to flooding than at any other phenological stage (Ghobadi et al., 2017). According to Ghobadi et al. (2017), grain yield decreases due to flooding in the tillering stage by 42 %. Also, analyses of yield components showed a 45 % decrease in grain number per spike, a 33.9 % decrease in the spike numbers per plant, and a 9% decrease in thousand-grain weight (Ghobadi et al., 2017).

Chapter 3. Data and Methodology

3.1 Extreme Weather Indices (EWI)

Extreme weather index design and calculation were based on two existing sets of indices. The first set was developed by the World Meteorological Organization (WMO), focusing on climate extremes, and named after the Expert Team on Climate Change Detection and Indices (ETCCDI, 2020; Aguilar et al, 2005). A peer-reviewed paper (Aguilar et al., 2005) that included detailed definitions of these indices was also consulted. Additionally, a set of weather indices was also developed by Environment and Climate Change Canada with a focus on the characteristics of climate change in Canada (Canadian Centre for Climate Modelling and Analysis, 2012). In total, 16 indices (Table 1) were used to detect the trends in moderate extremes (i.e., events that happen more than one time in a year) in the study region. Each of these indices gives meaningful information about the intensity, frequency, or magnitude of a specific extreme. Some of the indices were adapted to the characteristics of climate change in southern Ontario; for instance, the warm weather extremes (HWE) and cold weather extremes (CWE) indices consider the thresholds that winter wheat can tolerate. Knowing that winter wheat can tolerate temperature ranges up to 25-30 °C, 30 °C that was considered the maximum threshold that this crop can tolerate during the growing season. On the other hand, -23 °C was considered the minimum that the crop can tolerate in its most hardy state (OMAFRA, 2017a).

Table 1: Extreme weather indices with their definitions and units. These indices were developed by the Expert Team on Climate Change Detection and Indices (ETCCDI, 2020; Canadian Centre for Climate Modelling and Analysis, 2012).

Indicator ID	Indicator name	Indicator definition	Variable	Unit
PRCPTOT	annual total of wet-day precipitation	annual total precipitation of wet days when daily PRCP >= 1 mm	precipitation	mm
R95p	very wet day events	annual total Precipitation when daily precipitation is greater than the 95th percentile $R95p_j = \sum Ww=1 \sum w=1 WRR_{wj}$ *where* $RR_{wj} > RR_{wn}95$	precipitation	mm
R10	number of heavy precipitation days	annual count of days when precipitation is greater than or equal to 10 mm $RR_{ij} \geq 10mm$	precipitation	days
Rx1day	max 1-day precipitation amount	monthly maximum 1-day precipitation $Rx1day_j = max\ (RR_{ij})$	precipitation	mm
Rx5day	max 5-day precipitation amount	monthly maximum consecutive 5-day precipitation $Rx5day_j = max\ (RR_{kj})$	precipitation	mm
SDII	simple daily intensity index	simple precipitation intensity index $SDII_j = \sum Ww=1 RRwj/W$	precipitation	mm/day
HWE	warm extremes	TMax >= 30	maximum temperature	°C
CWE	cold extremes	TMin <= -23	minimum temperature	°C
DTR	diurnal temperature range	daily temperature range: monthly mean difference between TX and TN	temperature	°C
CDD	consecutive dry days	maximum length of dry spell: maximum number of consecutive days with daily precipitation less than 1mm $RR_{ij} < 1mm$	precipitation	days
ID	number of icing days	annual count of days when daily maximum temperature is less than 0°C $TX_{ij} < 0°C$	maximum temperature	days
TX90p	warm days	percentage of days when daily maximum temperature is greater than the 90th percentile $TX_{ij} > TX_{in}90$.	maximum temperature	%
TX10p	cool days	percentage of days when daily maximum temperature is less than the 10th percentile $TX_{ij} < TX_{in}10$.	maximum temperature	%
FD	number of frost days	annual count of days when daily minimum temperature is less than 0°C $TN_{ij} < 0°C$	minimum temperature	days
TN90p	warm nights	percentage of days when daily minimum temperature is greater than the 90th percentile $TN_{ij} > TN_{in}90$	minimum temperature	%
TN10p	cool nights	percentage of days when daily minimum temperature is less than the 10th percentile $TN_{ij} = TN_{in}10$.	minimum temperature	%

The extreme weather indices were calculated using data from a daily spatially-interpolated climate model developed by Natural Resources Canada, Canadian Forest Service (CFS), the Australian National University (ANU), Environment Canada (EC), and the National Oceanic and Atmospheric Administration (NOAA) for the period from 1950 to 2017 (McKenney et al., 2011). The model covers Canada and depends on daily weather records (daily minimum temperature, daily maximum temperature, and daily precipitation) mainly collected by Environment Canada from meteorological stations across the country from 1950 to 2017 (McKenney et al., 2011). The daily climate model was generated using ANUSPLIN climate modeling software (McKenney et al., 2011), which uses interpolation methods that consider topographic elevations when interpolating temperature and precipitation across the region (accounting for spatially varying dependences on elevation). ANUSPLIN considers all data points available in the model fitting and validation, which is a key strength that permits a robust determination of dependencies on the predictor variables, particularly in regions where data are scarce (McKenney et al., 2011). The data products are gridded data interpolated between weather stations at a 10 km spatial resolution over Canada for daily minimum temperature, daily maximum temperature, and daily precipitation.

The R-language for statistical and data processing (R Core Team, 2021), and ArcGIS Desktop GIS software (Esri Inc, 2022) were used to subset the gridded data and aggregate them to the geo-township level, using Geographic Township Improved boundaries for the Ontario region (Ministry of Natural Resources, 2018), and the Geographic Township Improved subdivision of the province (Statistics Canada, 2017c). ArcGIS Pro software was used to extract the centroid coordinates of each township's polygon, then these coordinates were read in R to extract and stratify the gridded weather data values within each township (the R script is provided in the Appendix 1, Script 1.1).

Finally, to calculate township-level extreme weather indices (EWIs) and investigate trends, minimum temperature, maximum temperature, and precipitation were extracted from the gridded weather data product, at the centroid of each township for each day of the year from 1950 to 2017. Using the interpolated data to extract the value at the centroid of each township was intended to better represent weather conditions for each township rather than relying on where individual weather stations happen to be located. Raw data recorded at weather stations has challenges since one has to take into consideration missing data (gaps), the changes in weather station's locations over time, and often, especially in sparsely-populated regions, sparse weather station presence. The data source sampled here takes advantage of the significant quality control processing already accomplished prior to interpolation and obtains a good estimate for the centroid of each township. Initial analyses checked to investigate whether there were appreciable differences between the values extracted from the centroid versus aggregate estimates across the entire county. Since the differences were very small (0.1ºC for minimum temperature, 0.09 ºC for maximum temperature, and 0.02 for precipitation mm), the simpler approach of using only the centroid was used for all further processing. Script 1.1 in Appendix 1 was used to calculate the centroids, and other scripts in Appendices 4 and 5 were developed to perform the trend analyses from 1950 to 2017. The EWIs were calculated using R-scripts prepared and designed by Zaytseva (2016) then modified for the purpose of this research.

3.2 Crop-specific Indices

Sets of phenological and agroclimatic indices representing southern Ontario's climatic conditions for field winter wheat and milling oat were designed and calculated, for the period from 1950 to 2017 (Appendix 1. Scripts 1.2, Appendix 1. Script 1.3, and Appendix 1. Script 1.4), and then analyzed for temporal trends. They were also examined using a random forest regression (RF) model to investigate their relationships to deviations from mean crop yields based on crop insurance data which was available only for winter wheat crop and for the period from 1987 to 2017.

Winter wheat- and milling oat-specific indices were calculated based on sets of agroclimatic and phenological data according to the crops' growth stages and their tolerance to extreme weather events in each of these growth stages. The agroclimatic indices (Tables 4) give essential information about the crop growth, whereas the phenological indices (Tables 2 and 3) help to identify the crops' thresholds and tolerance to weather events such as drought, frost, and heat.

Winter wheat phenological indices calculation were based on four periods since winter wheat is an overwinter crop, which means that winter wheat is planted in late summer or in the beginning of fall (depending on the planting optimum date specified by OMAFRA for each region of Ontario) and harvested in late July to the beginning of fall of the following year (OMAFRA, 2019b). These periods were defined in this study as planting season (PS) from August to October, dormancy season (DS) from November to April, growing season (GS) from May to July, and harvesting season (HS) from August to September (Script 1.2). Milling Oat seasons were divided into three periods since it is not a dormant crop and is often planted as spring cereal or after winter wheat harvest. These periods start with the planting season (PS) defined as the period from April to May,

the growing season defined as the period from May to July (GS), and the harvesting season (HS) which is defined as the period from July to August (Script 1.4).

The agroclimatic indices calculation for winter wheat and milling oat were based on Table 4, using a base temperature for winter wheat growing season length (GSL) and growing degree days (GDD) calculations of 5°C, and a base temperature of 0°C for milling oats.

The crop-specific indices were designed based on a careful literature review. In addition to experts' reports from Agriculture and Agri-food Canada, research from similar climate regions around the world and research from the Ontario Ministry of Agriculture were consulted. Also, reports and studies from Alberta about crop phenology and tolerance to climate variables such as minimum temperature, maximum temperature and precipitation were considered, taking into consideration that the climate in Alberta differs from that in Ontario.

The information gathered was used to study the crops' pheno-phases and investigate their thresholds and tolerance to weather events in the southern Ontario region. Additionally, the information helped to understand the sensitivity of the crops to different variabilities in weather conditions in the region, and how the crops react, resist, and tolerate these variabilities. It also helped to determine the thresholds of winter wheat and milling oats to weather conditions. These investigations provided information on potential risks to the crops' growth as a result of adverse weather conditions at particular stages of the plants' growth.

Table 2: Winter Wheat-specific indices. The indices were designed according to the crop's sensitivity to climatic conditions in Ontario. Thresholds are extracted from the literature according to the crop phenology and growth stages and sensitivity to extreme weather conditions.

Stressor name	ID	Threshold and definition	Growth stage sensitivity	unit
Fall Precipitation Intensity	FPI	sum of days where the daily amount of precipitation exceeds 10 mm in September, October, and November	germination, tillering (Fall) (Heil et al., 2020)	days
Fall killing frost	FKF	sum of days where Tmin<= -2 °C in August, September, October	seeding, germination, tillering (Li et al., 2015)	days
Winter warming index (WWI)	WWI	sum of days where the maximum temperature is above 5°C from November to April	dormant period, causing plants to die because of ice sheet formation or de-hardening	days
Cool wave index	CWI	sum of period where the maximum temperature is below 5°C in March, April, May, and June	growing season as a whole (Li et al., 2015)	days
Spring killing frost	SKF	sum of days where Tmin<= -2 °C in March, April, and May	early spring Joining stage (Hayhoe et al., 2003)	days
Drought indices (stem extension, heading, tillering)	DI	sum of days when the amount of precipitation is equal to 0. P= 0 mm	all seasons heading and flowering and post-anthesis periods (Heil et al., 2020; Agriculture and Agri-Food Canada, 2019)	days
Precipitation amount Index	PAI	sum of days when the amount of Precipitation exceeds 10 mm PAI> 10 mm	early stages early fall (optimum planting period), and in early spring (Heil et al., 2020)	days
Cool Wave Days	CWD	sum of period where the minimum temperature is less than 5°C T min < 5	early spring jointing stage (Li et al., 2015)	days
Growing degree-days	GDD	total amount of GDD available for winter wheat	most critical for wheat is when head is out and the grain fill period GDD is an indicator of potential maturity, heat stress, and optimal planting dates (OMAFRA, 2018) (OMAFRA, 2017)	GDDs

Table 3: Oat-specific indices, Ontario, Canada. The indices were designed according to the oats' sensitivity to climatic conditions in Ontario. Thresholds are extracted from the literature according to oat phenology and growth stages and sensitivity to extreme weather conditions

Stressor name	ID	Threshold and definition	Growth stage sensitivity	unit
Heat waves- anthesis	HW	sum of days where the maximum temperature is above 25°C	from May to July anthesis stage (Ziesman et al., 2010; OMAFRA, 2016)	days
Growing degree days	GDD	total amount of GDD[1] available for Milling oat to grow in each season (PS, GS, HS)	(Robertson et al., 2013; OMAFRA, 2017)	GDDs
Jointing and anthesis drought period	DP	sum of days when the amount of precipitation is equal to 0. P= 0 mm	from April to July jointing to the end of anthesis growth stage (Fatima et al., 2020; Ziesman et al., 2010; Peltonen-Sainio, 1991)	days
Early frost	EF	sum of days where the minimum temperature is less than -2°C T min < -2°C	planting season (Ziesman et al., 2010)	days
precipitation amount index	PAI	amount of precipitation available during the growing season	the whole growing season (Hakala et al., 2020)	mm
Precipitation intensity	PI	sum of days when the amount of precipitation is more than 10 mm	the whole growing season (Heil et al., 2020)	days
Early Floods	EFL	amount of precipitation is more than 125 mm during the planting season	planting season (Hakala et al., 2020)	Yes/no

1 GDD refers to growing degree days

PS, DS, GS, and HS refer to Planting Season, Dormancy Season, Growing Season, and Harvesting Season respectively. These abbreviations will be frequently used in this study, especially in maps in the results section.

Table 4: Winter wheat and milling oats agroclimatic indices. These indices were used and calculated for both crops taking in consideration the difference in growing periods starts and ends.

Index ID	Index name	Index definition	unit
GSL	**growing season length**	growing season length, defined as the number of days with temperature above 5°C (Mueller et al., 2015)	days
GSS	**growing season start**	mean minimum air temperature has reached 5 °C for five consecutive days (Qian et al., 2010)	days
GSE	**growing season end**	mean minimum air temperature has dropped and stayed below 5 °C for five consecutive days (Qian et al., 2010)	days

3.3 Trend Analyses

Trend significance was assessed for minimum temperature, maximum temperature, and precipitation, evaluated over a time series of 67 years from 1950 to 2017. The trend analyses were conducted at annual and seasonal time scales (planting, growing, dormancy in case of winter wheat, and harvesting seasons, as well as at regional [i.e. Ontario] and local levels [i.e. for each township] in the study region). The Mann-Kendall (MK) trend test was performed, a test that is widely used to detect monotonic trends in meteorological variables since it does not assume that data are normally distributed and independent (Cheng et al., 2014; Cao and Ma, 2009; Zaytseva, 2016). The method proposes dividing the difference between two observations in a time series by the length of the period to estimate a linear trend between the two observations. Subsequently, trends calculated from all possible data pairs are ranked, and the median values of the trends are used for the final results.

The statistical significance of the trends was evaluated by Kendall's tau (one of the outputs of the MK test), which is used to measure the ordinal association between two measured quantities. Trends are significant when the null hypothesis is rejected which occurs when the two-sided p-value is less than 0.05. A “prewhitening” method known as lag-1 autoregressive process AR (1) was used to address auto-correlations in the time series, since the existence of positive serial correlation in a time series increases the probability of detection of a significant trend by the MK test (Bronaugh and Werner, 2019; Cao and Ma, 2009).

Trend directions (positive or negative) and their significance (highly significant when the p-value is less than 0.01, or significant when the p-value is between 0.01 and 0.05) were mapped annually and seasonally at the township scale. Mapping trend directions and significance helps show the changes in the trends and their magnitudes across the region.

Furthermore, an understanding of the changes in extreme weather event occurrence during the period of study was achieved by using the probability density function (PDF), which is known as the probability of occurrence of values of a weather variable (IPCC, 2013). The period of study was divided into two intervals, 1961-1990 and 1990-2017, to help understand the temporal changes and variabilities in weather extremes in the study region. As well, PDF graphs were generated to compare changes in the climate extremes at annual and seasonal scales. Trends for crop specific indices were also investigated and assessed using the MK test and a 5% confidence level.

3.4 Wheat production statistics

Historical time-series data of annual winter wheat yields for the 33-year period 1987 to 2019 were obtained from the Agricorp Insurance Company for 188 townships. These historical yield data were used to study the relationship between the crop-specific indices and the yield variance in the

study region. This study helps to understand how the yields changed over the 33 years and how these changes could be explained by weather extremes in the region.

The yields across the region trended upward due to technology and other factors such as improved varieties. Linear trend was removed from the level of yield to restrict further analysis to yield residuals, referring to the differences between the estimated yields (red line in Figure 8) and the reported yields.

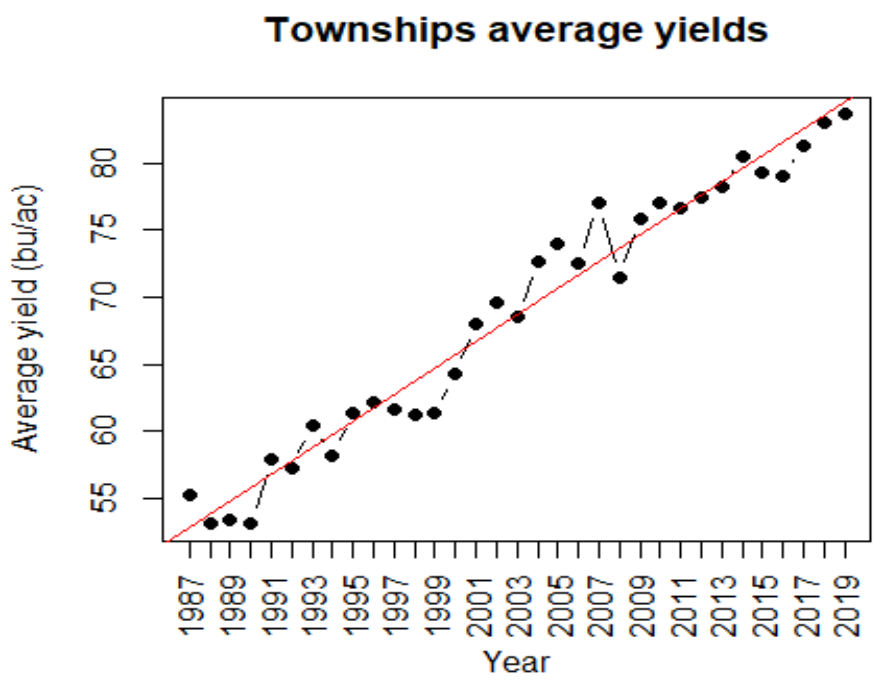


Figure 8: Winter wheat yield variability for southern Ontario townships from 1987 to 2019.

Residuals proportionality to average yield was investigated. If the residuals were found to be proportional to average yield, this proportionality needs to be addressed in advance (Roberts et al., 2012), the residuals were plotted against average yields and no correlation was observed (Figure 9).

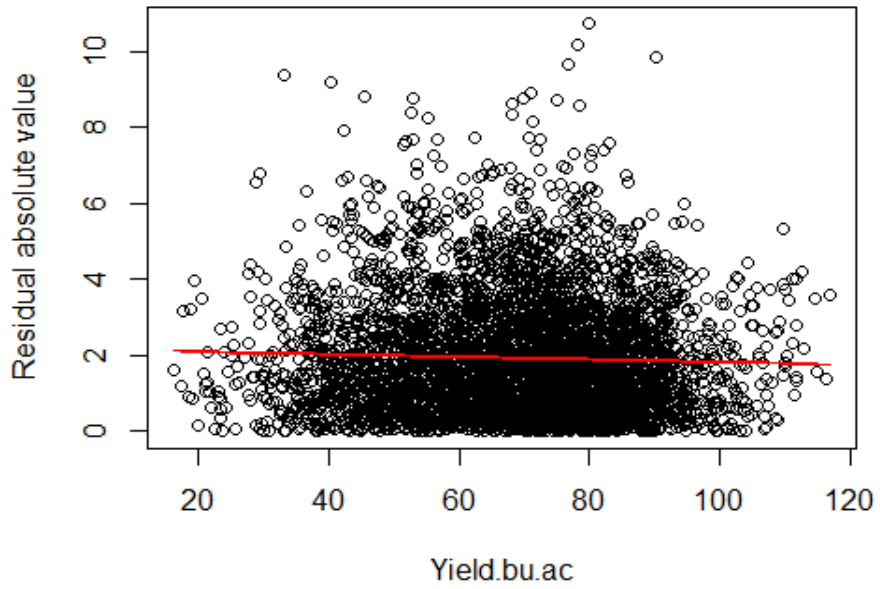


Figure 9: Residual yields vs. yield correlations. A linear trend estimate is shown in red.

Although the variance does not seem to be proportional to the yields, a common standardization approach was applied to the residual with the aim of eliminating all the factors other than the extreme weather indices that could potentially cause yield variances in the region. The standardized residual was calculated as:

Standardized residual = resid-mean(resid) / sd(resid)

Then, to study the relationships between individual indices and deviations from average crop yields, regression analyses for the crop-specific indices and the yield data for 188 townships were done using the random forest (RF) model (Script 1.6 is provided in Appendix 1). The RF regression model proposed by Breiman (2001) has been widely adopted for testing nonlinear interactions between response variables and predictors (Konduri et al., 2020); in particular, the RF

method is known for its strong ability to predict crop yield responses to climate variables at global and regional scales (Jeong et al., 2016).

3.5 Soil texture

Soil texture is one of the factors influencing yield variability that farmers do not have much control over (Godwin and Miller, 2003; Boenecke et al., 2018). Soil texture is an important property determining agricultural activities across the region depending on factors such as nutrient retention and drainage capabilities(Bowman, 1967). Yield variability can be affected by the conditions of the soil (dry or wet) mainly when the plant is at the peak of its growth during the growing season (June, July) (Boenecke et al., 2018). For instance, water-limiting environments may affect tiller numbers. In drought conditions, tillers are unable to support fertile spikes regarding winter wheat crop which could contribute to yield losses (Hyles et al., 2020).

In Ontario, it has been noted that winter wheat is planted on loam soil fields that have a high risk of frequent winter flooding and ice sheet formation. Thus, winterkill was found to be high when and where these conditions occurred. As a result, winter survival models that rely on weather variables alone do not adequately account for spatial variations in winter damage (Hayhoe et al., 2003b), especially since farms in Ontario are generally not irrigated. Therefore, in this research, we were concerned that soil texture could alter the relationships between crop yields and extreme weather indices, so information about texture was included in the analysis.

A soil texture data set published by EnvirometriX Ltd as a raster image containing soil texture information for the planet, except for Antarctica, was downloaded from Google Earth Engine (GEE) (EnvirometriX Ltd, 2018). It consists of soil texture classes (USDA system) for 6 soil depths (0, 10, 30, 60, 100, and 200 cm) at 250 m spatial resolution. A Geo-tiff image was obtained

for the study region and was processed using R (Script 5 provided in Appendix 6) to extract texture estimates at four depths (0, 10, 30, 60 cm). After that, the pixel values for each township were extracted, and the township median values were calculated and was found to be mainly loamy across the region. This information was then included in RF modelling.

3.6 Random Forest Analysis and Univariate Correlation

Several studies have recently shown that the relationship between weather indices and yield variability is nonlinear and is characterized by the existence of critical thresholds (Konduri et al., 2020). Multivariate analyses, particularly RF, have been found to be efficient in capturing the relationships between extreme weather events and winter wheat yield variances (Ekanayake et al., 2021), and this method has been adopted in many recent studies (Beillouin et al., 2020; Jeong et al., 2016; Konduri et al., 2020).

First, exploratory bivariate analyses were done using Pearson's correlation coefficient to measure the association and to determine the direction of the relationship between the dependant variable (i.e standardized yield residuals) and the predictors. Correlation coefficients are scaled from –1 to +1, where 0 indicates that there is no linear or monotonic association between the variables, and the relationship gets stronger when moving away from zero (Schober et al., 2018). These bivariate correlations were not considered to be sufficient descriptors of the overall relationships between crop specific indices and yields, but were used to determine the presence and nature of relations of specific bivariate pairings. Further analyses using multivariate regression approach (RF) was applied to better understand the relationship between specific indices and yields.

The Random Forest method is a commonly-used machine learning model for classification and regression (Konduri et al., 2020). Random Forest uses a technique called bootstrap aggregation,

or bagging, which involves random sampling of data with replacement which helps control model variance (overfitting) (Breiman, 2001). The "forest" refers to an ensemble of Classification and Regression Trees (CART), each of which is an attempt to divide a dataset into an optimal set of partitions (leaves). The bootstrapping process evaluates and builds an ensemble (forest) of multiple independent decision trees, overcoming some of the disadvantages of single tree-based methods, such as overfitting. This description is highly simplified, and readers are directed to Breiman (2001) for more details. For the purposes of this study, it was selected due to the ability of the algorithm to identify variables that explain the variance in a response variable without assumptions about the distributions of or independence between the variables;

RF regression was performed in R using the Random Forest package (Breiman et al., 2022) (Appendix 1. Script 1.6). Extreme weather indices, winter wheat crop-specific indices, soil data, and winter wheat yield data were imported to R, and data preparation and cleaning were done before running the model, especially that the time series insurance data had different lengths for each township. Those datasets were imported and joined into one data frame in which all the missing values were deleted. For RF regression analyses, the period of study was set to 33 years, from 1987 to 2017, the extent in common between the winter wheat yield data (1987-2019) and the interpolated daily weather data (1950 to 2017) since RF analyses require yield and weather data as inputs for every year. See flow chart Figure 1 in Appendix 2 that shows the raw data (gridded data, yield data, and soil texture data) and generated datasets (extreme weather indices, crop specific indices, and random forest), and the related analyses.

Potential temporal autocorrelation issues were checked for all the variables included in RF model using the ACF function in R, and were judged not to have appreciable impacts on the RF regression

analyses. Temporal autocorrelation was present in only 35% of the townships when considering all lags, and it was found to be limited to the first lags. Additionally, potential lag correction methods could not be applied in the dataset used in the RF due to the data structure (having time series with different length for each township merged in one data file). Therefore, it was assumed that the level of autocorrelation was low enough to be ignored. Spatial autocorrelation was also checked using Monte-Carlo simulation. Moran's I as a function of a distance band was adopted on all the variables (dependant and independent variables used in the RF regression model) which is based on defining neighbors on distance to polygon centers, then creating a search radius for neighbors (Cliff and Ord, 1973). Moran's I test indicated that there is no spatial autocorrelation in the dataset. The observed statistic values were very close to zero (between -0.002 and -0.006) with P-values > 0.05, which indicates that the observed values had no significant spatial clustering.

Standardized residual yield was set to be the response variable, and the model was trained on 75% of the data and tested on the remaining 25%. The algorithm's hyperparameters such as the number of trees, maximum tree depth, the maximum number of features considered at each split, and the minimum samples at each split were determined by using exploratory runs. The error rate of the model was plotted after each run, and then the hyperparameter values were set depending on the minimal error rate. The variables' importances were determined by the increases in the RF prediction error (decrease in accuracy) when out of bag (OOB) data for that variable were permuted, while all others were left unchanged (c.f. Liaw and Wiener, 2002)

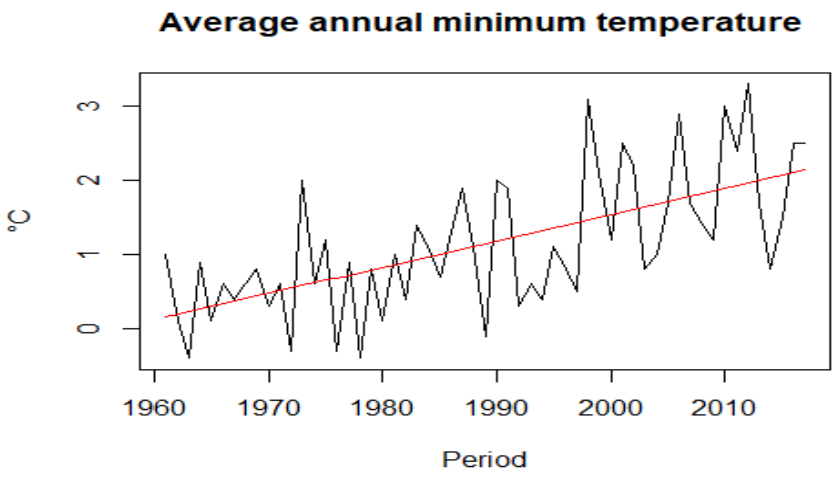
While the main objective of this study was to develop indices to highlight relationships between extreme weather events and yield variance, this portion investigate how the designed indices did in explaining the winter wheat yield variance in southern Ontario. To aid in this, further

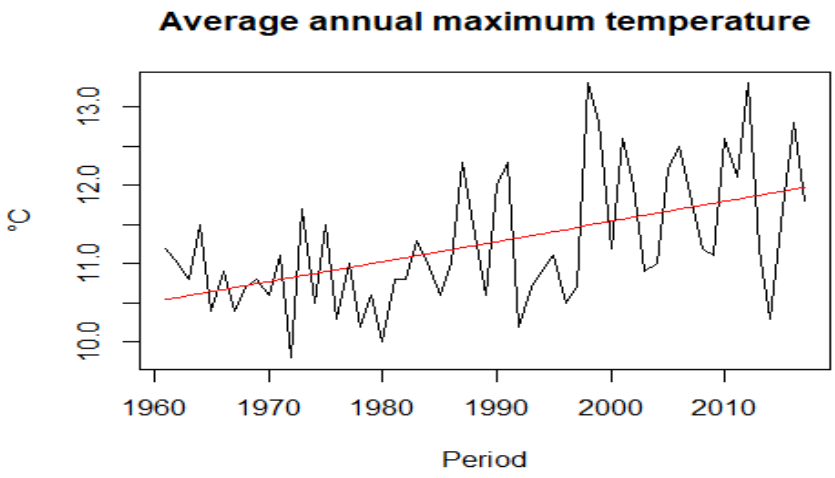
investigations were carried out to determine which sets of indices would be most useful. The RF analysis was performed four times using different sets of predictors with the purpose of better understanding the relationship between the response variable and the different predictors (namely extreme weather indices and crop specific indices) and thus to investigate whether all predictors are essential to explain the response variable, particularly giving the fact that many indices are related. In the first run, all the pertinent predictors (extreme weather indices, winter wheat crop-specific indices, and soil data) were used in the RF model. In the second run, only the extreme weather indices and soil predictors were applied. The third run was performed with crop specific indices and soil data while the fourth one was conducted using only the crop specific indices. The variance explained was used to determine the most valuable set of input variables to use to predict the explained variance in winter wheat yields (i.e., yield-standardized residuals).

Chapter 4. Results

4.1 Annual trends in extreme weather events

The trends in minimum and maximum temperature and total precipitation were investigated for the whole southern Ontario region (as defined in section 2.1) and at the township level by using the MK test (Figure 10).





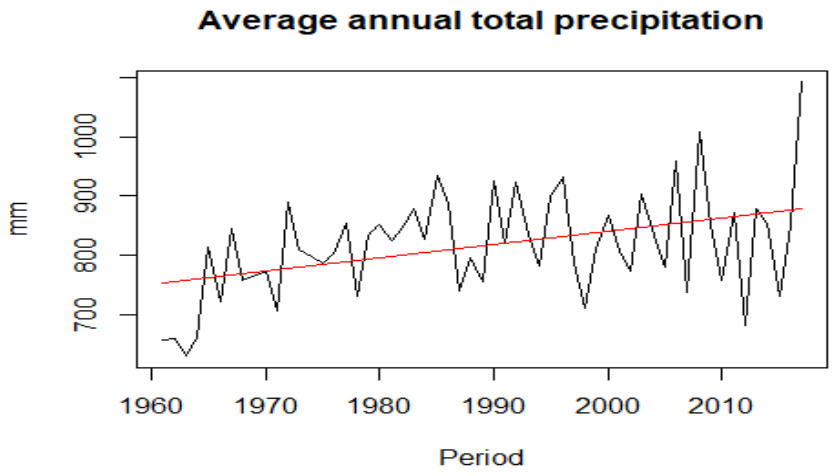


Figure 10: Average annual minimum and maximum temperature and average annual total precipitation (rain and snow) in southern Ontario from 1960 to 2017. Linear trends are shown in red

Evaluating the three variables' linear trends indicated an increase of 0.04 °C per year in average annual minimum temperature, an increase of 0.02 °C per year in average annual maximum temperature, and an increase of 2 mm per year in average total precipitation. Based on the regional trend analyses, a statistically significant increase was seen in all the variables at the regional scale. The average annual minimum temperature and the average maximum temperature showed the highest significant upward trend in the region, while the average annual precipitation showed the lowest significant increase (Table 5).

Table 5: The trend (Sen's slope) in average minimum and maximum temperatures (°C/year) and total precipitation (mm/year) in southern Ontario. Sig is the significance of the trends expressed as a P-value, trends were considered significant when p-value < 0.05.

Variable	**Trend**	**Significance value**
Average minimum temperature	0.04	0.00
Average maximum temperature	0.02	0.00
Total Precipitation	2.00	0.01

Throughout the townships, annual average minimum temperature (Figure 11) showed a statistically significant upward trend. Similarly, an upward trend in annual total precipitation (Figure 12) was noted in most of the townships except for small pockets in southern regions, whereas increases in annual average maximum temperatures (Figure 13) were limited to the central and eastern townships. Please note that the order in which figures are presented depends on statistical trend significance and highlighting the most important results. Some indices such as warm extremes (HWE) for the PS, DS and HS were not shown at all when trends were not statistically significant.

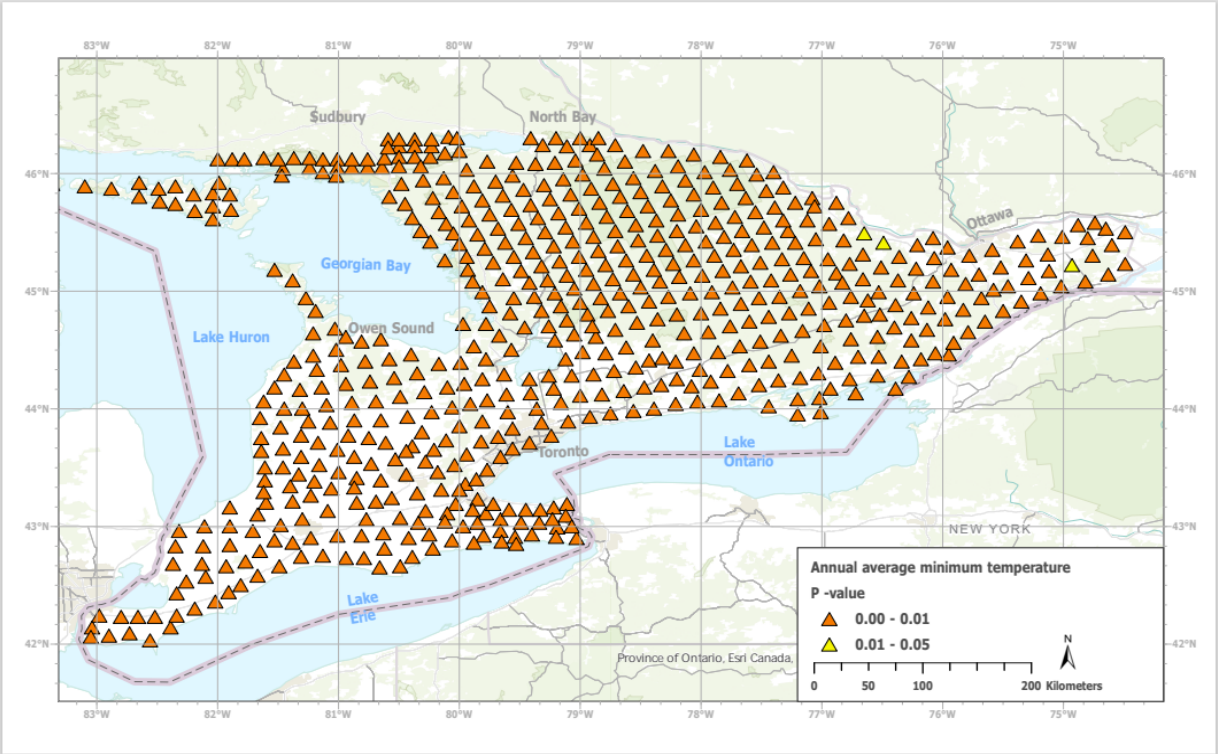


Figure 11: Map of trend significance for annual average minimum temperatures, in southern Ontario townships. Yellow upright triangles represent significant upward trends (P-value from 0.01 to 0.05). Red upright triangles represent high-ranking significant upward trends (P-value less than 0.01). Empty spaces represent townships where trends were not significant.

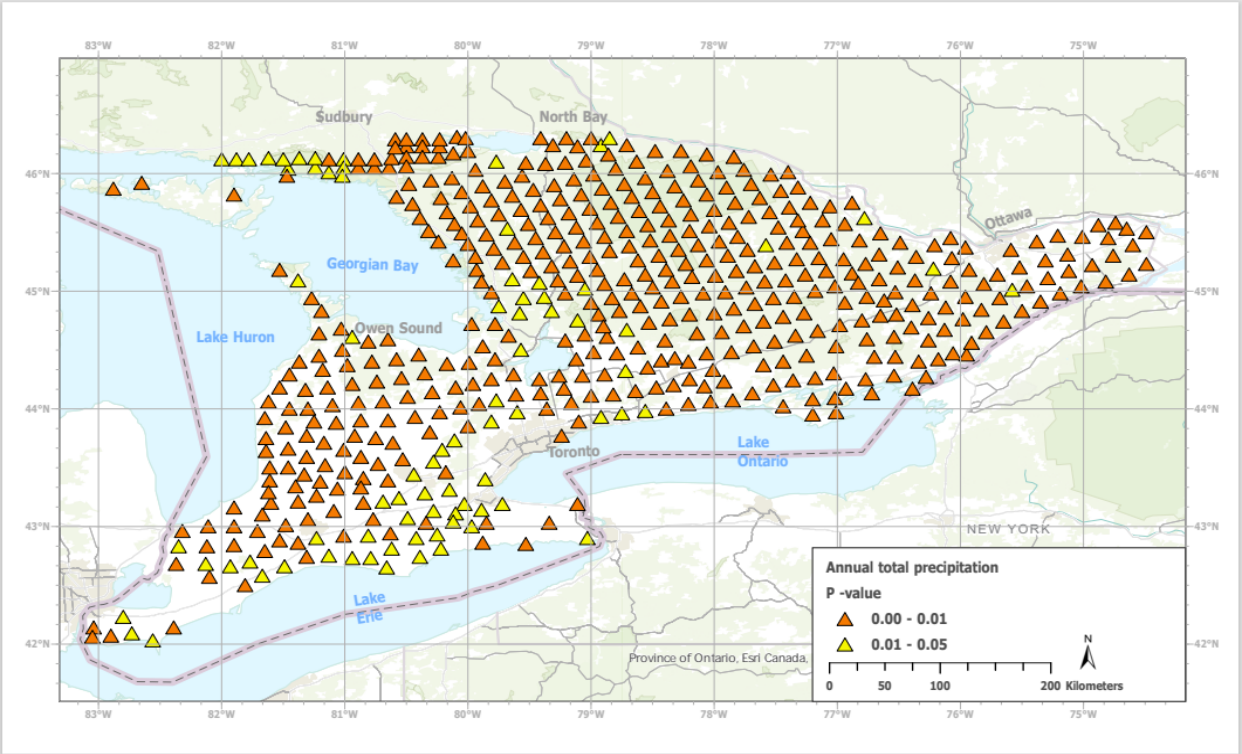


Figure 12: Map of trend significance for annual total precipitation in southern Ontario townships. Yellow upright triangles represent significant upward trends (P-value from 0.01 to 0.05). Red upright triangles represent high-ranking significant upward trends (P-value less than 0.01). Empty spaces represent townships where trends were not significant.

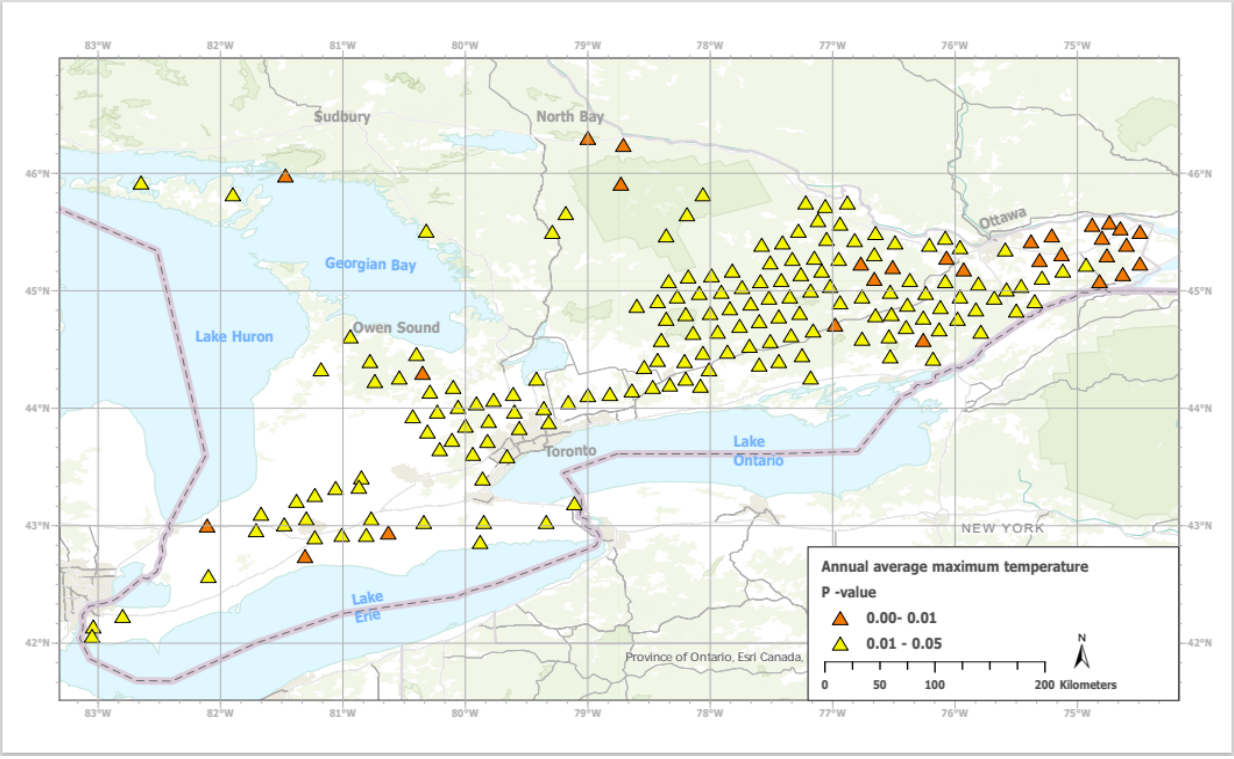


Figure 13: Map of trend significance for annual average maximum temperatures in southern Ontario townships. Yellow upright triangles represent significant upward trends (P-value from 0.01 to 0.05). Red upright triangles represent high-ranking significant upward trends (P-value less than 0.01). Empty spaces represent townships where trends were not significant.

4.2 Seasonal trends in extreme temperature and precipitation events

The seasonal trend analyses of the temperature indices showed an increase in the average minimum temperature in all seasons across the townships. This increase was largely observed with a high level of significance in the planting season (PS) (Figure 14), growing season (GS) (Figure 16), and harvesting season (HS) (Figure 17), while in the dormancy season (DS) (Figure 15), the significance level was variable. Regarding the DS and a high level of significant increase was observed in the average minimum temperature in the northern and central areas especially the eastern shores of Lake Huron.

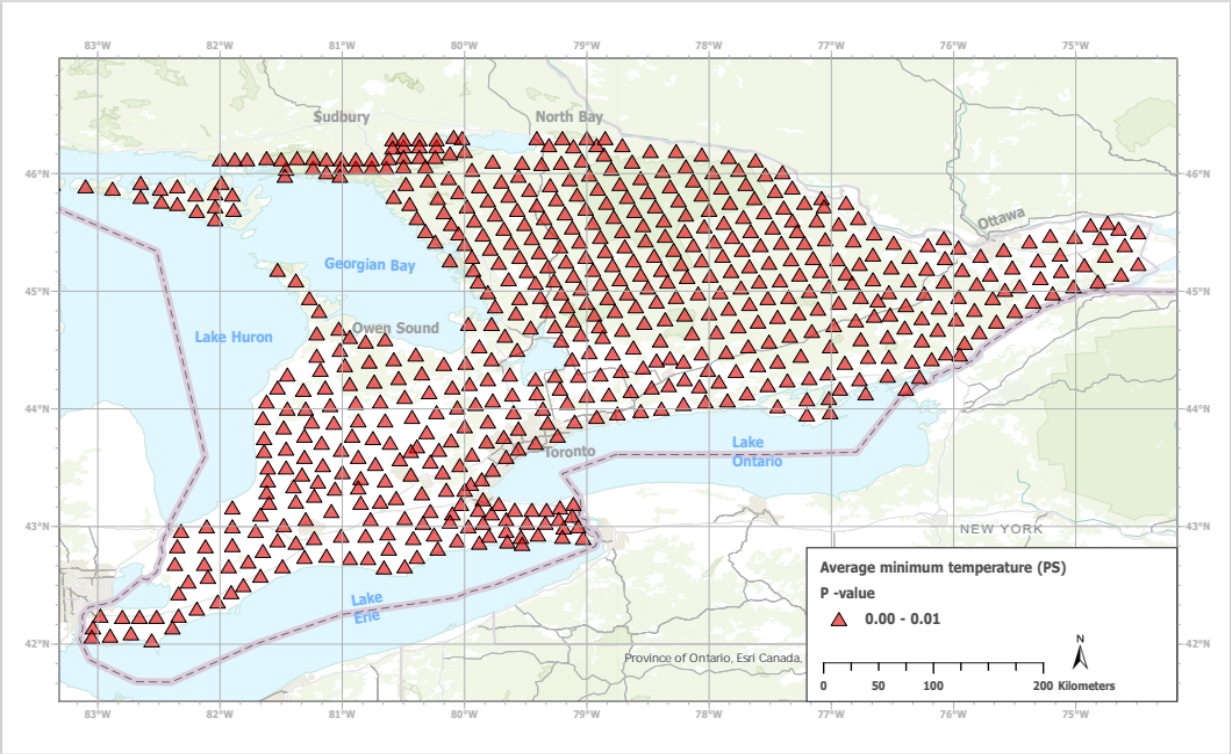


Figure 14: Map of trend significance for seasonal average minimum temperatures (PS) in southern Ontario townships. Red upright triangles represent high-ranking significant upward trends (P-value less than 0.01), and empty spaces represent townships where the trends were not statistically significant.

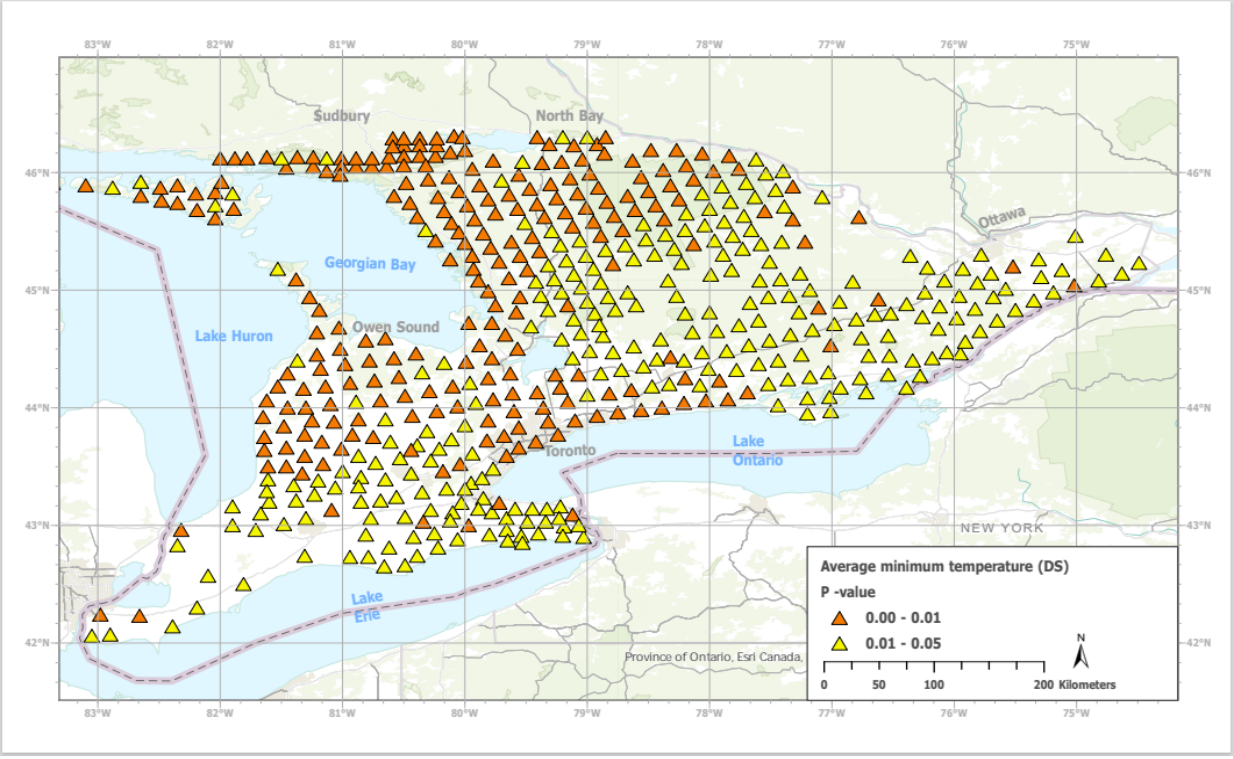


Figure 15: Map of trend significance for seasonal average minimum temperatures (DS) in southern Ontario townships. Yellow upright triangles represent significant upward trends (P-value from 0.01 to 0.05). Red upright triangles represent high-ranking significant upward trends (P-value less than 0.01), and empty spaces represent townships where the trends were not statistically significant.

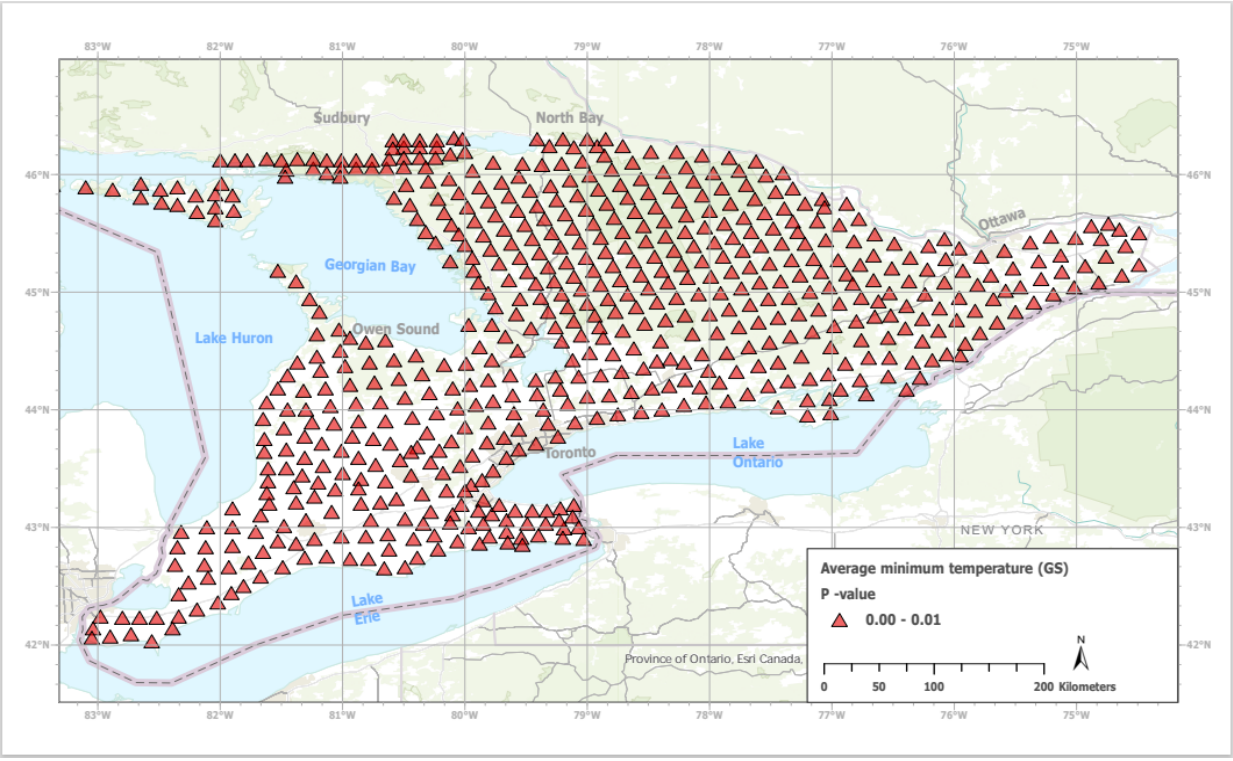


Figure 16: Map of trend significance for seasonal average minimum temperatures (GS) in southern Ontario townships. Red upright triangles represent high-ranking significant upward trends (P-value less than 0.01), and empty spaces represent townships where the trends were not statistically significant.

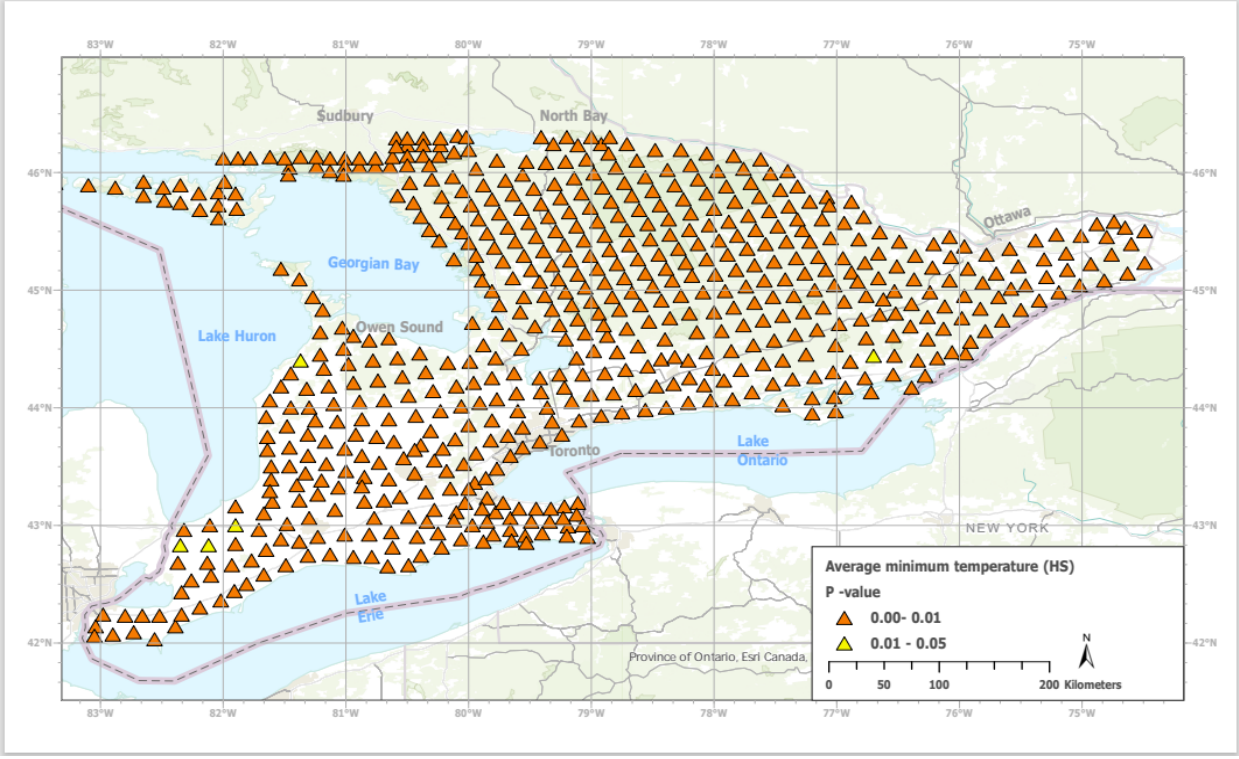


Figure 17: Map of trend significance for seasonal average minimum temperatures (HS) in southern Ontario townships. Red upright triangles represent high-ranking significant upward trends (P-value less than 0.01), and empty spaces represent townships where the trends were not statistically significant.

The local seasonal maximum temperature trend analyses showed a significant increase in the HS (Figure 20), mostly in the northeastern and northern townships. Also, a significant increase was noted in the GS (Figure 19), particularly in northern areas. Regarding the DS, a significant increase was noted in Bruce Peninsula to the western shores of Lake Erie and Lake Ontario and some eastern townships (Figure 18), while the PS showed a few significant increases that were limited to some townships in the extreme east of the study region (Appendix 3, Figure 1).

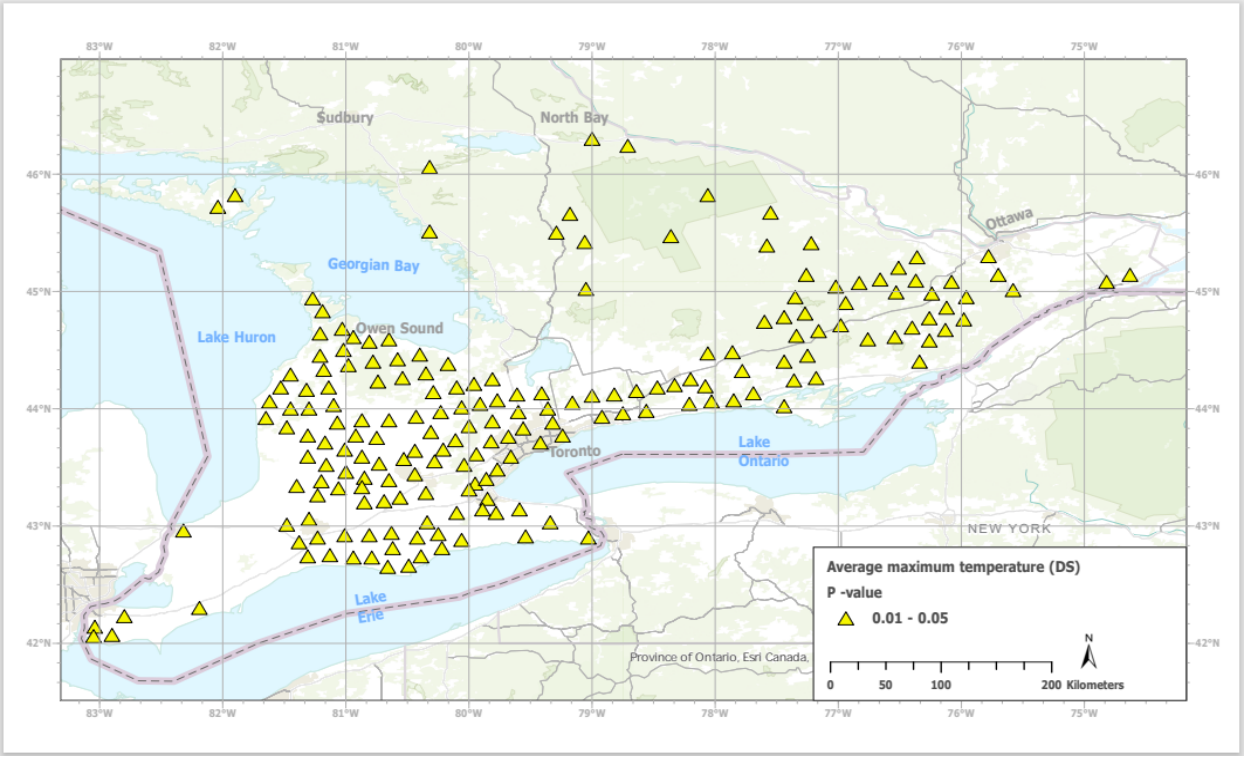


Figure 18: Map of trend significance for seasonal average maximum temperatures in southern Ontario townships for the DS. Yellow upright triangles represent significant upward trends (P-value from 0.01 to 0.05). Empty spaces represent townships where the trends were not statistically significant.

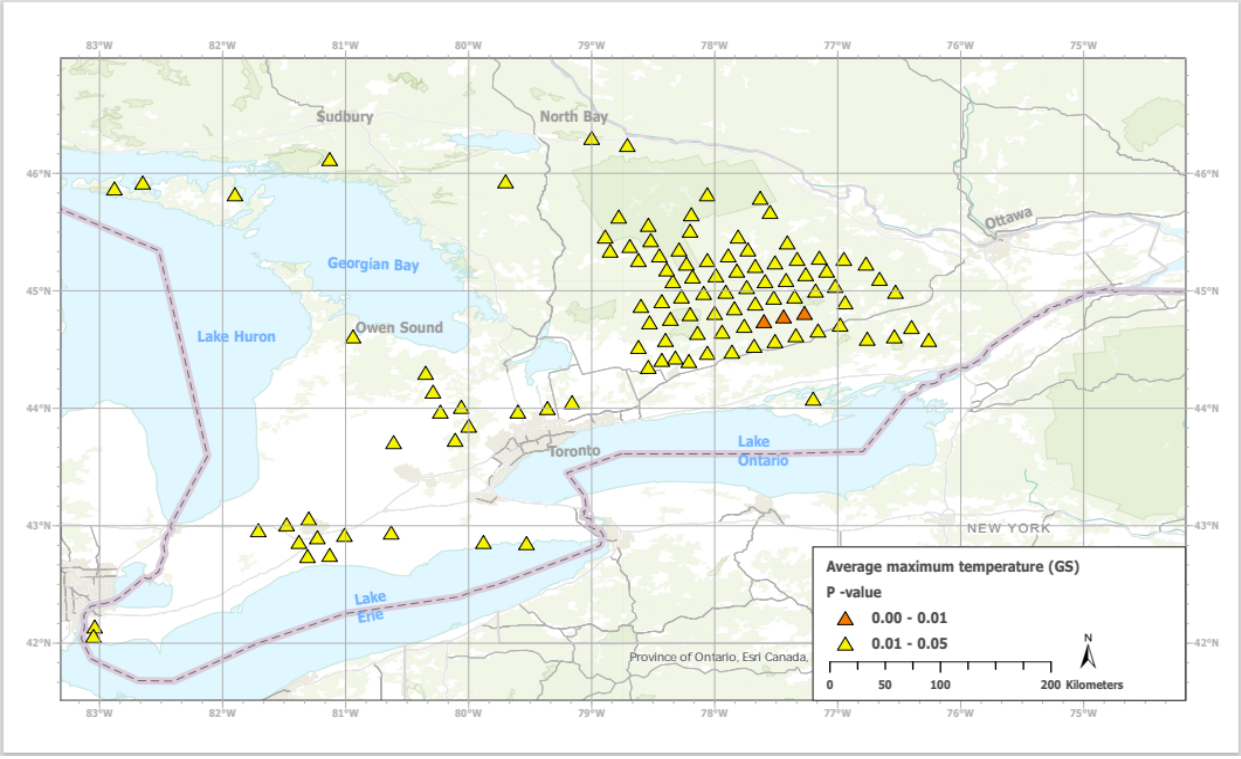


Figure 19: Map of trend significance for seasonal average maximum temperatures in southern Ontario townships for the GS. Yellow upright triangles represent significant upward trends (P-value from 0.01 to 0.05). Red upright triangles represent high-ranking significant upward trends (P-value less than 0.01), and empty spaces represent townships where the trends were not statistically significant.

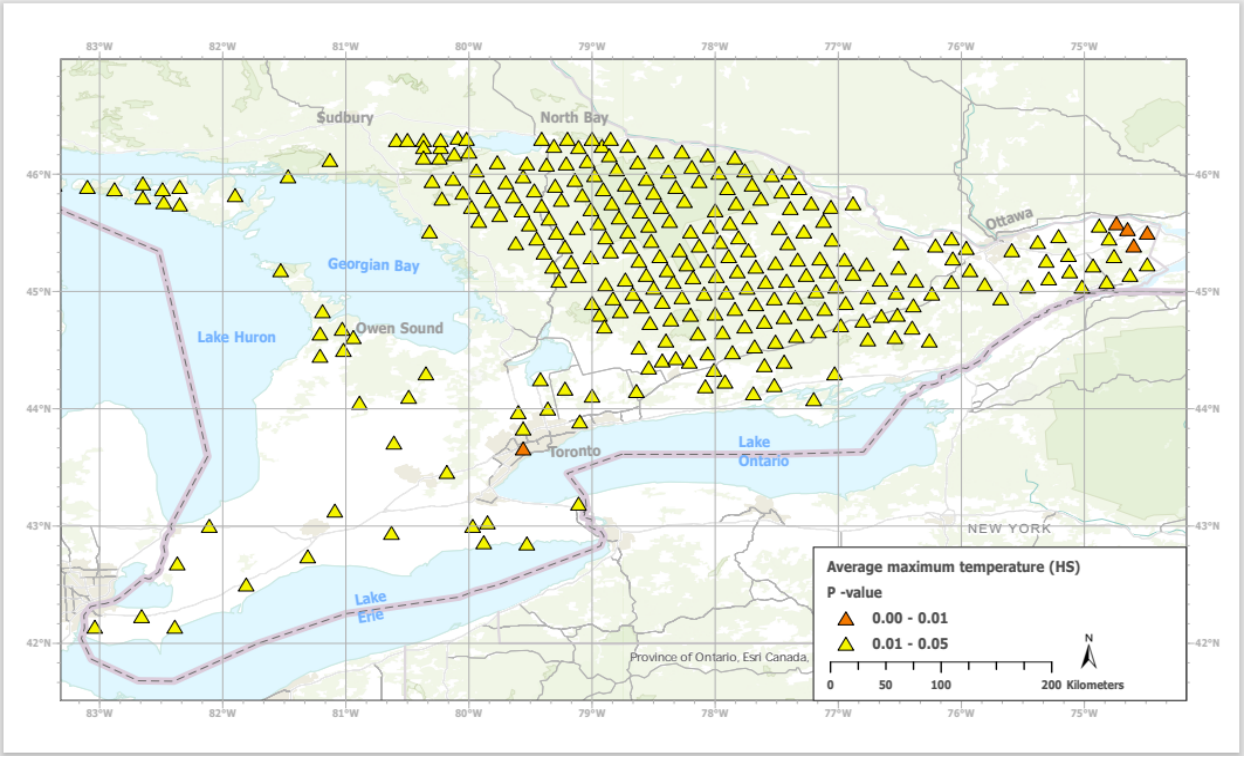


Figure 20: Map of trend significance for seasonal average maximum temperatures in southern Ontario townships for the HS. Yellow upright triangles represent significant upward trends (P-value from 0.01 to 0.05). Red upright triangles represent high-ranking significant upward trends (P-value less than 0.01), and empty spaces represent townships where the trends were not statistically significant.

Regarding seasonal trends in total precipitation, there was a significant increase in GS in most of the townships across the region (Figure 23). Also, significant increases in the PS (Figure 21) and the DS (Figure 22) were mostly observed in the northern townships and in the northern and in the Bruce Peninsula region which could be related to lake effects. However, the HS showed fewer significant trends that were mainly observed in some eastern townships (Appendix 3, Figure 2).

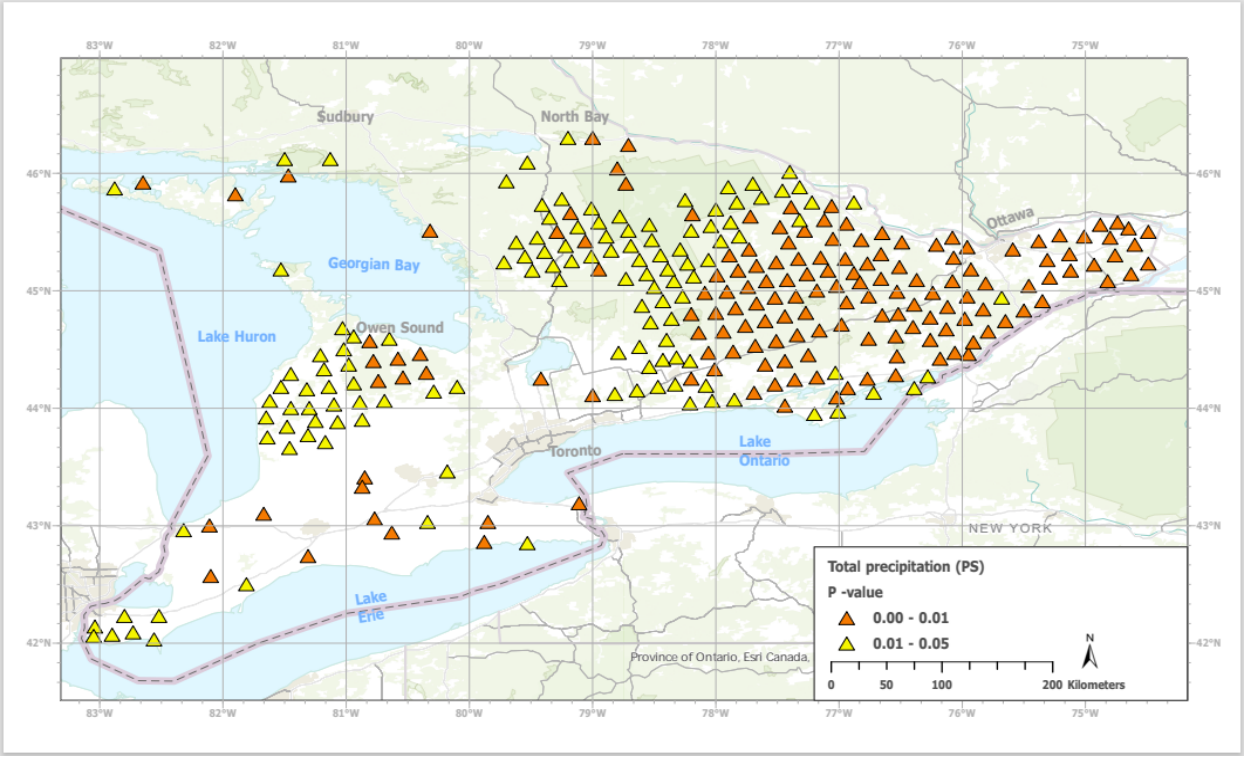


Figure 21: Map of trend significance for seasonal total precipitation in southern Ontario townships for the (PS). Yellow upright triangles represent significant upward trends (P-value from 0.01 to 0.05). Red upright triangles represent high-ranking significant upward trends (P-value less than 0.01), and empty spaces represent the townships where the trends were not statistically significant.

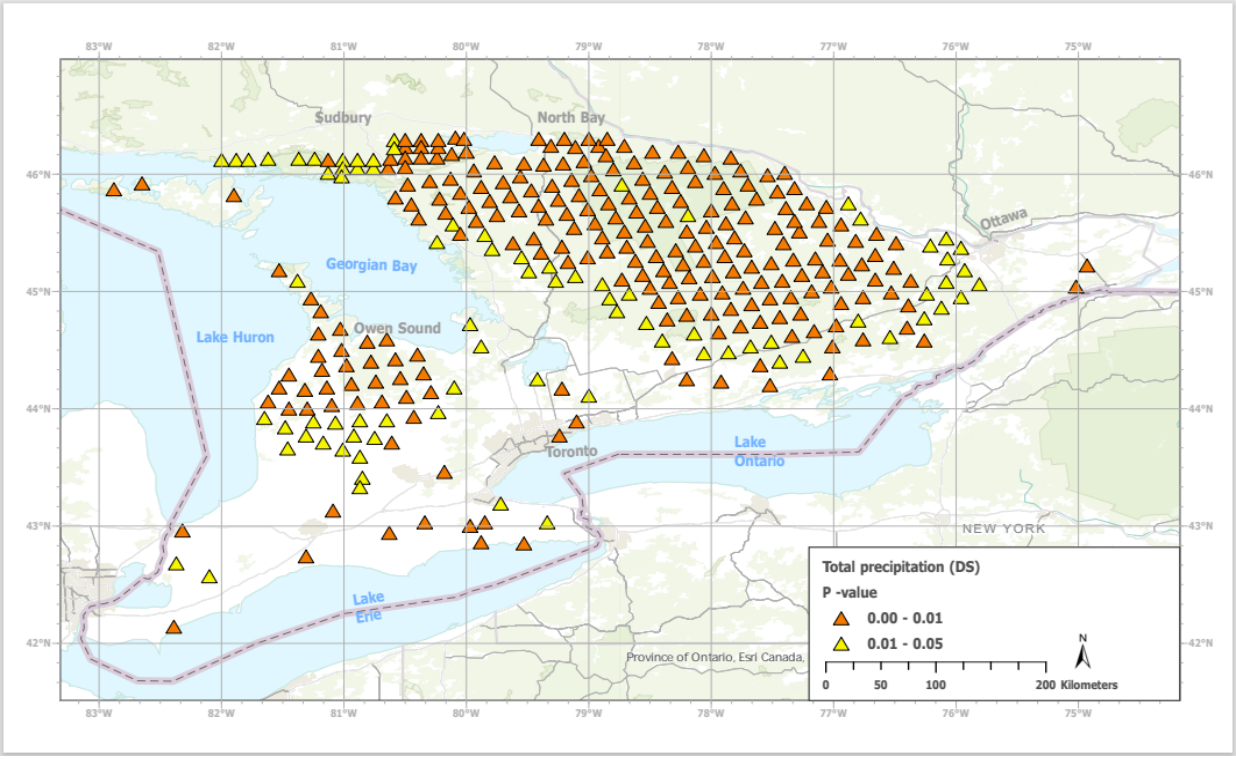


Figure 22: Map of trend significance for seasonal total precipitation in southern Ontario townships for the (DS). Yellow upright triangles represent significant upward trends (P-value from 0.01 to 0.05). Red upright triangles represent high-ranking significant upward trends (P-value less than 0.01), and empty spaces represent the townships where the trends were not statistically significant.

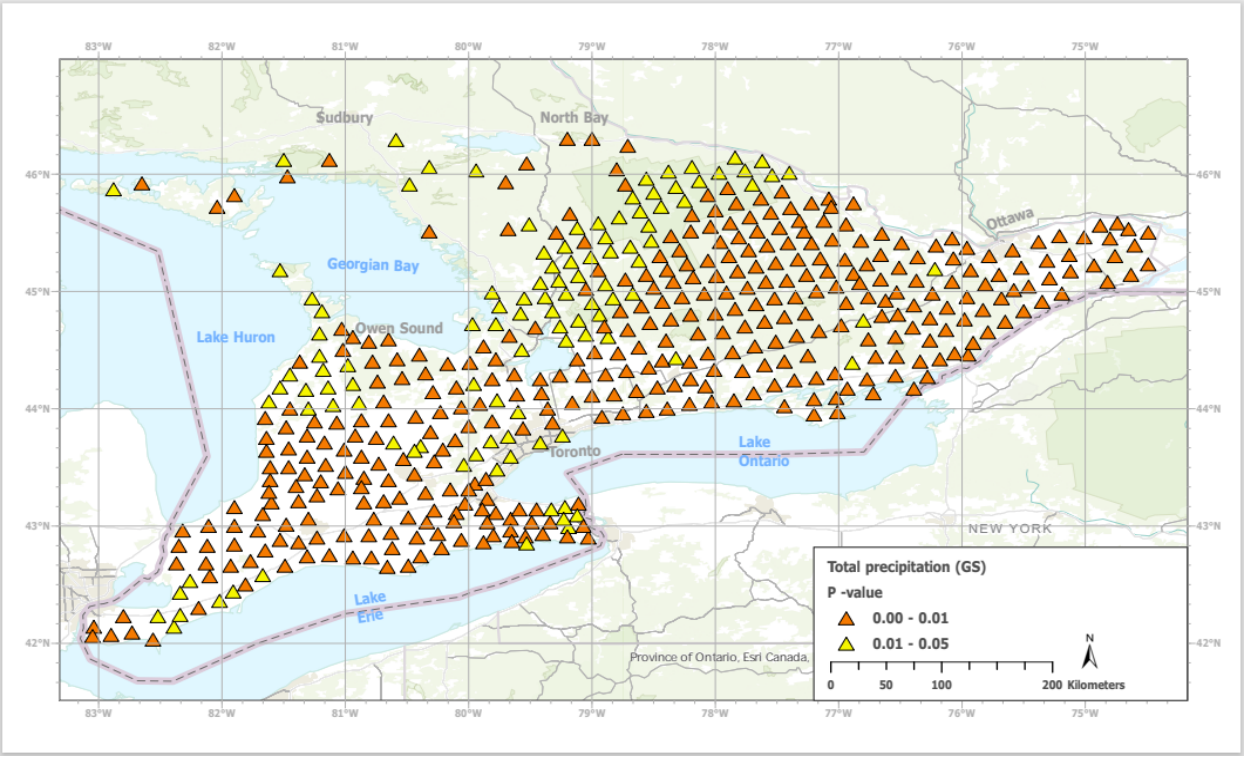


Figure 23: Map of trend significance for seasonal total precipitation in southern Ontario townships for the (GS). Yellow upright triangles represent significant upward trends (P-value from 0.01 to 0.05). Red upright triangles represent high-ranking significant upward trends (P-value less than 0.01), and empty spaces represent the townships where the trends were not statistically significant.

Concerning extreme weather indices at an annual time scale, a strong- significant upward trend in annual warm nights (TN90p) was observed across the townships (Figure 25), as well as a significant upward trend in annual warm days (TX90p) in most of the townships across the region (Figure 24). In contrast, there was a strong significant downward trend in annual cool days (TX10P) (Figure 26) and annual cool nights (TN10p) (Figure 27) in all the townships. The diurnal temperature range (DTR) saw a significant downward trend in all the townships except in some regions in the eastern and southern parts of southern Ontario (Figure 28). This implies that the

daily minimum temperature in the study region increased more significantly (higher trend and/or less variability in the trend) than the daily maximum temperature.

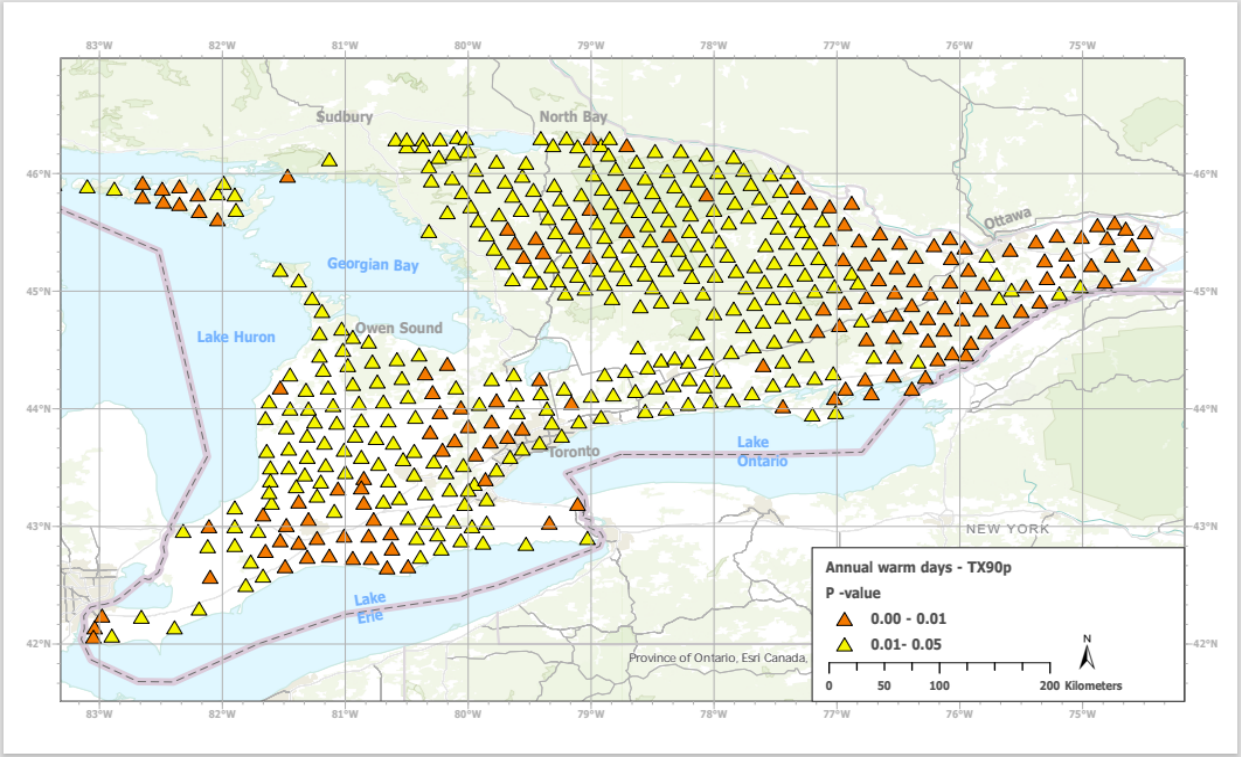


Figure 24: Map of trend significance for annual extreme weather indices for warm days (TX90p). Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant. Upright triangles indicate an upward trend while downward triangles indicate a downward trend.

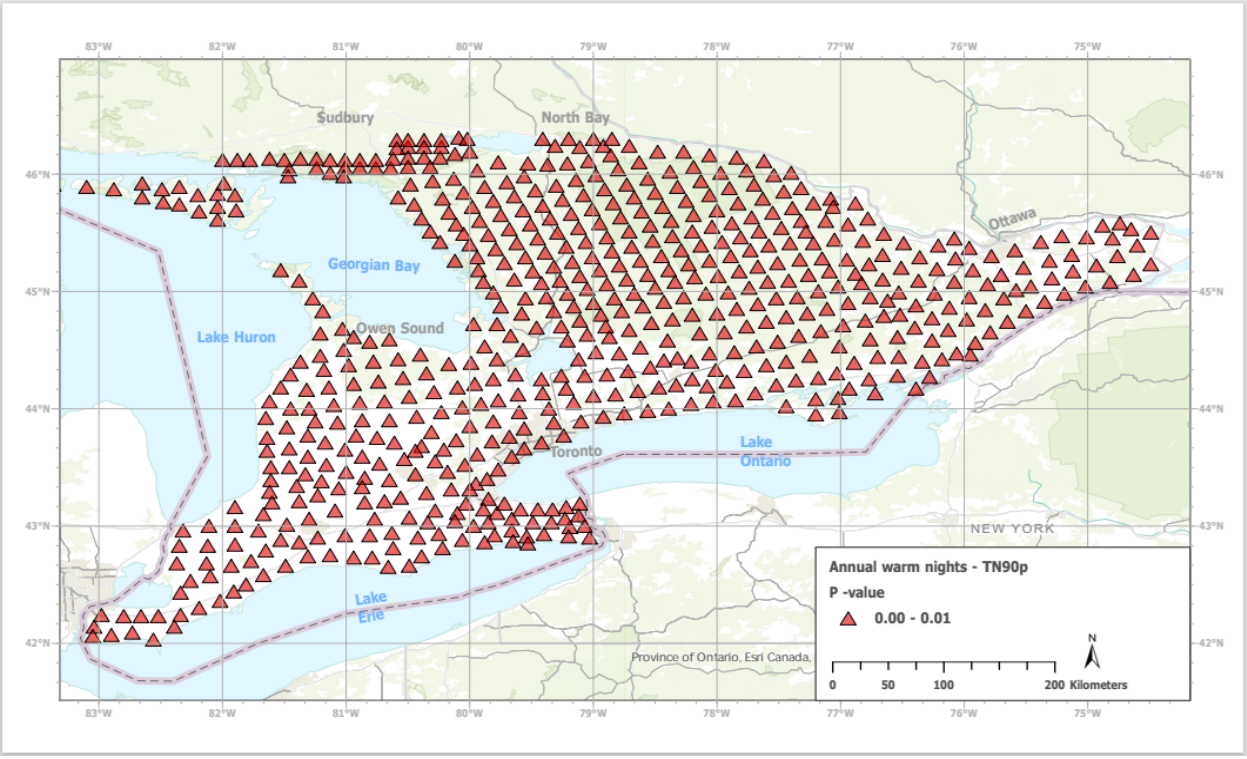


Figure 25: Map of trend significance for annual extreme weather indices for warm nights (TN90p). Red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant. Upright triangles indicate an upward trend while downward triangles indicate a downward trend.

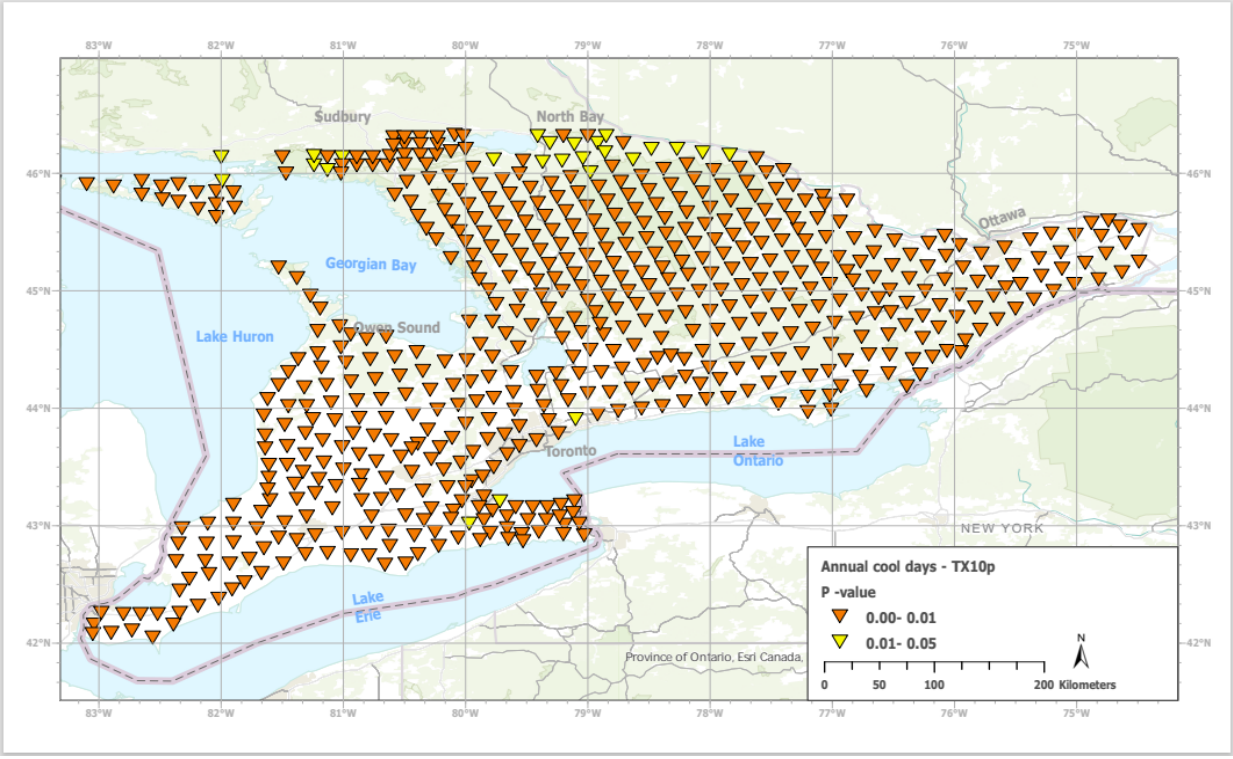


Figure 26: Map of trend significance for annual extreme weather indices for cool days (TX10P). Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant. Upright triangles indicate an upward trend while downward triangles indicate a downward trend.

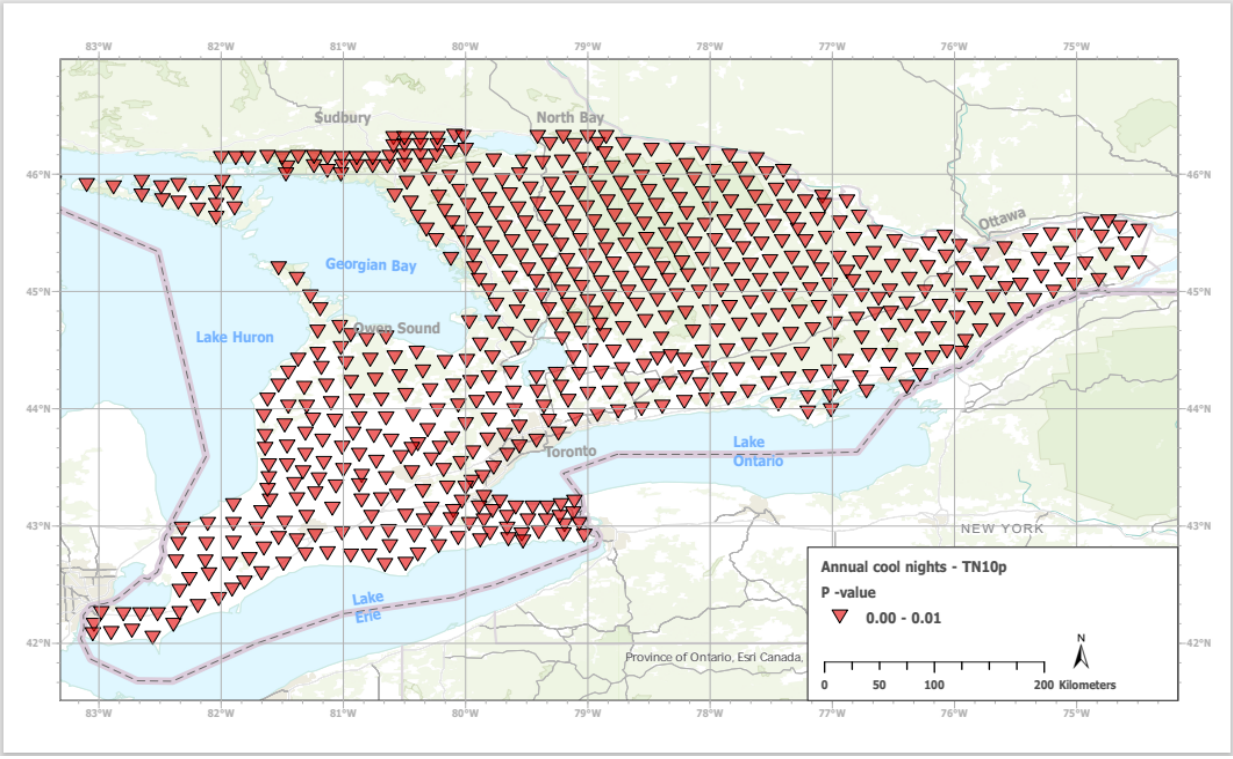


Figure 27: Map of trend significance for annual extreme weather indices for cool nights (TN10p). Red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant. Upright triangles indicate an upward trend while downward triangles indicate a downward trend.

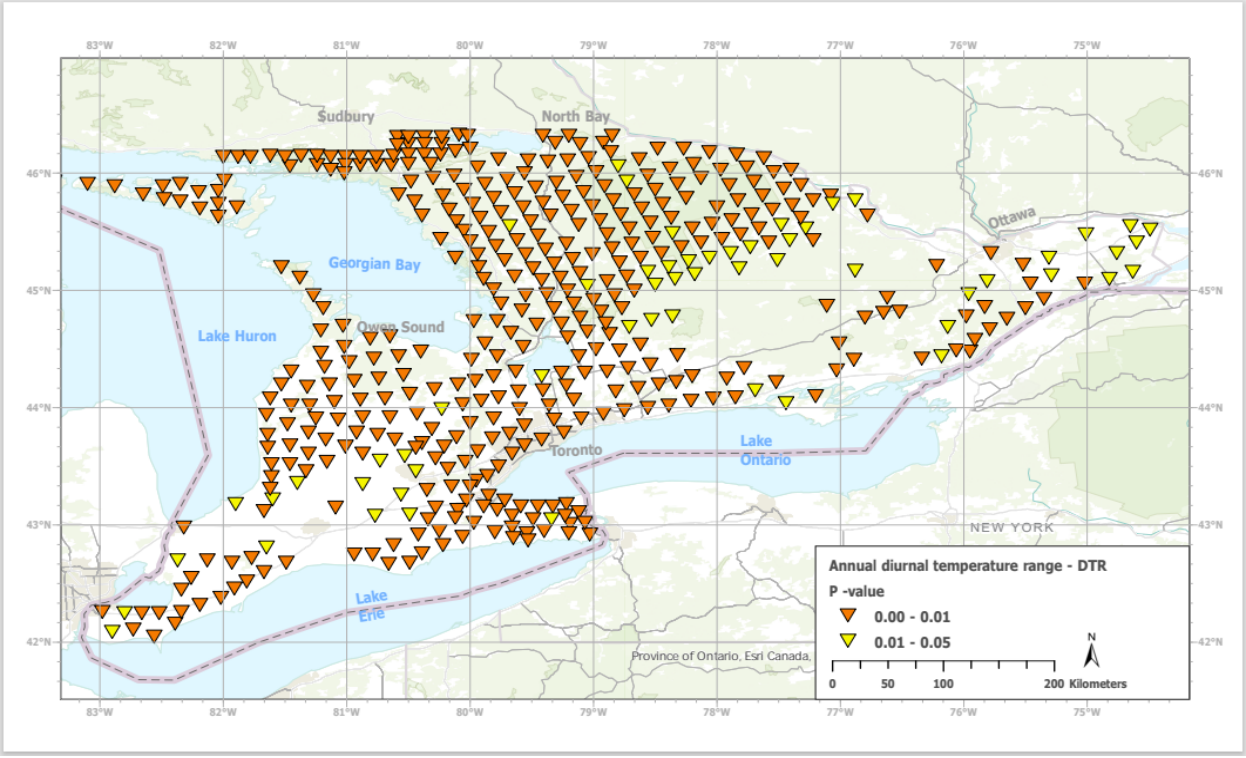


Figure 28: Map of trend significance for annual extreme weather indices for diurnal temperature range (DTR). Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant. Upright triangles indicate an upward trend while downward triangles indicate a downward trend.

Cold weather extremes (CWEs) demonstrated a downward trend in all the townships, but it was only significant in some townships, mostly in the northern area between Manitoulin Island and North Bay (Appendix 3, Figure 3). In contrast, warm weather extremes (HWEs) showed mostly upward but also downward, however, none was significant, and they are not presented graphically.

Annual frost days (FD) showed a downward trend in all the townships, and this trend was statistically significant in some townships in different parts of eastern Ontario and some of the townships at the eastern shore of Lake Huron of the study region (Appendix 3, Figure 4). Annual

icing days (IDs) saw a statistically significant downward trend in all the townships across the region (Figure 29). The growing season length (GSL) trend analyses showed an upward trend in all the townships, but many were not significant. Most of the significant increases were in the region between the Bruce Peninsula, London, and Niagara region, and in some northern townships between Manitoulin Island and North Bay (Appendix 3, Figure 5).

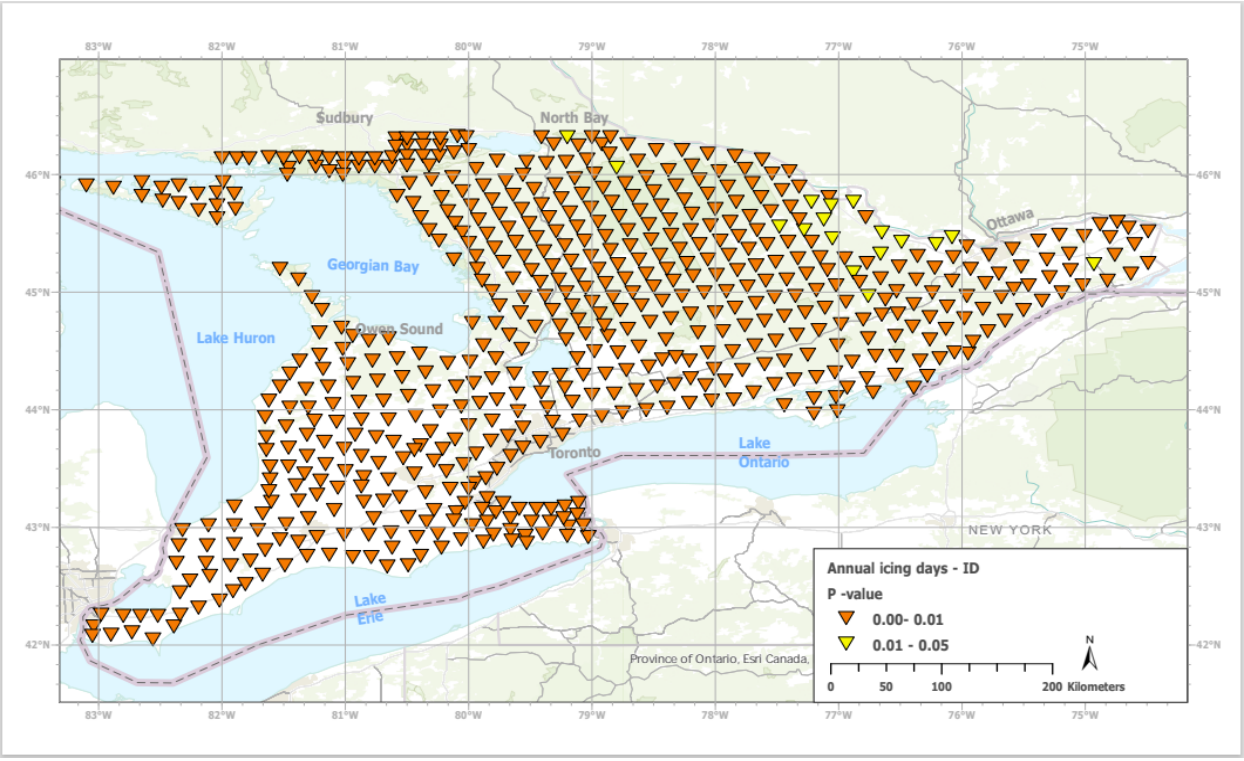


Figure 29: Map of trend significance for annual extreme weather indices: annual icing days (IDs). Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend.

Annual precipitation indices demonstrated upward trends in the simple daily intensity index (SDII) (Figure 30), heavy precipitation days (R10) (Figure 31), 1-day precipitation amounts (RX1)

(Appendix 3, Figure 6), 5-day precipitation amounts (RX5) (Appendix 3, Figure 7), and annual total wet-day precipitation (PRCPTOT) (Figure 32). While annual heavy precipitation days (R10) showed a high significant upward trend in most of the townships, this trend was significant and showed a similar pattern mainly in the townships in the northern, eastern and around Bruce Peninsula area regarding SDII, RX1, and PRCPTOT indices. On the other hand, consecutive dry days (CDDs) showed a significant downward trend in some townships in the northern part of the study region (Appendix 3, Figure 8)

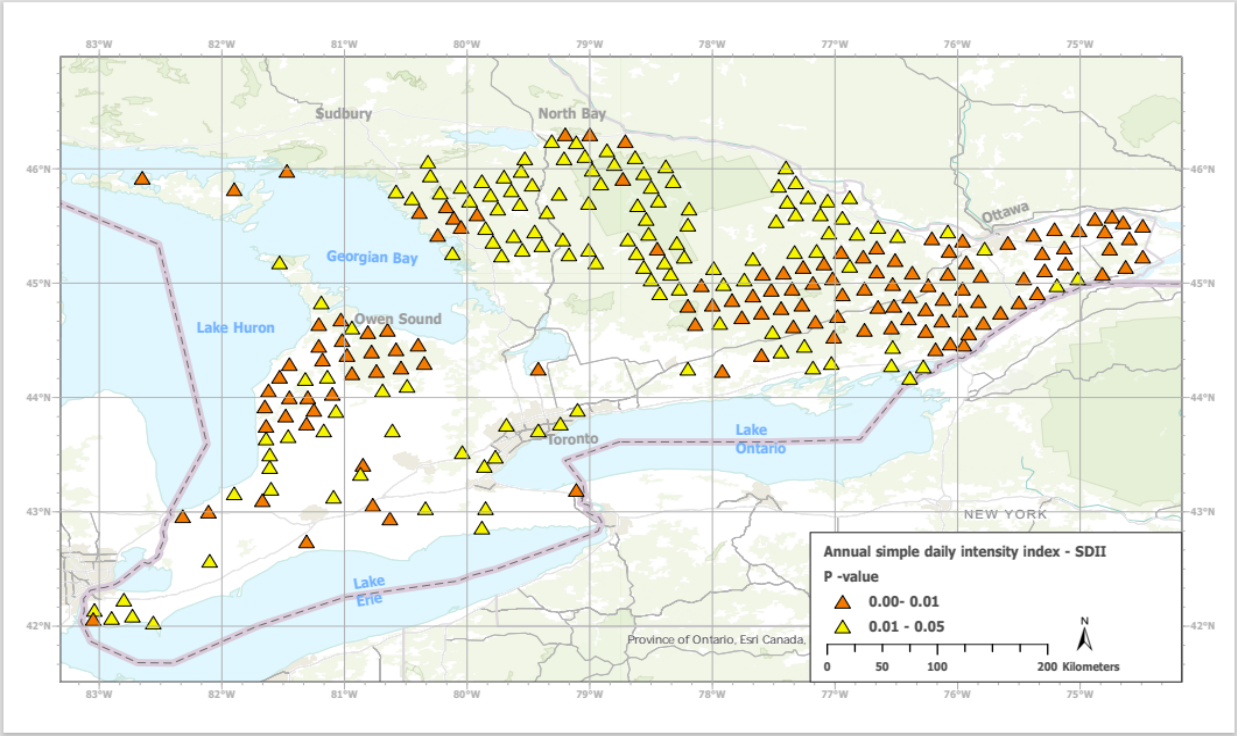


Figure 30: Map of trend significance for annual extreme weather indices: simple daily intensity index (SDII). Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant. Upward triangles indicate an upward trend, while downward triangles indicate a downward trend.

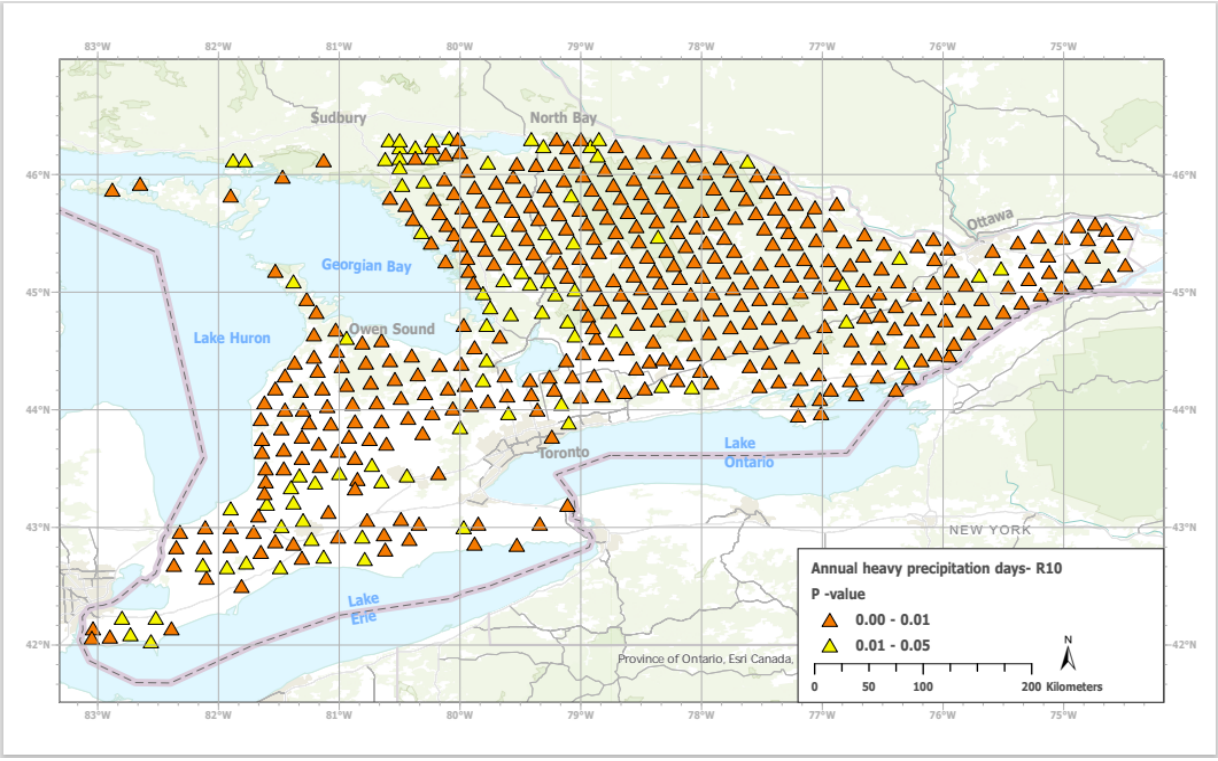


Figure 31: Map of trend significance for annual extreme weather indices: heavy precipitation days (R10). Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant. Upward triangles indicate an upward trend, while downward triangles indicate a downward trend.

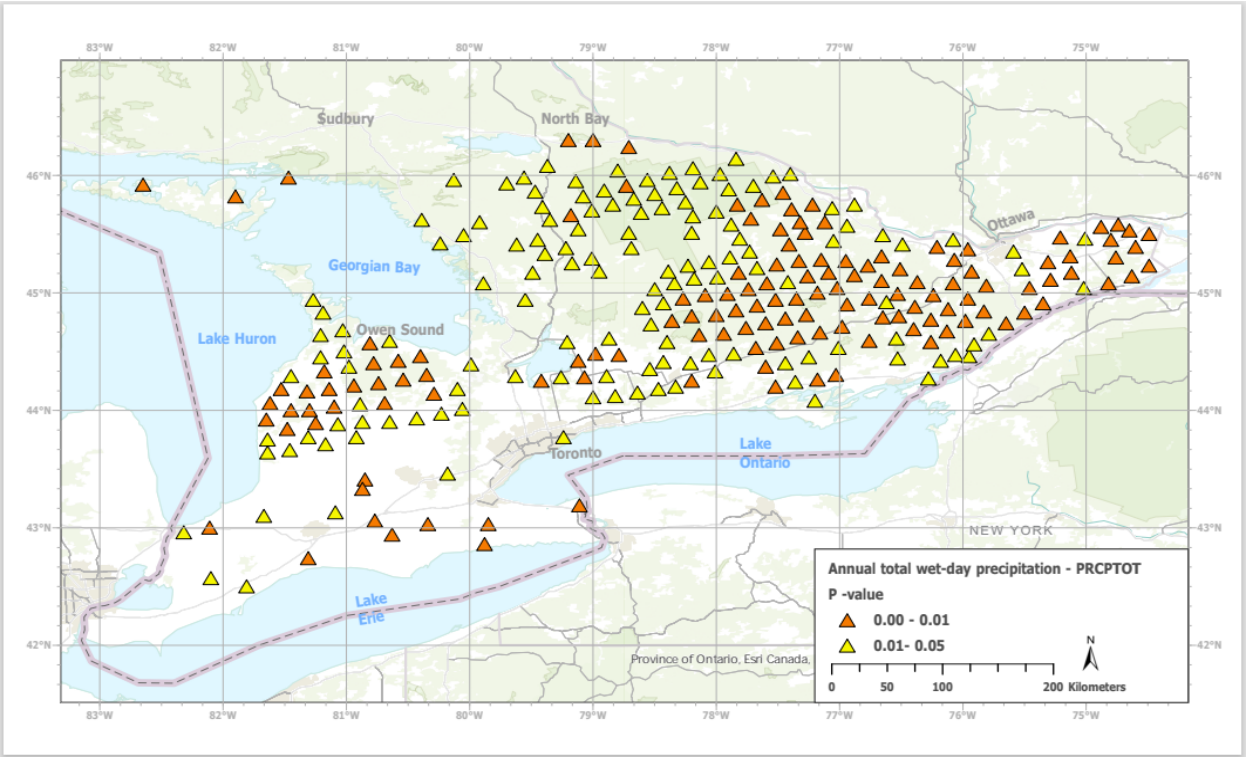


Figure 32: Map of trend significance for annual total wet-day precipitation (PRCPTOT), Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant. Upward triangles indicate an upward trend, while downward triangles indicate a downward trend.

As with the annual extreme weather indices, seasonal extreme weather trends for each index were also investigated. Warm days (TX90p) showed a significant upward trend in all seasons, but the most important increases were observed in the GS in all the townships (Figure 34), a significant upward trend was observed in the DS mostly in all the townships except the southern areas (Figure 33). Regarding the HS a significant upward trend was observed particularly in the townships

between Manitoulin and eastern Ontario, with some townships around Bruce Peninsula and London areas (Figure 35). Figure of TX90p for PS is presented in (Appendix 3, Figure 9).

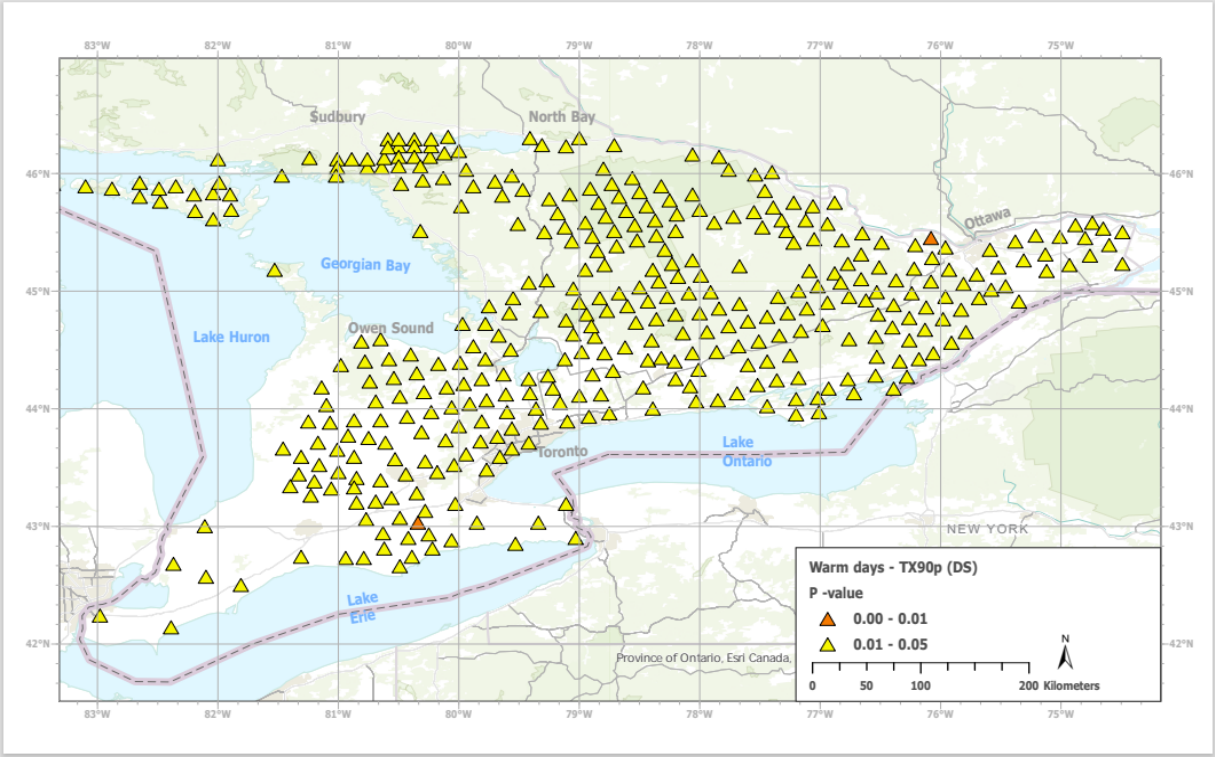


Figure 33: Map of trend significance of seasonal warm days (TX90P) index for the DS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant. Upward triangles indicate an upward trend.

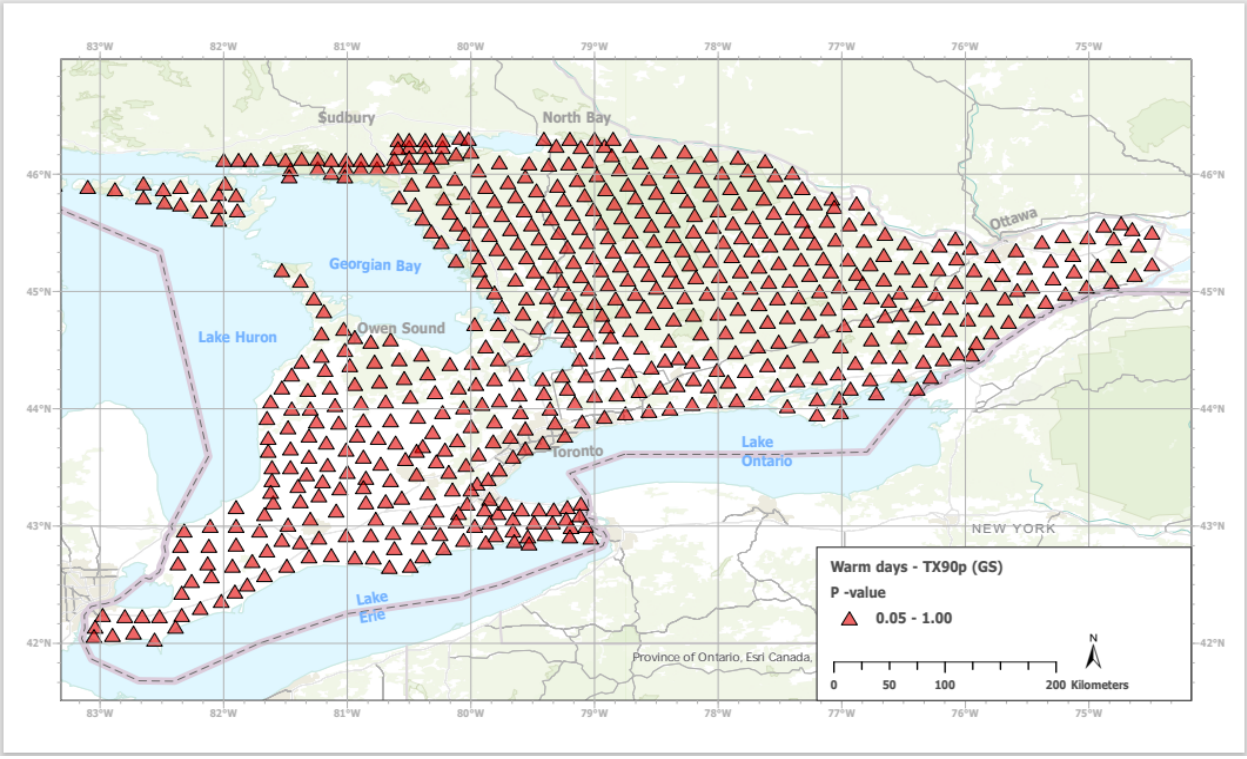


Figure 34: Map of trend significance of seasonal warm days (TX90P) index for the GS. Red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant. Upward triangles indicate an upward trend.

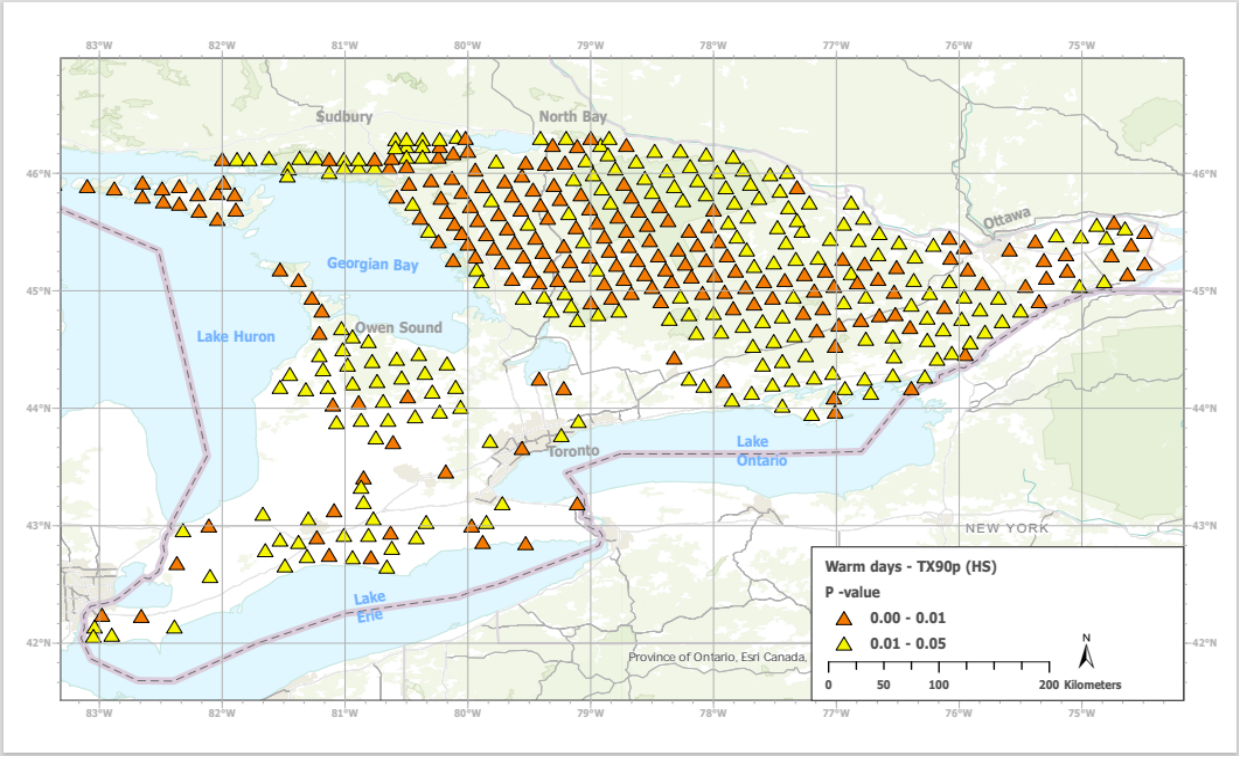


Figure 35: Map of trend significance of seasonal warm days (TX90P) index for the HS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant. Upward triangles indicate an upward trend.

Seasonal trend analyses showed a significant upward trend for warm nights (TN90P) for all the townships in the PS (Figure 36). This increase was noted as well for the GS except for a few townships in eastern Ontario (Figure 37). A significant upward increase occurs in the HS, except for a few townships in the south at the western shores of Lake Erie (Figure 38). For the DS, a significant upward trend was mainly seen in some townships between Manitoulin Island and the North Bay (Appendix 3, Figure 10).

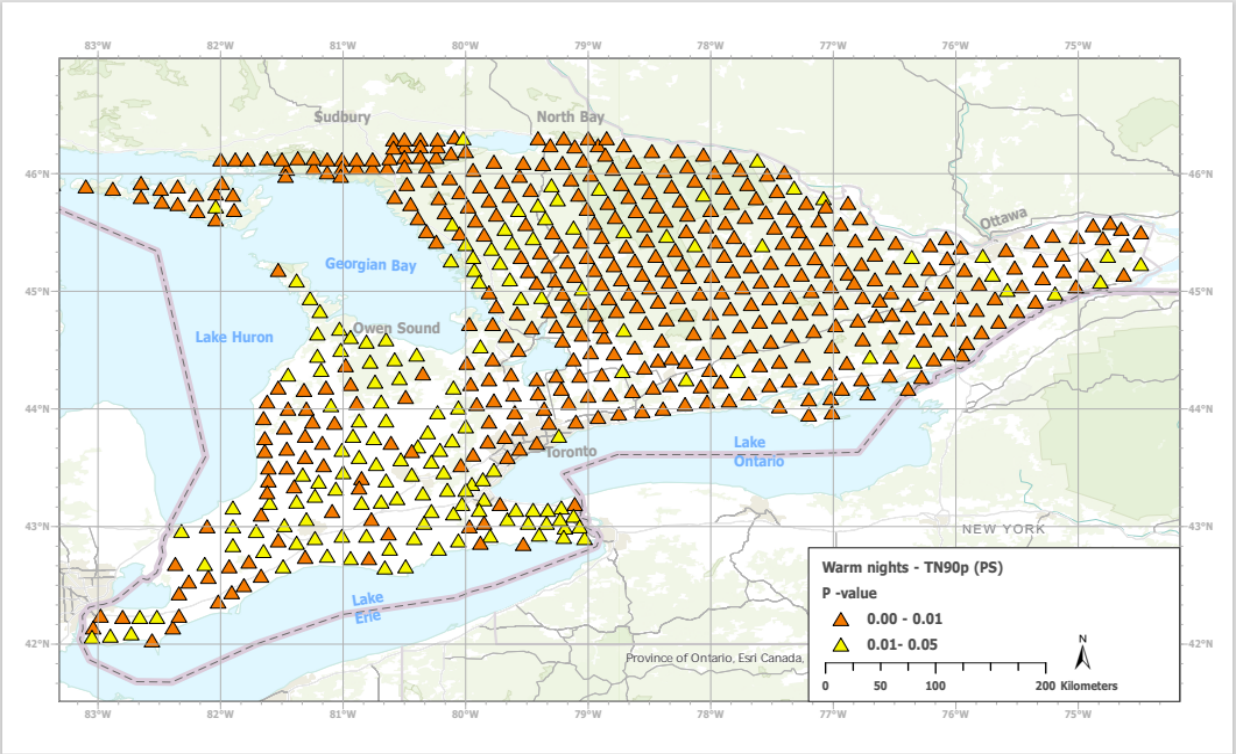


Figure 36: Map of trend significance for seasonal warm nights (TN90P) for the PS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant.

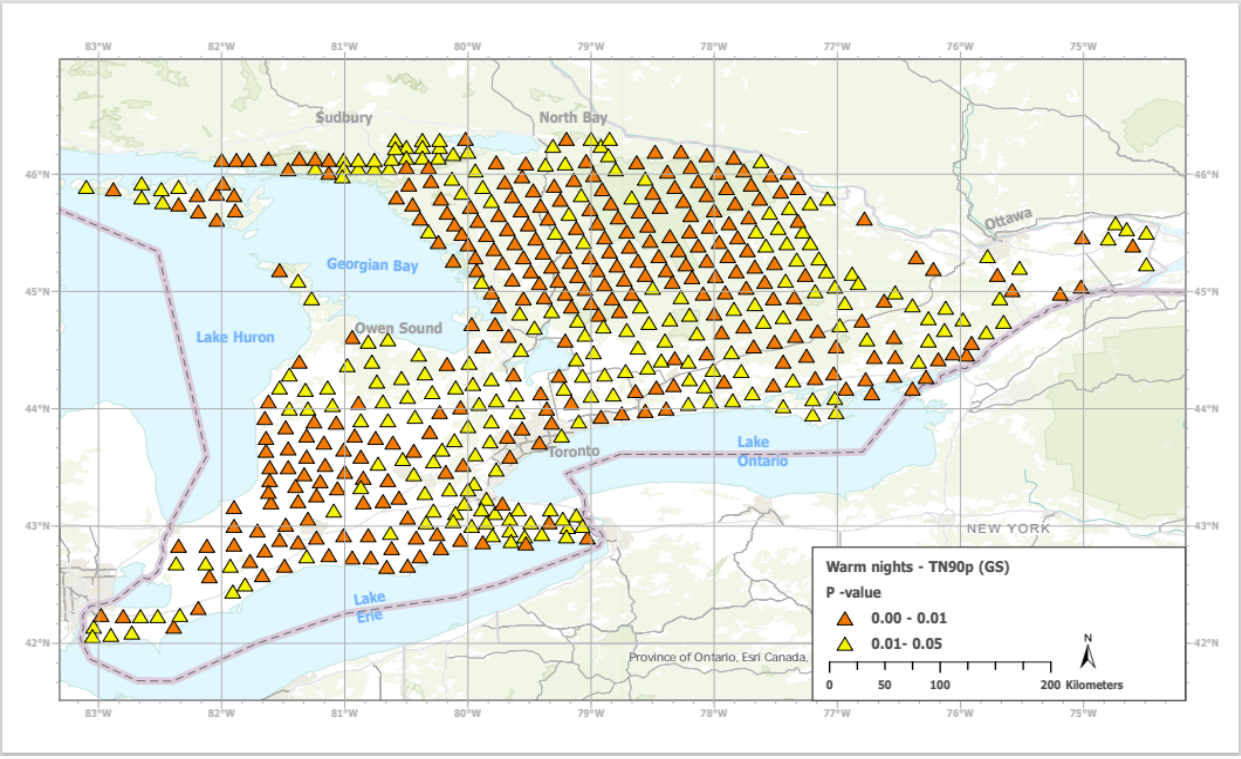


Figure 37: Map of trend significance for seasonal warm nights (TN90P) for the GS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant.

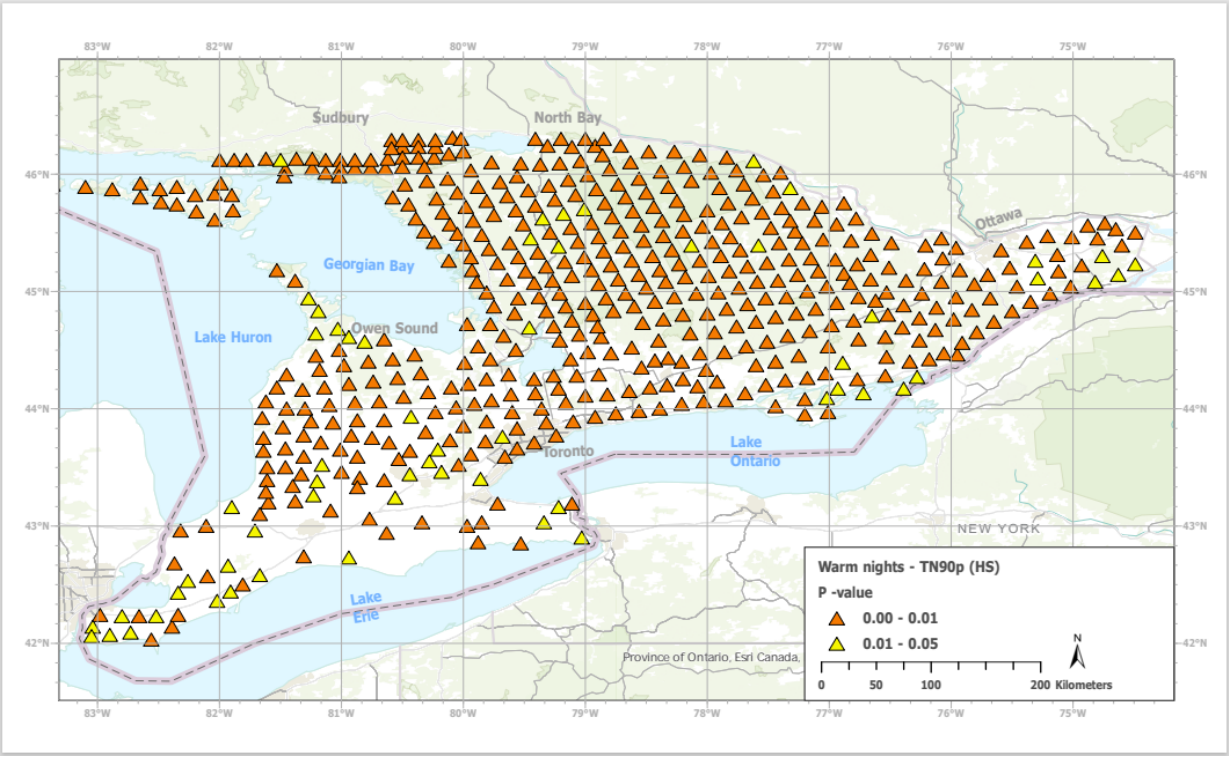


Figure 38: Map of trend significance for seasonal warm nights (TN90P) for the HS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant.

In contrast, cool days (TX10P) showed a downward trend for the PS, GS, and HS across the townships in southern Ontario (Figures 39, 40, and 41). The dormancy season (DS) had the least significant downward trend, since a significant decrease was mostly seen in the eastern Ontario townships (Appendix 3, Figure 11).

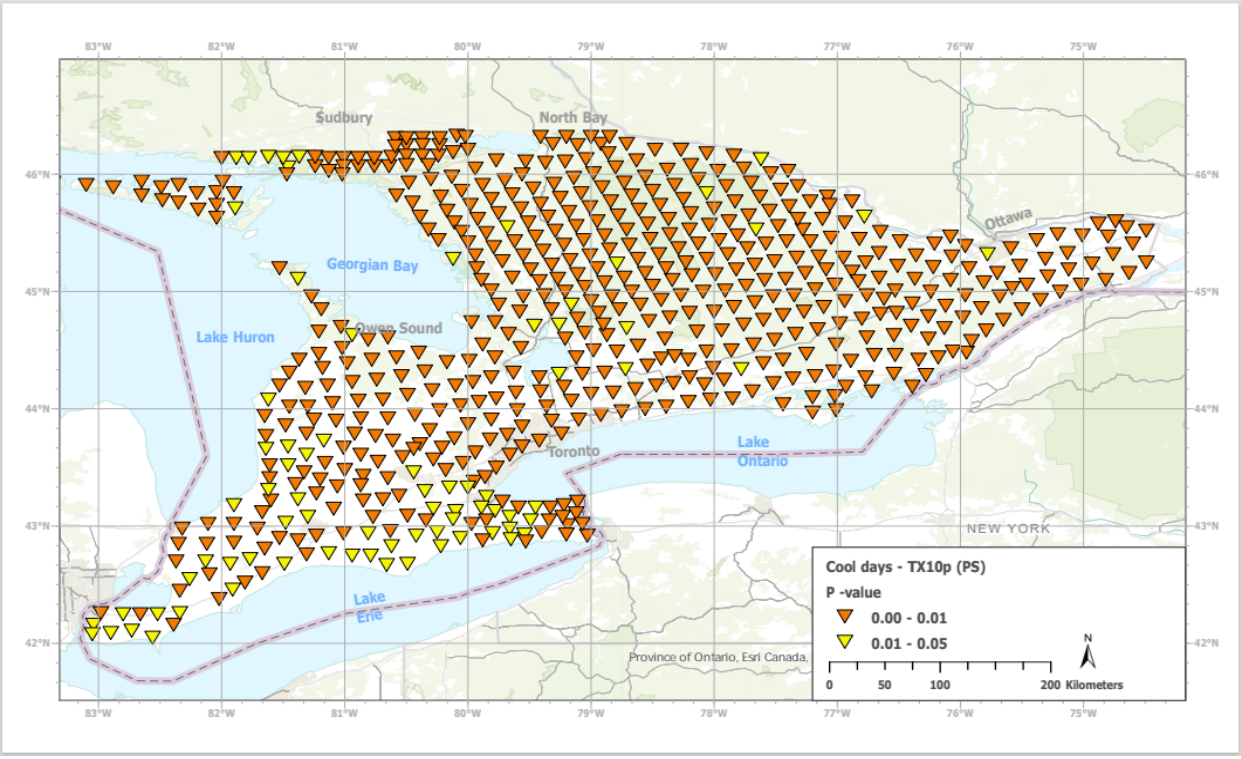


Figure 39: Map of trend significance for the seasonal cool days index (TX10P) for the PS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant. Downward triangles indicate a downward trend.

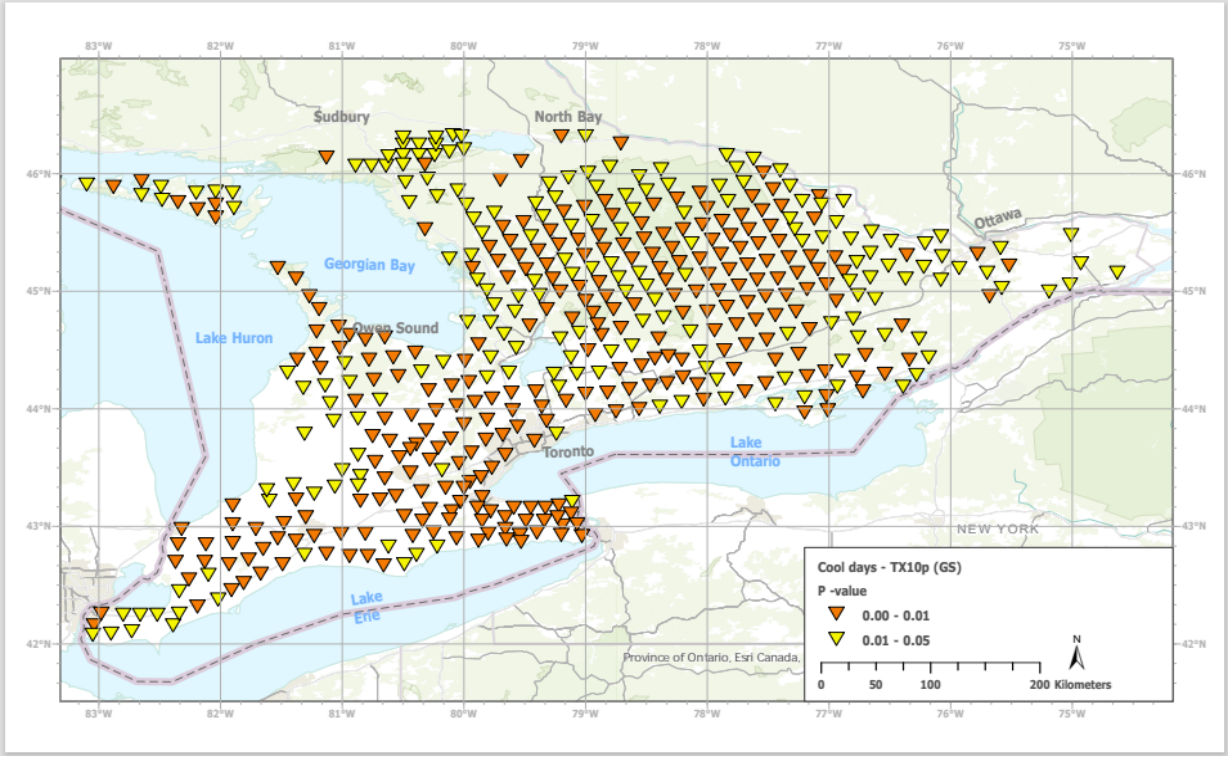


Figure 40: Map of trend significance for the seasonal cool days index (TX10P) for the GS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant. Downward triangles indicate a downward trend.

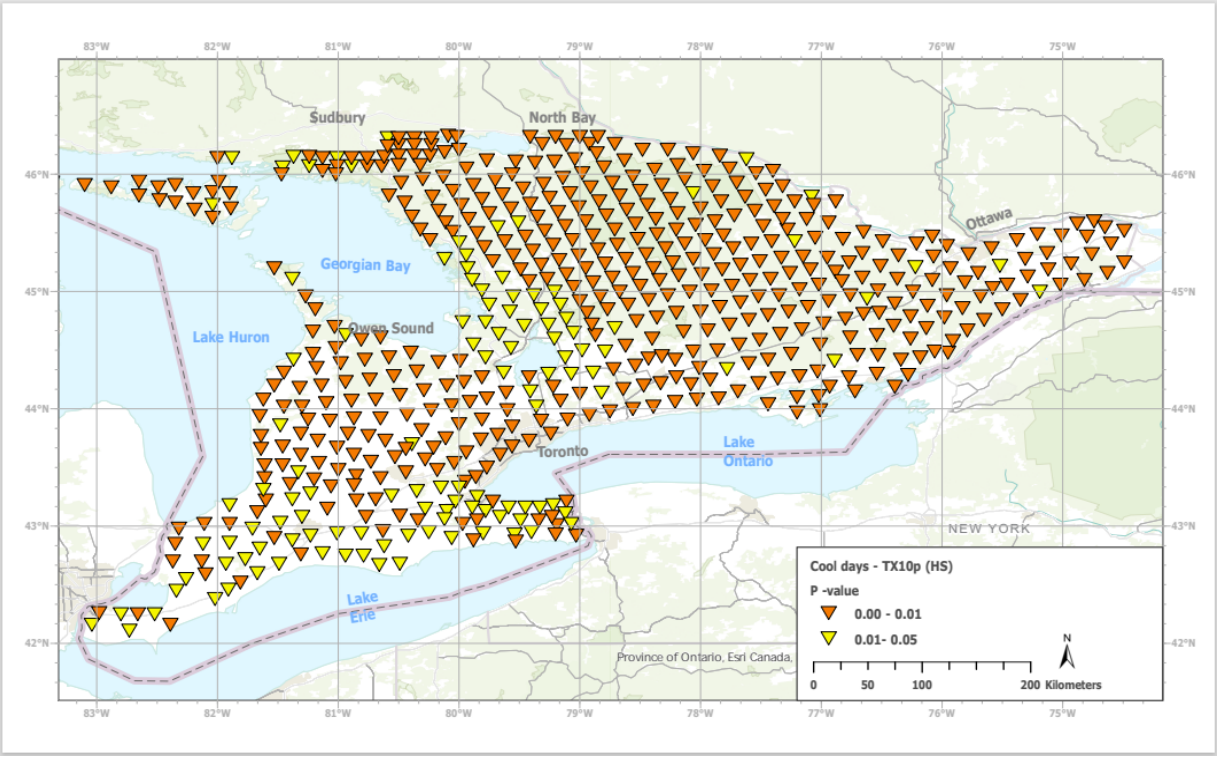


Figure 41: Map of trend significance for the seasonal cool days index (TX10P) for the HS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant. Downward triangles indicate a downward trend.

Similarly, cool nights (TN10P) followed the same seasonal patterns as the cool days (TX10P). A significant downward increase has been observed for the PS, GS, and HS in all the townships (Figure 42, 43,44), while the DS had the least significant decreases, which were spatially limited to scattered townships in the central and northern areas (Appendix 3, Figure 12).

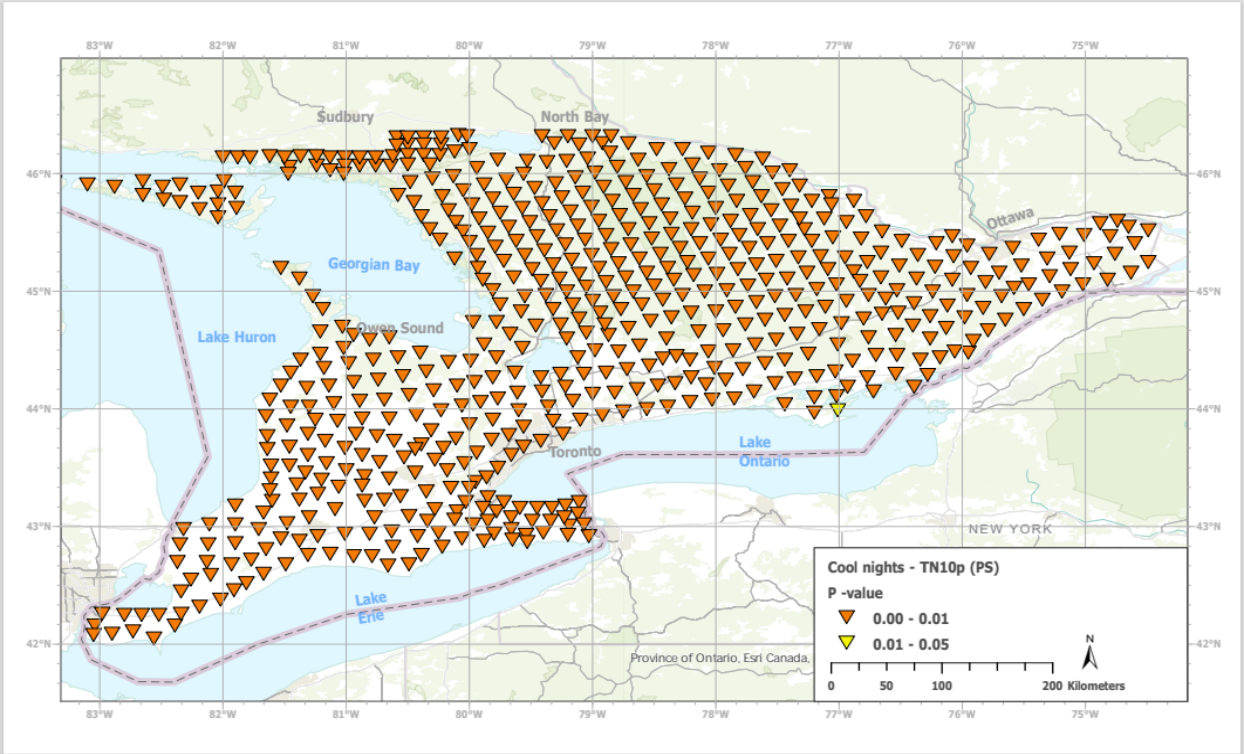


Figure 42: Map of trend significance for seasonal cool nights (TN10P) index for the PS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant, and a downward triangle indicates a downward trend.

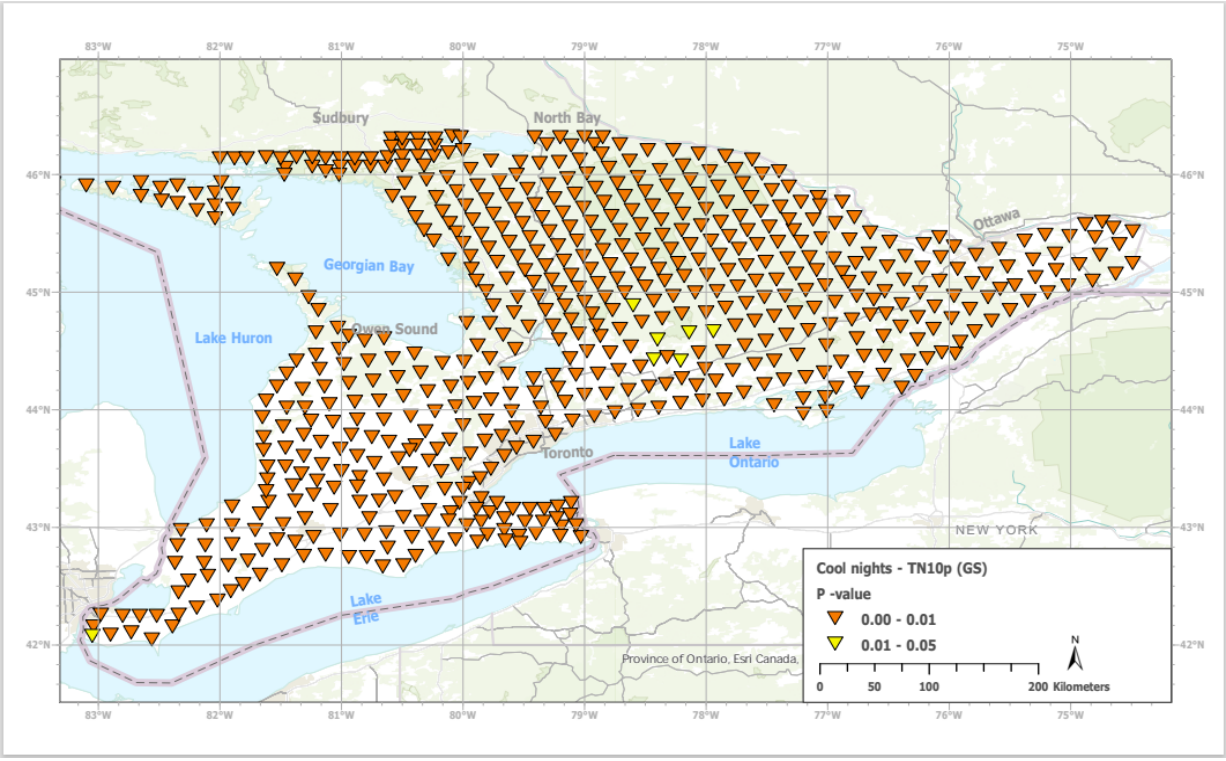


Figure 43: Map of trend significance for seasonal cool nights (TN10P) index for the GS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant, and a downward triangle indicates a downward trend.

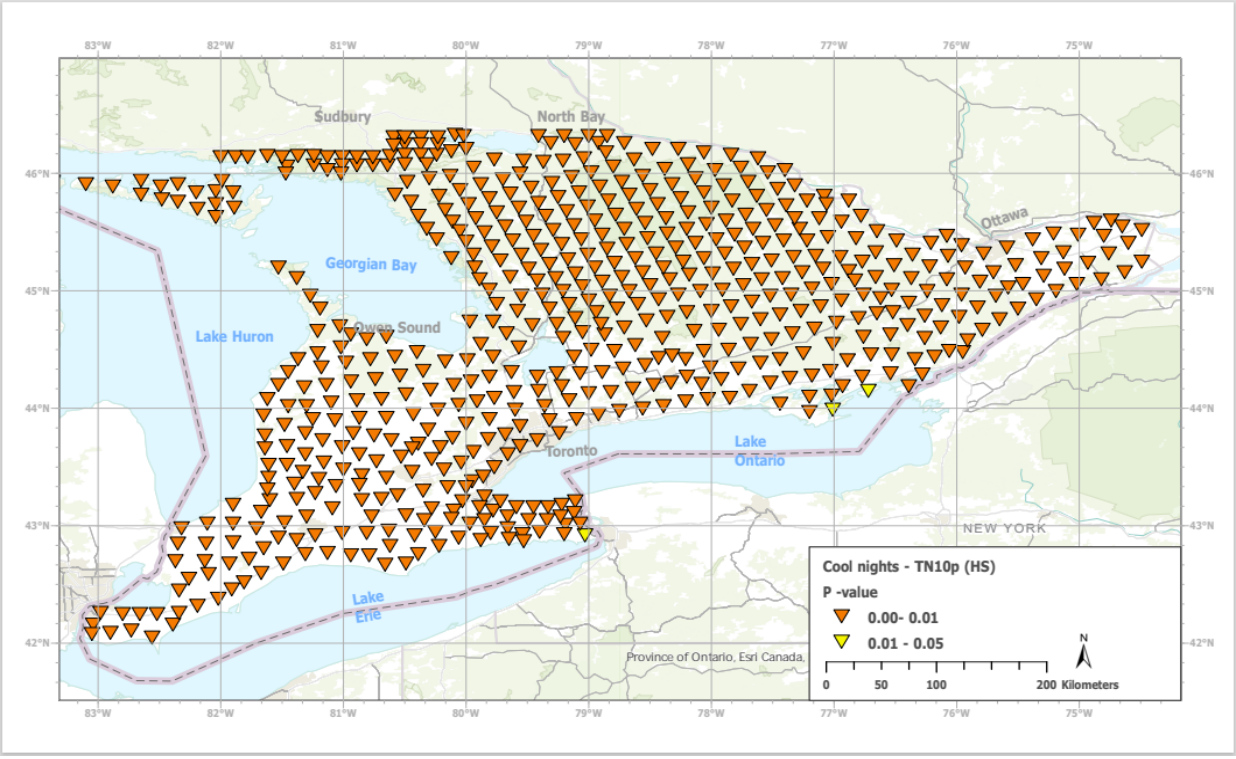


Figure 44: Map of trend significance for seasonal cool nights (TN10P) index for the HS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant, and a downward triangle indicates a downward trend.

A downward trend was observed for the diurnal temperature range (DTR) in all seasons. The most significant decreases were seen in the PS (Figure 45) and the GS (Figure 47), and this decrease was present in most of the townships across the region except for some townships in eastern Ontario. However, the DS (Figure 46) and the HS (Figure 48) showed fewer significant decreases in terms of townships affected by a downward trend.

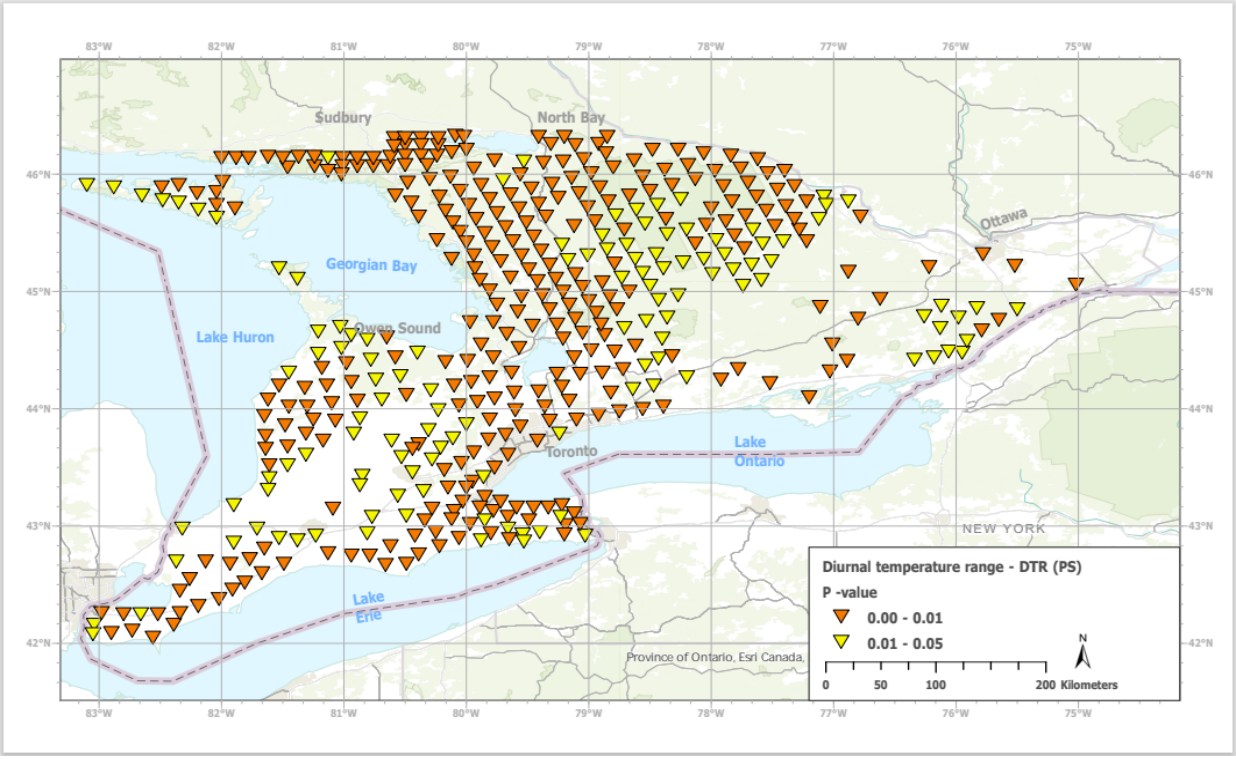


Figure 45: Map of trend significance for the seasonal diurnal temperature range (DTR) index for the PS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. A downward triangle indicates a downward trend.

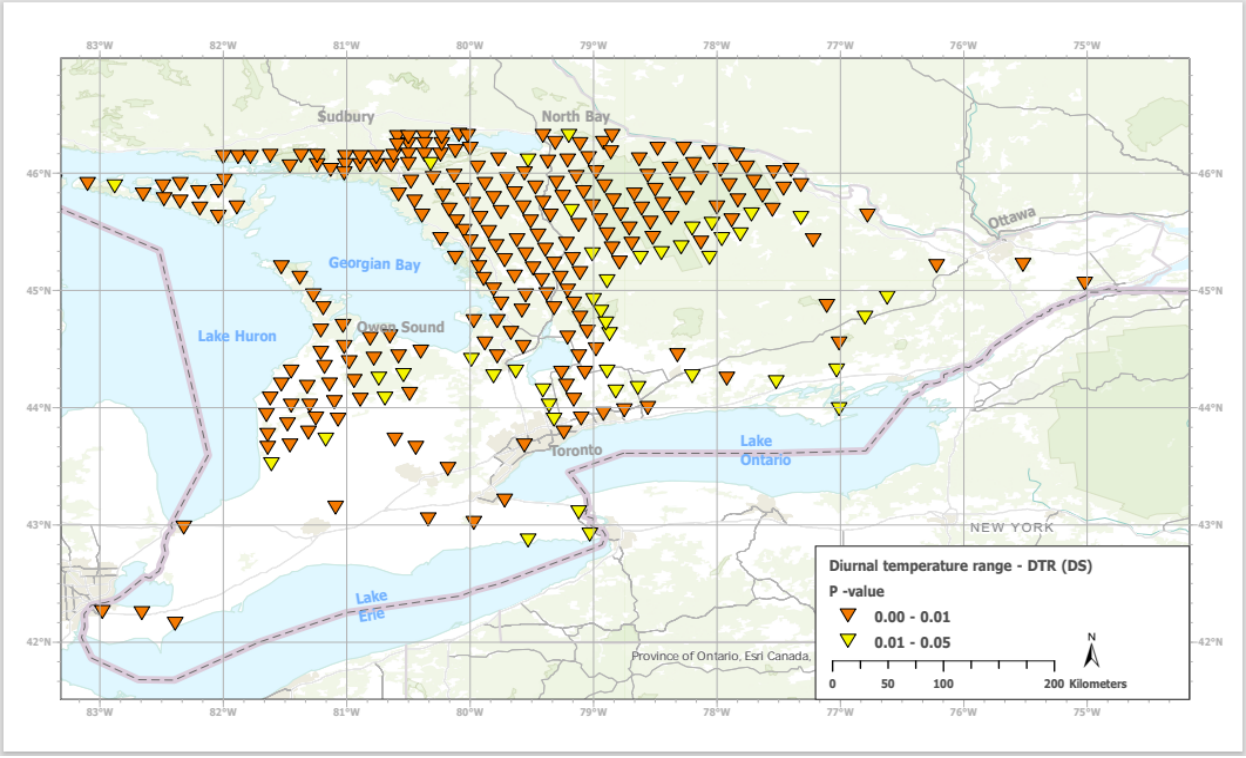


Figure 46: Map of trend significance for the seasonal diurnal temperature range (DTR) index for the DS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. A downward triangle indicates a downward trend.

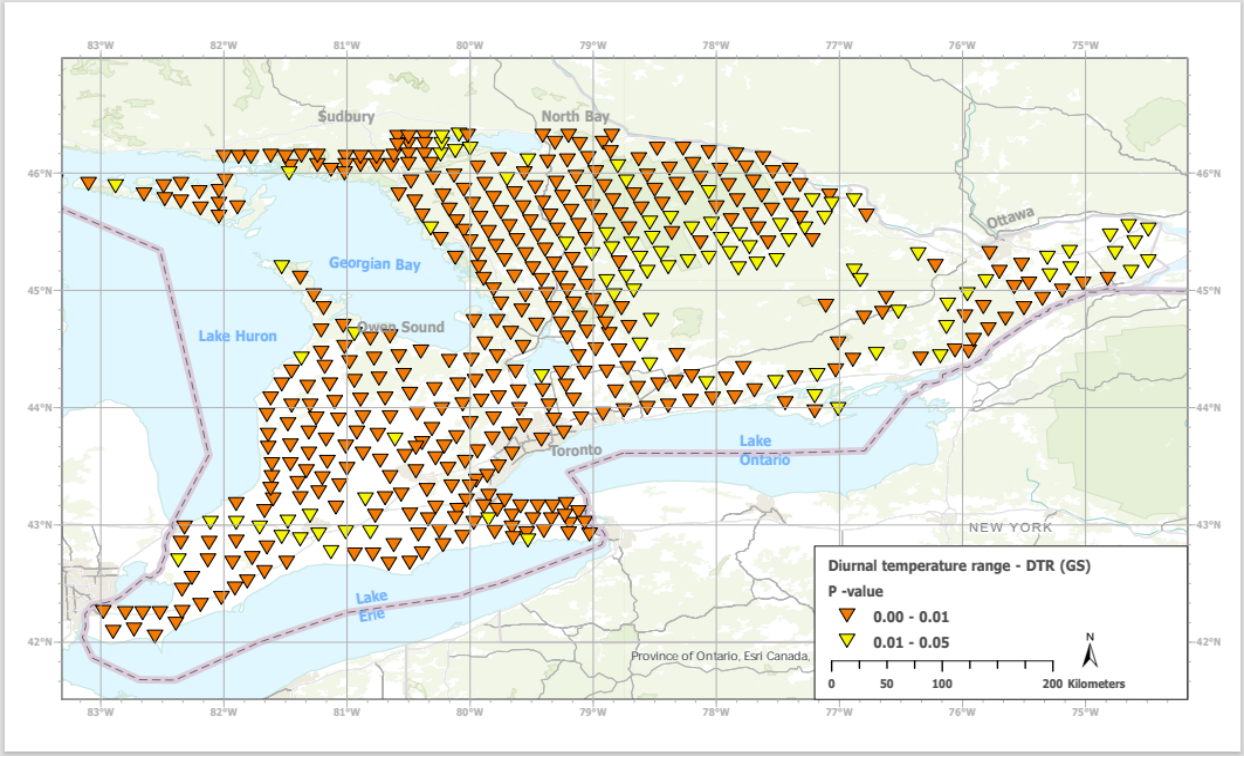


Figure 47: Map of trend significance for the seasonal diurnal temperature range (DTR) index for the GS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. A downward triangle indicates a downward trend.

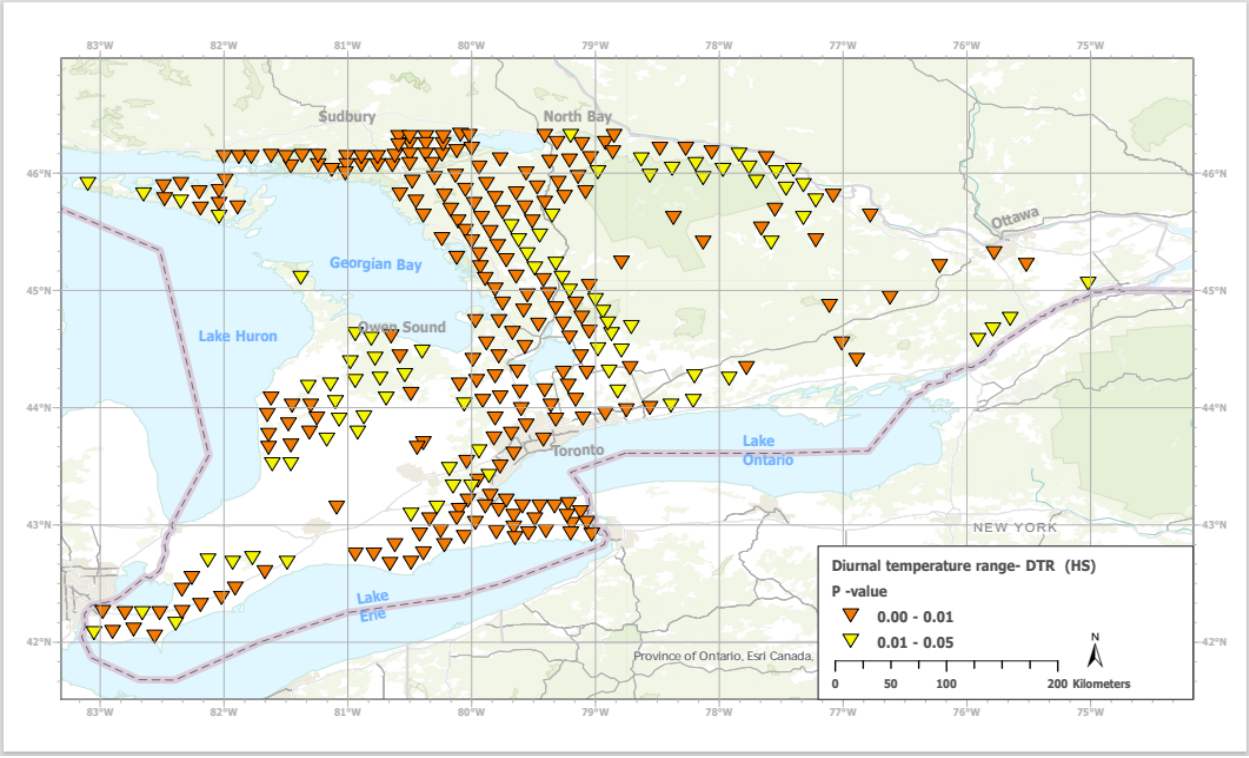


Figure 48: Map of trend significance for the seasonal diurnal temperature range (DTR) index for the HS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. A downward triangle indicates a downward trend.

Investigating seasonal warm extreme index (HWE) at the township level suggested that there was no significant upward trend in the region in all seasons and that the increase in extreme warm days was not very common except for a very few townships in the north during the GS (Appendix 3, Figure 13). Cold weather extremes (CWEs) relevant for the DS only showed a downward trend (Figure 49), which was found to be significant particularly in between Manitoulin Island and the North Bay. Frost days (FDs), also relevant for DS only, saw an important significant downward trend in most of the townships except the southern region (Figure 50).

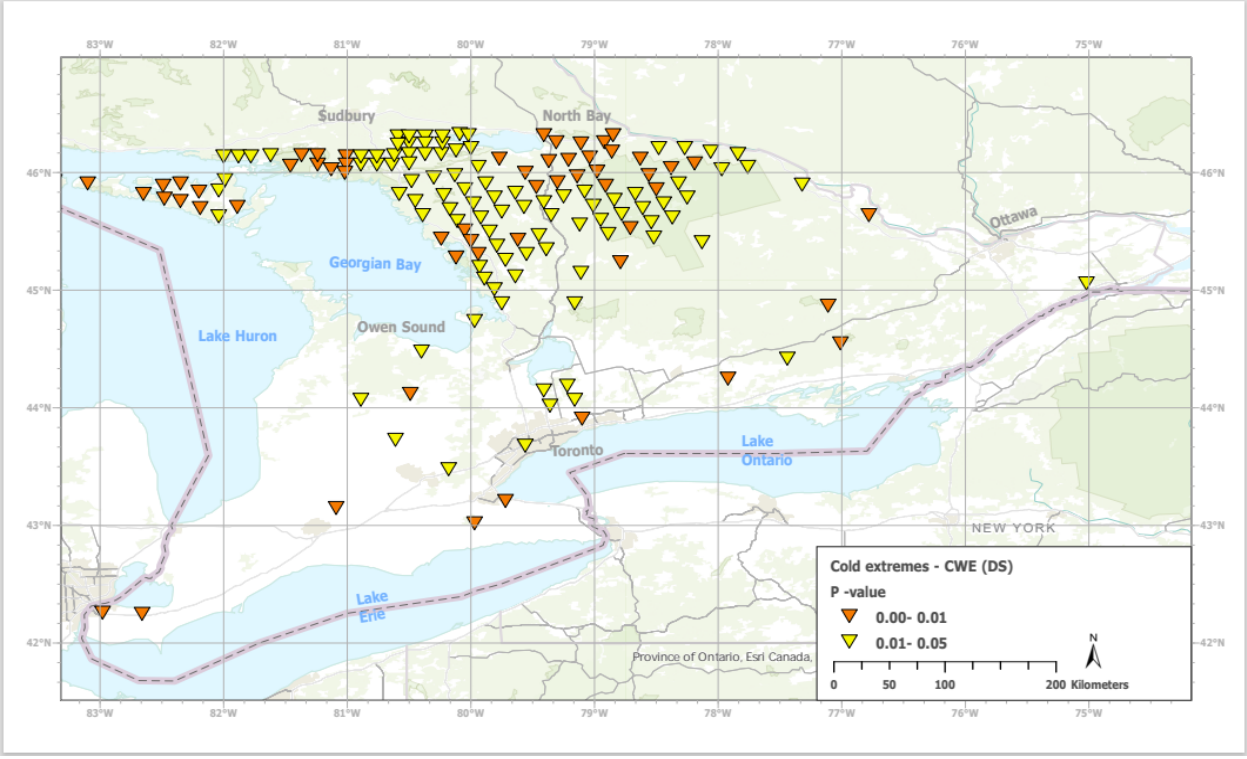


Figure 49: Map of trend significance for seasonal cold extreme (CWE) in the DS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend.

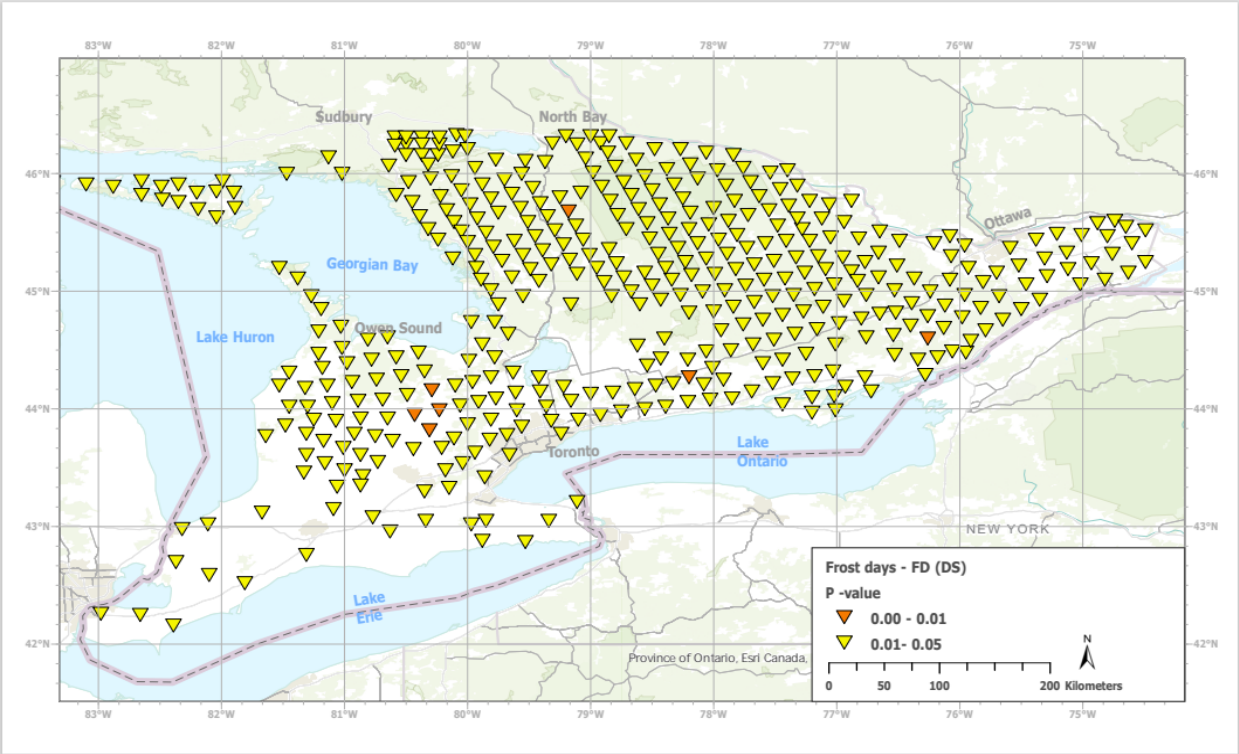


Figure 50: Map of trend significance for seasonal frost day (FD) indices in the DS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend.

Icing days (IDs) showed downward trends, with the highest significance being observed in the DS (Figure 52), and the GS for all the townships (Figure 53). Furthermore, downward trends were found to be significant in the PS for most of the townships (Figure 51).

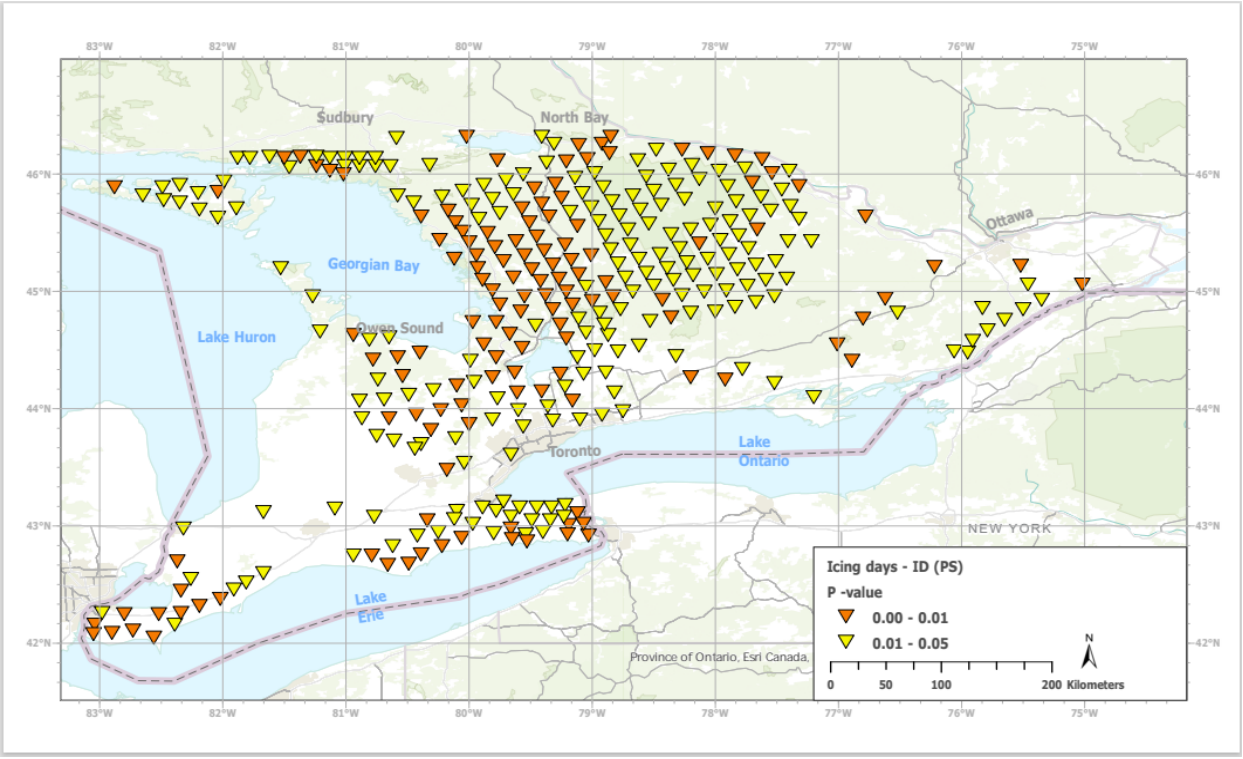


Figure 51: Map of trend significance for seasonal icing days (ID) in the PS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. A downward triangle indicates a downward trend.

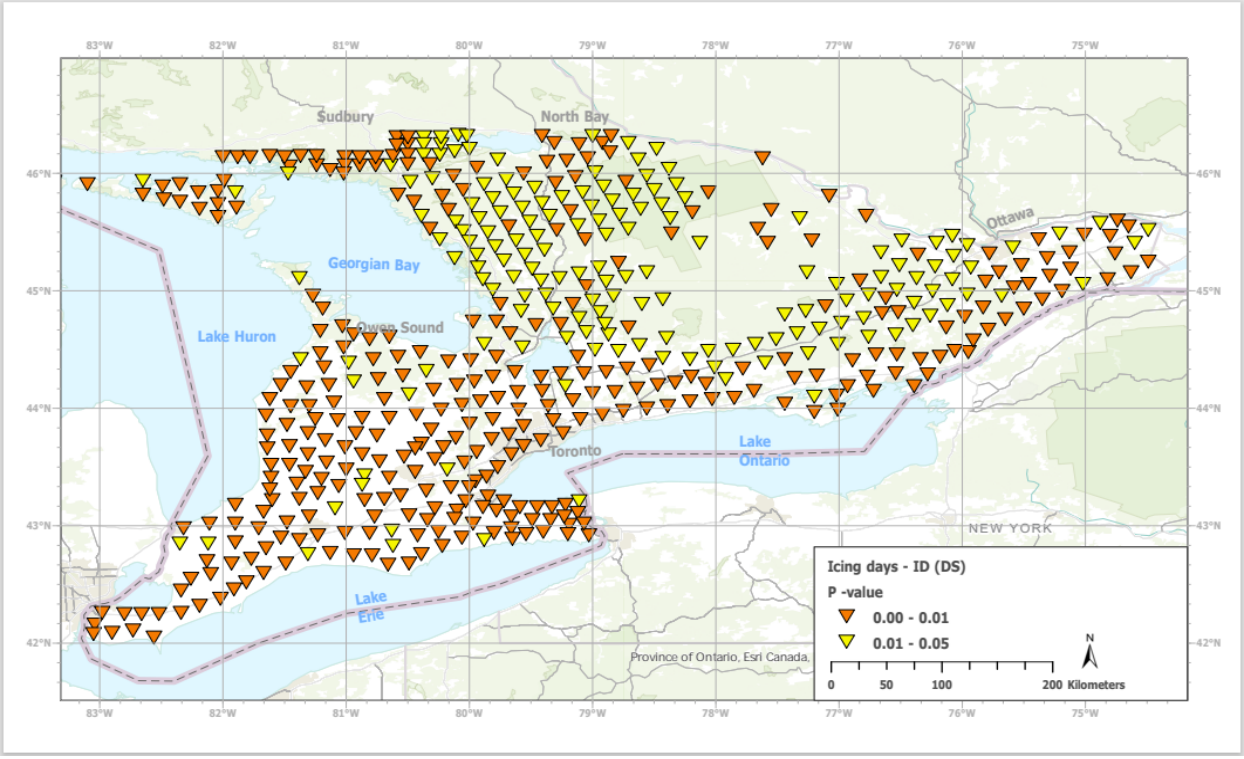


Figure 52: Map of trend significance for seasonal icing days (ID) in the DS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. A downward triangle indicates a downward trend.

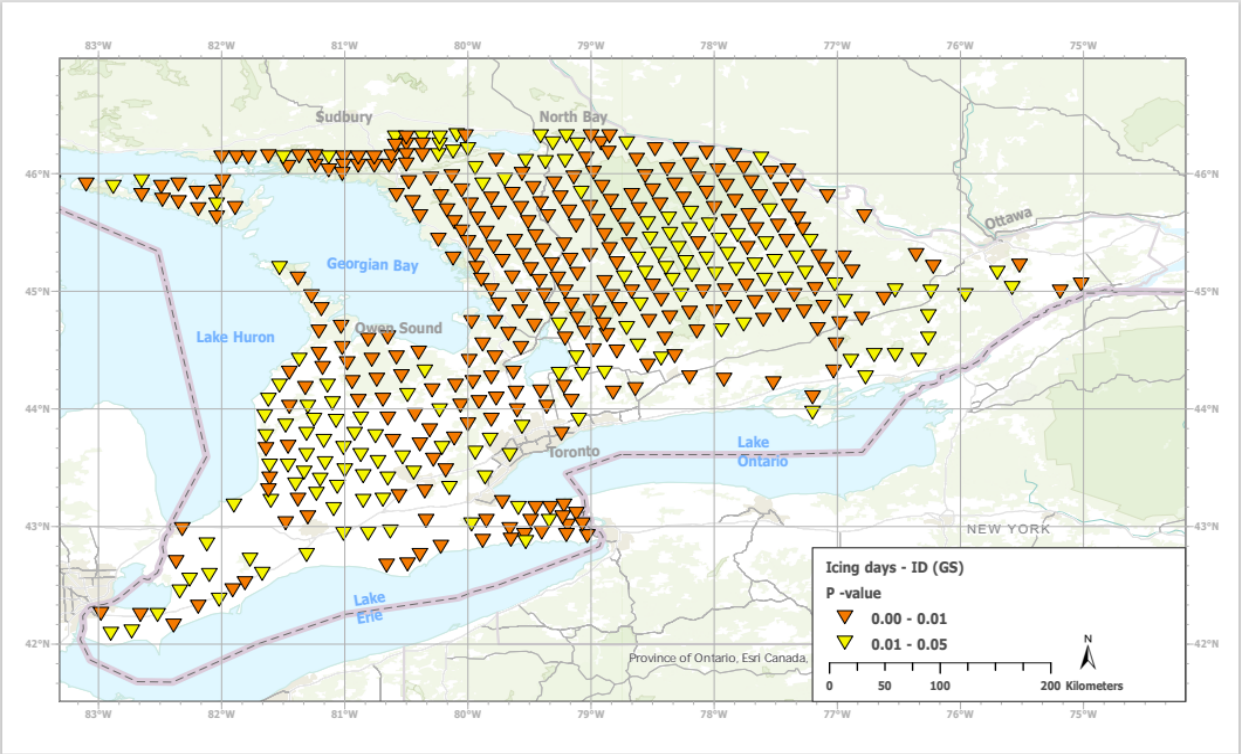


Figure 53: Map of trend significance for seasonal icing days (ID) in the GS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. A downward triangle indicates a downward trend.

Regarding precipitation indices, trend analyses indicate an upward trend in the simple daily intensity index (SDII) for most of the townships in the DS (Figure 55) and the GS (Figure 56), whereas significant increases in the PS season (Figure 54) and the HS season (Appendix 3, Figure 14) were mostly captured in the eastern townships. Comparing the trends of the 1-day precipitation amount index (RX1) and the 5-day precipitation amount index (RX5), the RX1 had an upward trend and was mainly significant in the DS in the northern townships (Figure 57) (RX1 maps for the PS, the GS, and the HS are presented in Appendix 3, Figures 15, 16, and 17 respectively), while the RX5 showed a significant upward trend in the PS (Figure 58), the GS (Figure 59), and

the HS in all the townships across the region (Figure 60) (RX5 map for the DS is presented in Appendix 3, Figure 18). The heavy precipitation index (R10) showed an important significant upward trend in the GS (Figure 62), the DS for most of the townships (Figure 61) (R10 maps for the PS and the HS are presented in Appendix 3, Figures 19 and 20 respectively). Additionally, the total wet-day precipitation index (PRCPTOT) showed an upward trend for all seasons, yet this significant trend has shown to be limited to some townships in the northeastern part of the study region for the PS, the GS, and the HS season (Appendix 3 Figures, 21, 22, and 23 respectively).

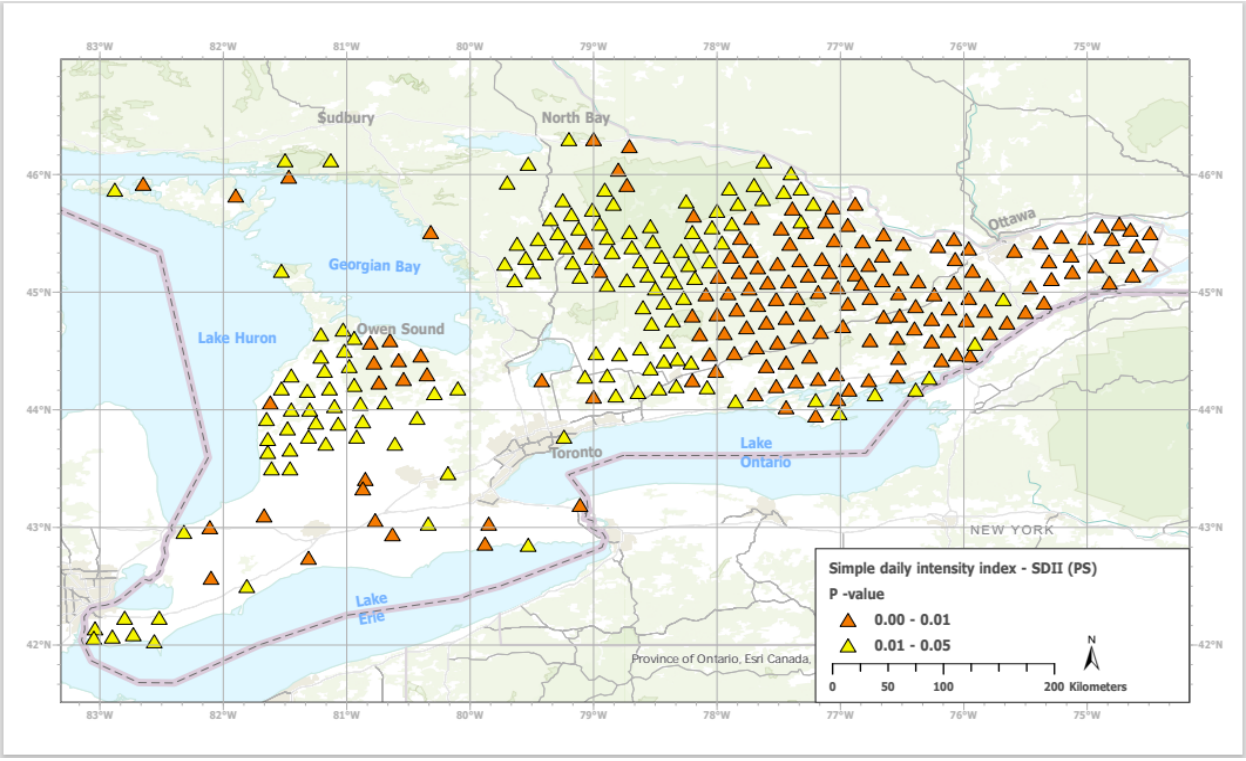


Figure 54: Map of trend significance for seasonal simple daily intensity (SDII) for the PS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend.

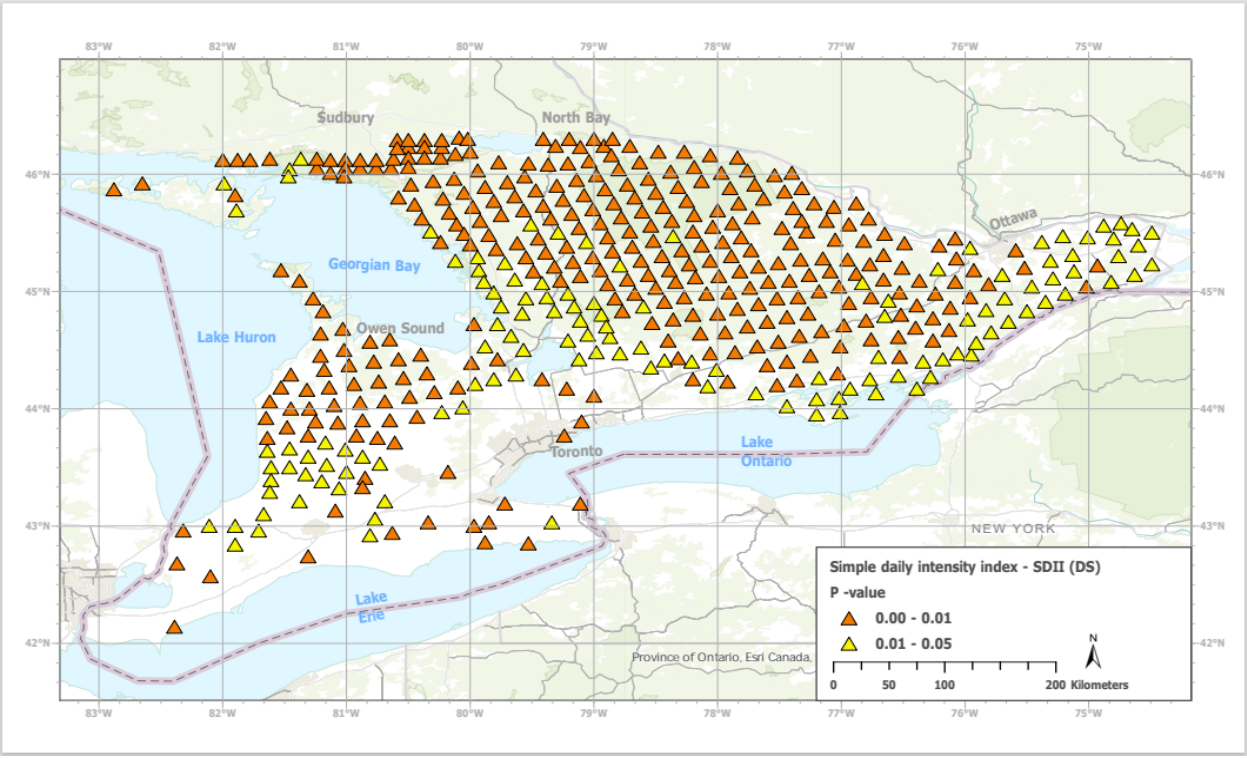


Figure 55: Map of trend significance for seasonal simple daily intensity (SDII) for the DS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend.

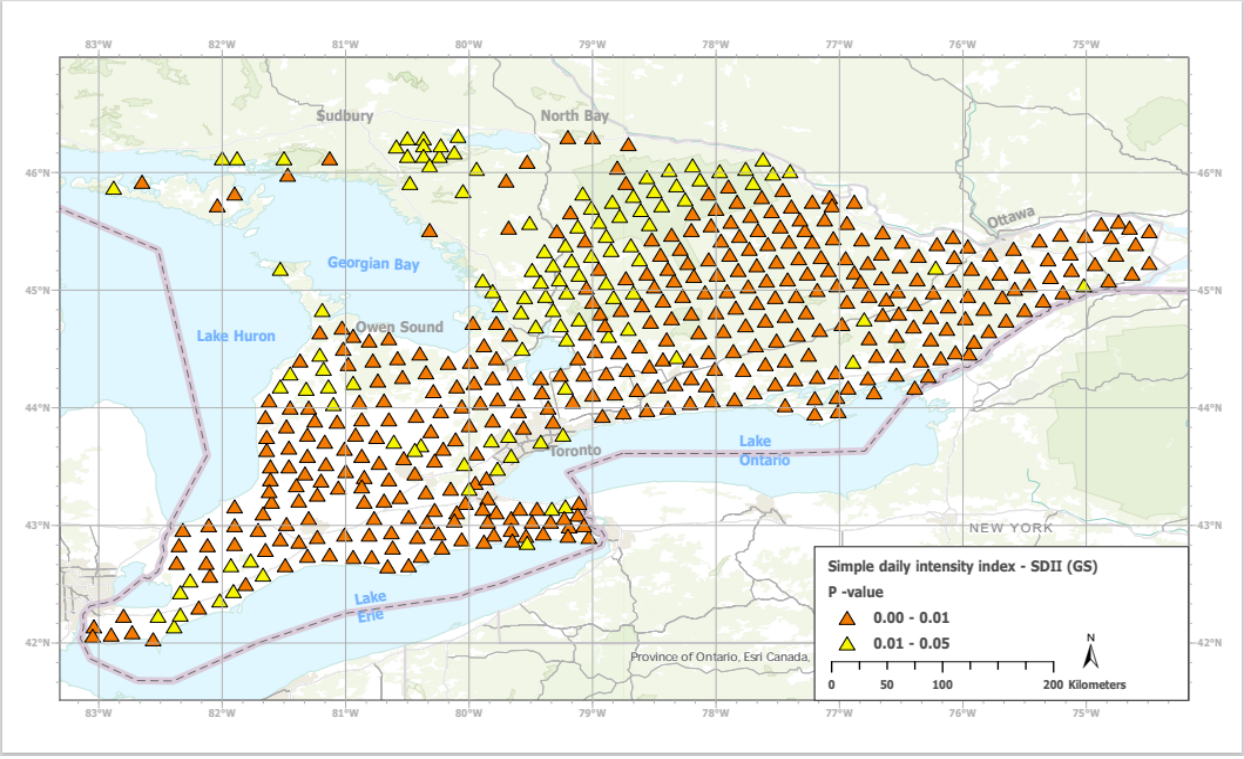


Figure 56: Map of trend significance for seasonal simple daily intensity (SDII) for the GS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend.

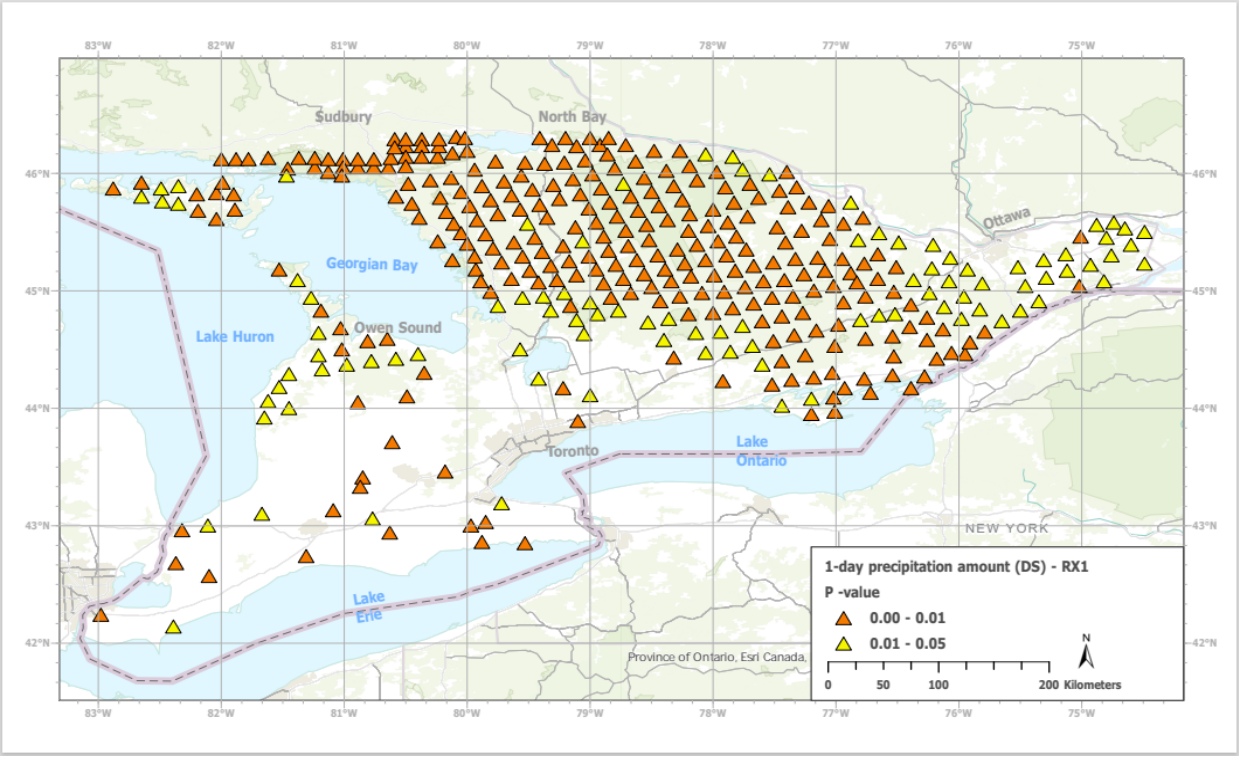


Figure 57: Map of trend significance for seasonal 1- day precipitation amount (RX1) for the DS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend.

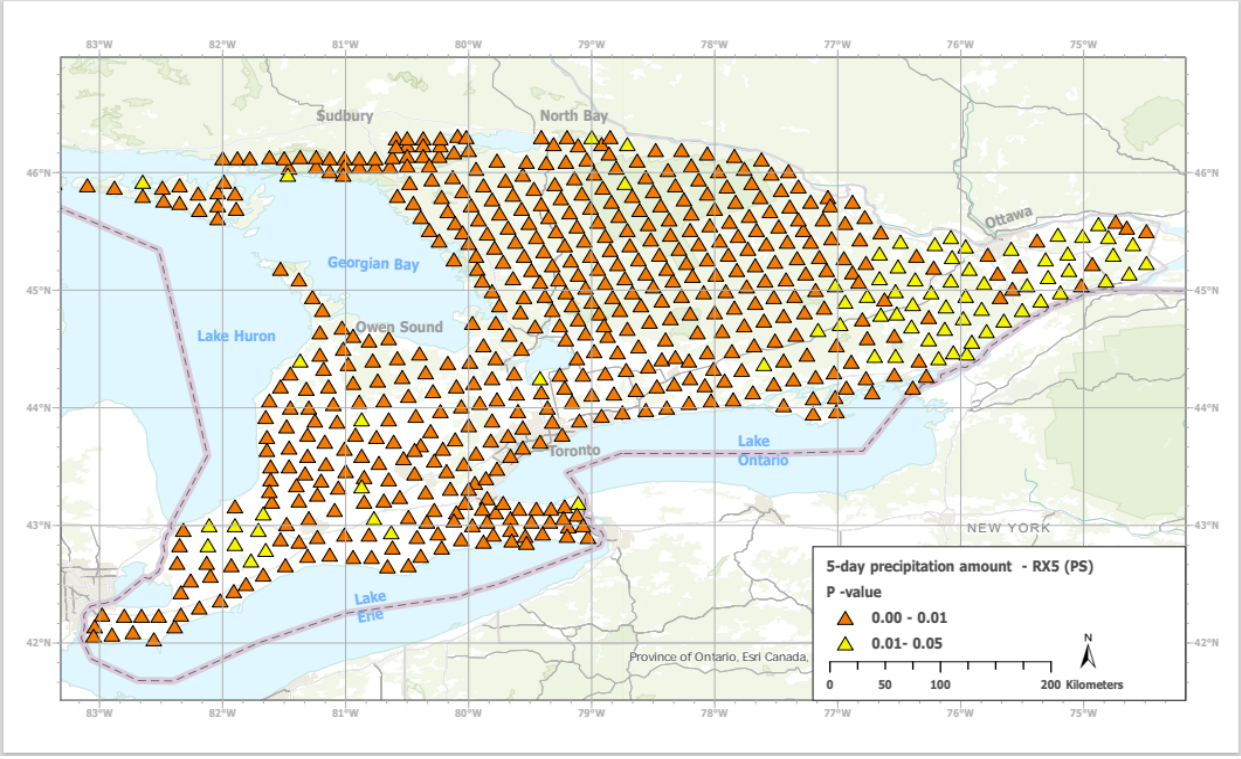


Figure 58: Map of trend significance for seasonal 5- day precipitation amount (RX5) for the PS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend.

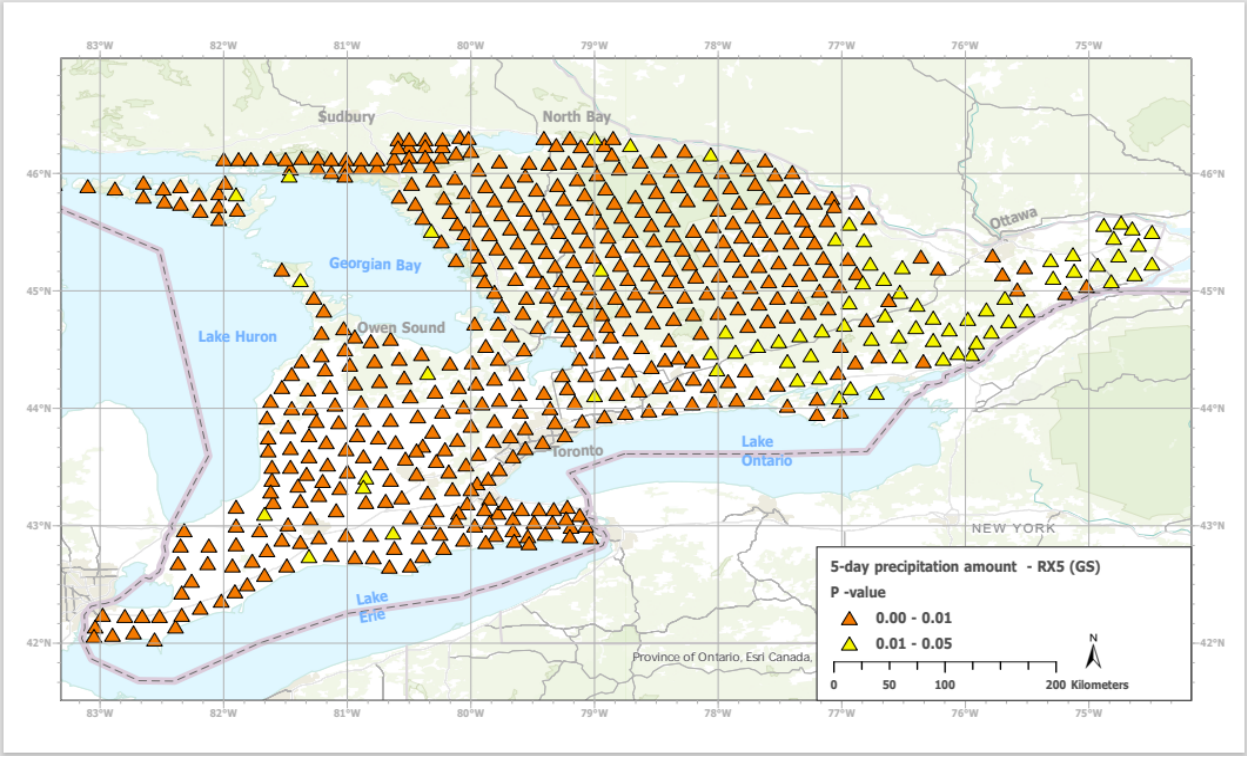


Figure 59: Map of trend significance for seasonal 5- day precipitation amount (RX5) for the GS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend.

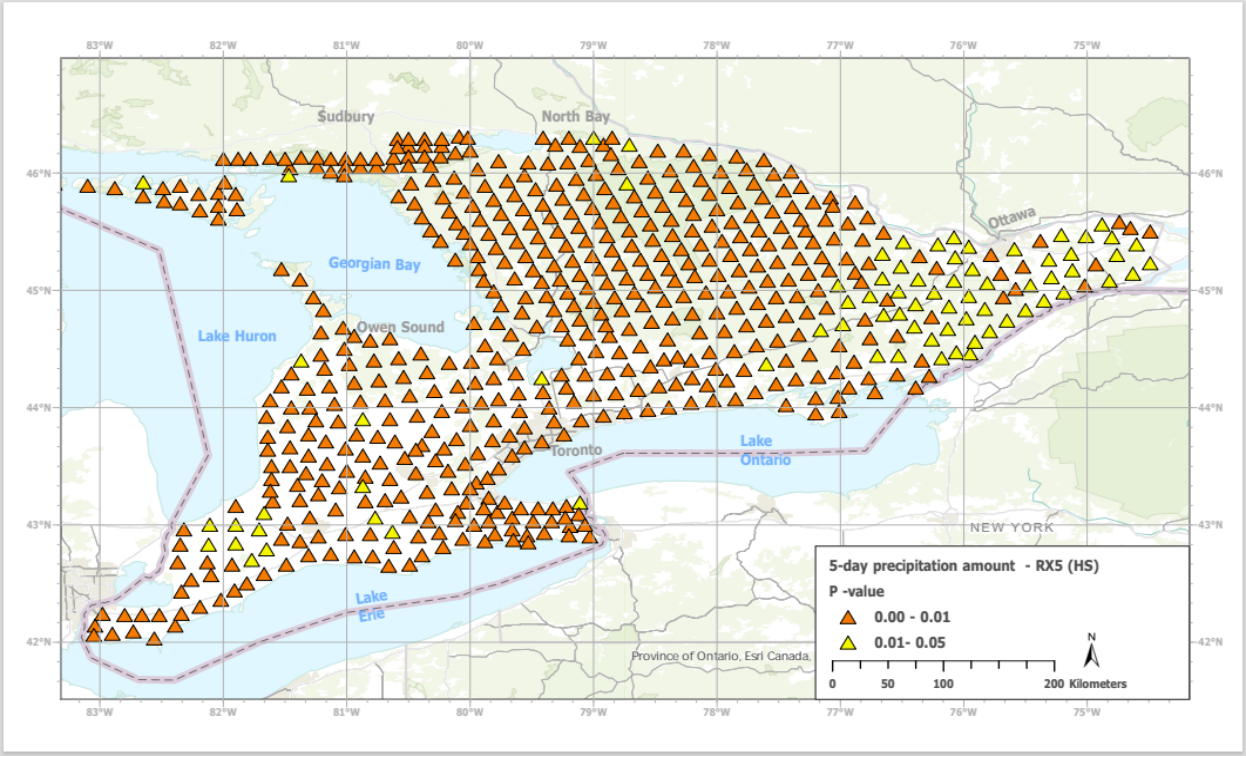


Figure 60: Map of trend significance for seasonal 5- day precipitation amount (RX5) for the HS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend.

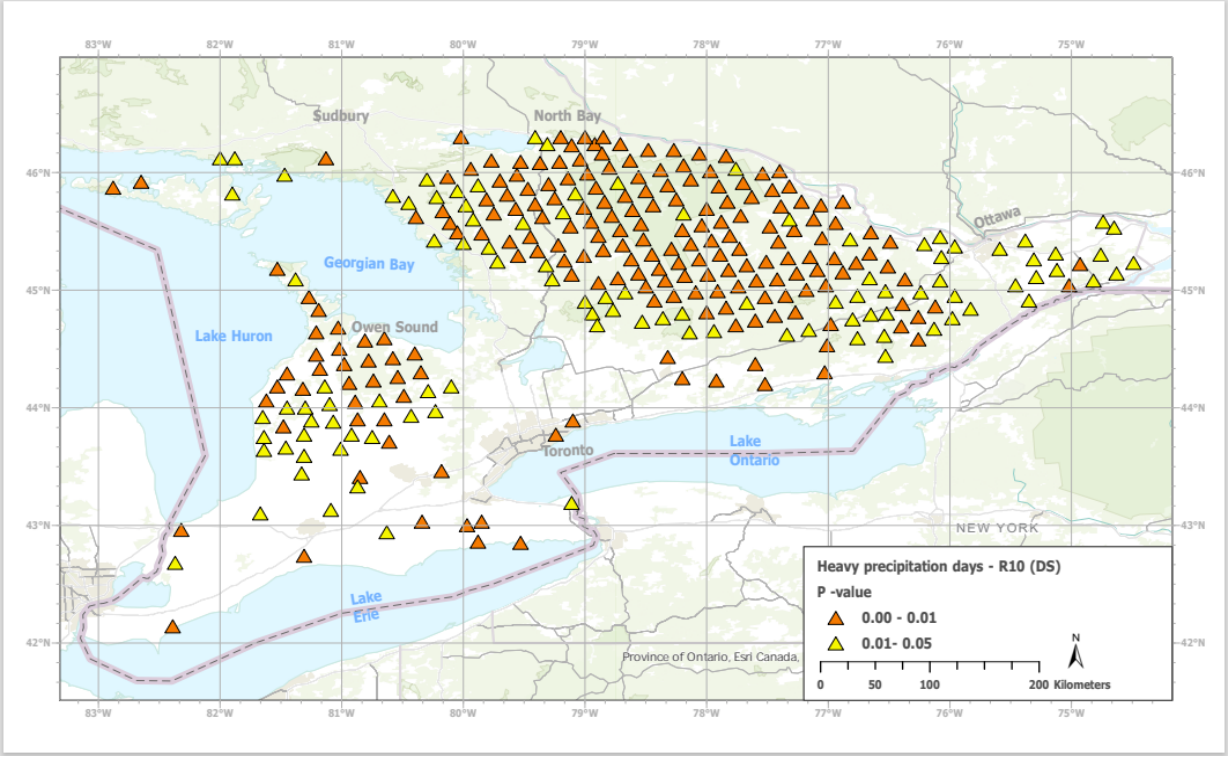


Figure 61: Map of trend significance for seasonal heavy precipitation days (R10) for the DS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend.

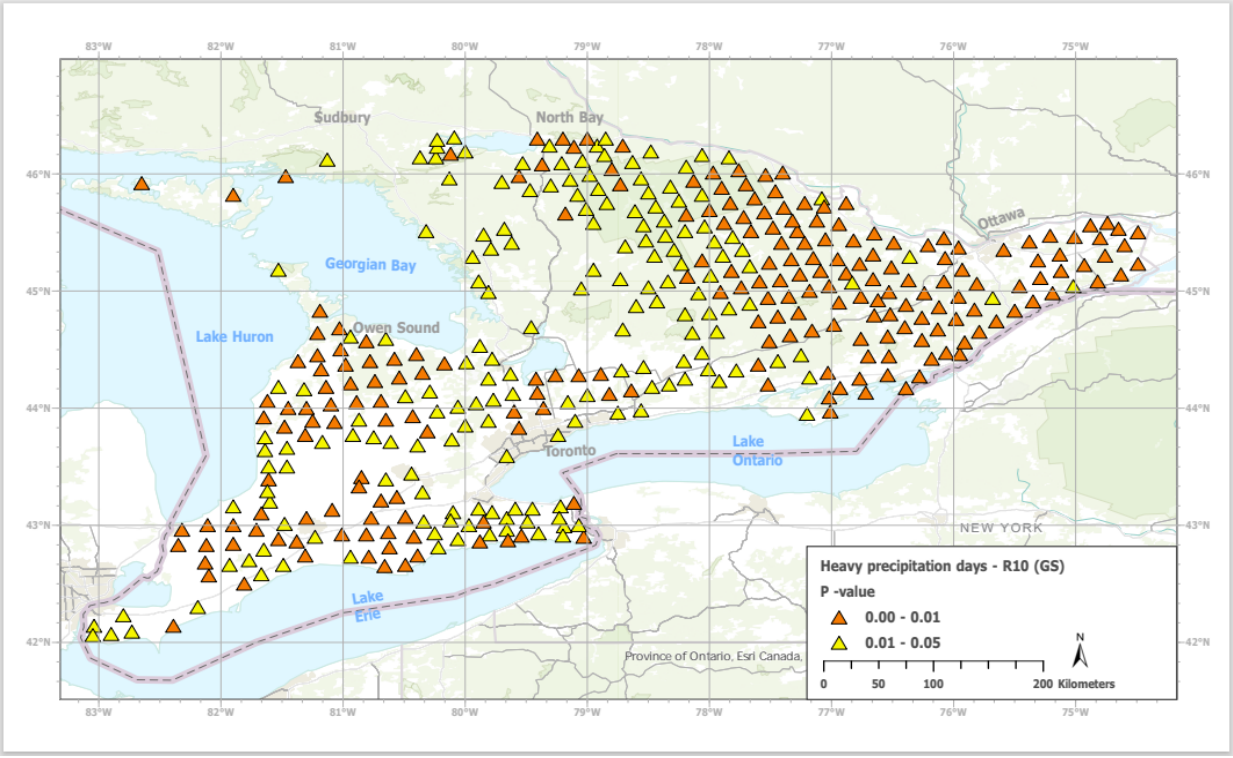


Figure 62: Map of trend significance for seasonal heavy precipitation days (R10) for the GS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend.

Finally, a decreasing trend in consecutive dry days (CDD) was noted in the DS (Figure 63) and GS for most townships, however, this decrease was mostly found to be significant in the DS in the eastern townships of the study area and those along the northern shores of Lake Huron and on Manitoulin Island.

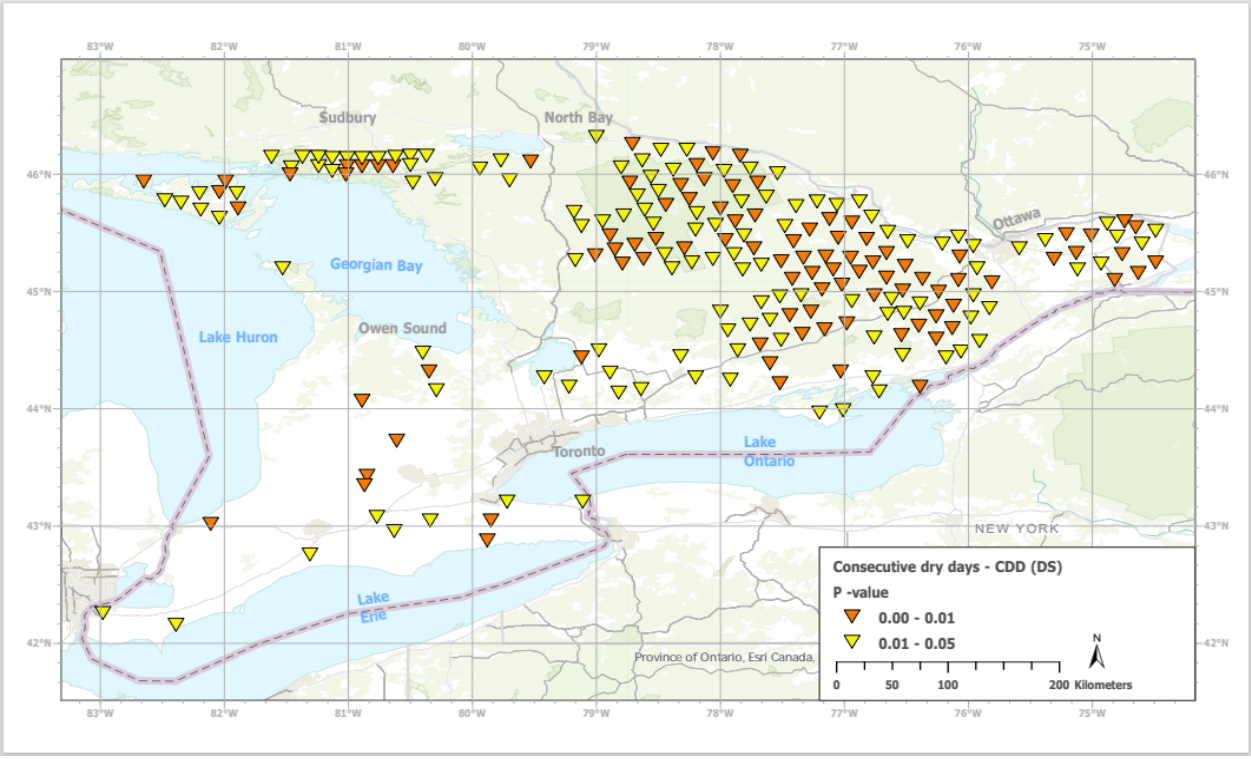


Figure 63: Map of trend significance for consecutive dry days (CDD) in the DS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend.

4.3 Probability distributions

Probability density function graphs were produced annually and seasonally for two subperiods, 1961-1990 and 1991-2017, to investigate changes in the variability and frequency of extreme events.

4.3.1 Probability distributions for minimum, maximum temperatures, and sum precipitation

Evaluating the changes in the average minimum temperature distributions shows that there are shifts toward warmer conditions in all seasons. The distribution of average daily minimum temperatures were shifted right during the period from 1991 to 2017 (Figure 64). Thus, there is more occurrence of extreme high minimum temperatures in all seasons, and this was more pronounced in the DS and GS. In addition, there is more variability in average minimum temperatures in the PS and the DS. To be noted this variability is higher in the DS. The graphs show that there is more occurrence of extreme low minimum temperatures too. These frequencies and variabilities in average minimum temperatures in the DS make the season presenting very tough conditions (more occurrence of extremes for both high and low minimum temperatures).

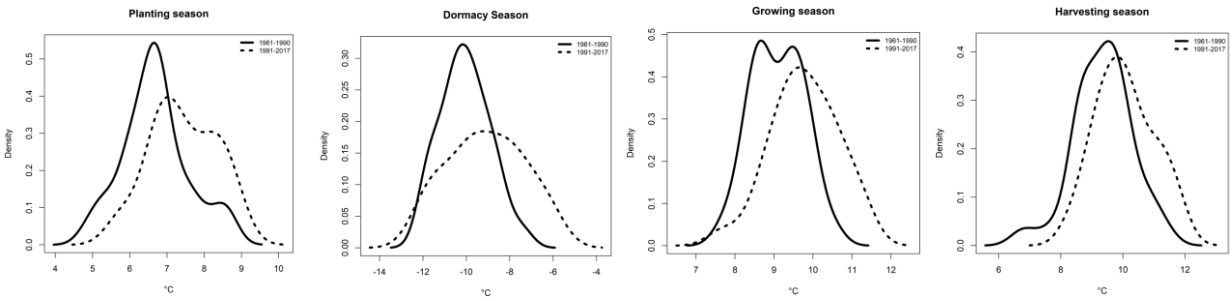


Figure 64: Temporal changes in probability distributions for seasonal (PS, DS, GS, HS) average daily minimum temperatures in southern Ontario (averaged across southern Ontario townships).

There was a shift toward an increase in average maximum temperature in all seasons. There were more occurrences of extreme high maximum temperatures in all seasons, and this was clear in the DS, GS, and HS (Figure 65). Moreover, there was more variability in the maximum temperatures in the DS and the GS. This variability seems to be higher in the DS, and there is more occurrence of extreme maximum low temperatures. This means the season presents challenging conditions for overwintering crops (more occurrence of extremes for both high and low maximum temperatures).

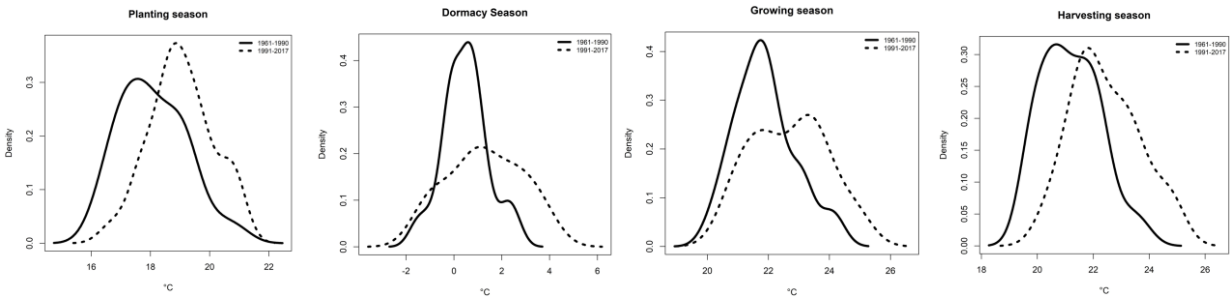


Figure 65: Temporal changes in probability distributions of seasonal (PS, DS, GS, HS) average daily maximum temperatures in southern Ontario (averaged across southern Ontario townships).

The PDF indicate a shift in total precipitation toward events with higher amounts of precipitation in the GS and the DS; the graphs indicate a greater occurrence of extreme precipitation events in the DS and the GS, with a higher level of variability in the DS (Figure 66).

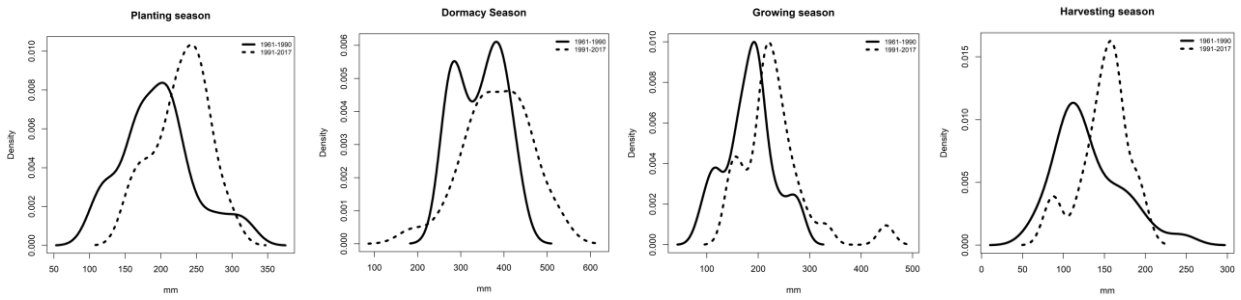


Figure 66: Temporal changes in probability distributions of seasonal (PS, DS, GS, HS) total precipitation in southern Ontario (averaged across southern Ontario townships).

4.3.2 Probability distributions of annual extreme weather event indices

Annually, temporal changes in the probability distributions of extreme weather event indices were examined at a regional scale (Figure 67), there was a decrease in cold extreme (CWE), diurnal temperature range (DTR), number of icing days (IDs), and number of frost days (FDs). Additionally, cool nights and cool days showed a considerable decrease. However, warm extreme events (HWE) and growing season length (GSL) showed annual increases, and likewise a notable increase in warm nights (TN90p) and warm days (TX90p).

The annual probability distribution analyses of extreme precipitation events have shown an important increase in the annual total precipitation (PRCPTOT) and very wet day events (R95p). Also, an increase in maximum single-day precipitation amounts (RX1day), maximum 5-day precipitation amounts (RX5day), and the number of heavy precipitation days (R10) have been noted. The simple daily precipitation intensity (SDII) showed an increase, indicating greater precipitation amounts in the period 1990 to 2017 compared to 1961-1990, while the number of consecutive dry days showed an annual decrease across the region.

Regarding temperature extremes, there was a higher occurrence for warm extreme (HWE) and warm days and warm nights (TN90P), and longer growing season periods (GSL) in 1991-2017

compared to 1961-1990. Additionally, there was more variability in hot extremes, growing season lengths, warm days, and warm nights for the same period. Regarding precipitation extremes, total precipitation, very wet days, and heavy precipitation events, occurrences have increased noticeably, with more variability in wet day events.

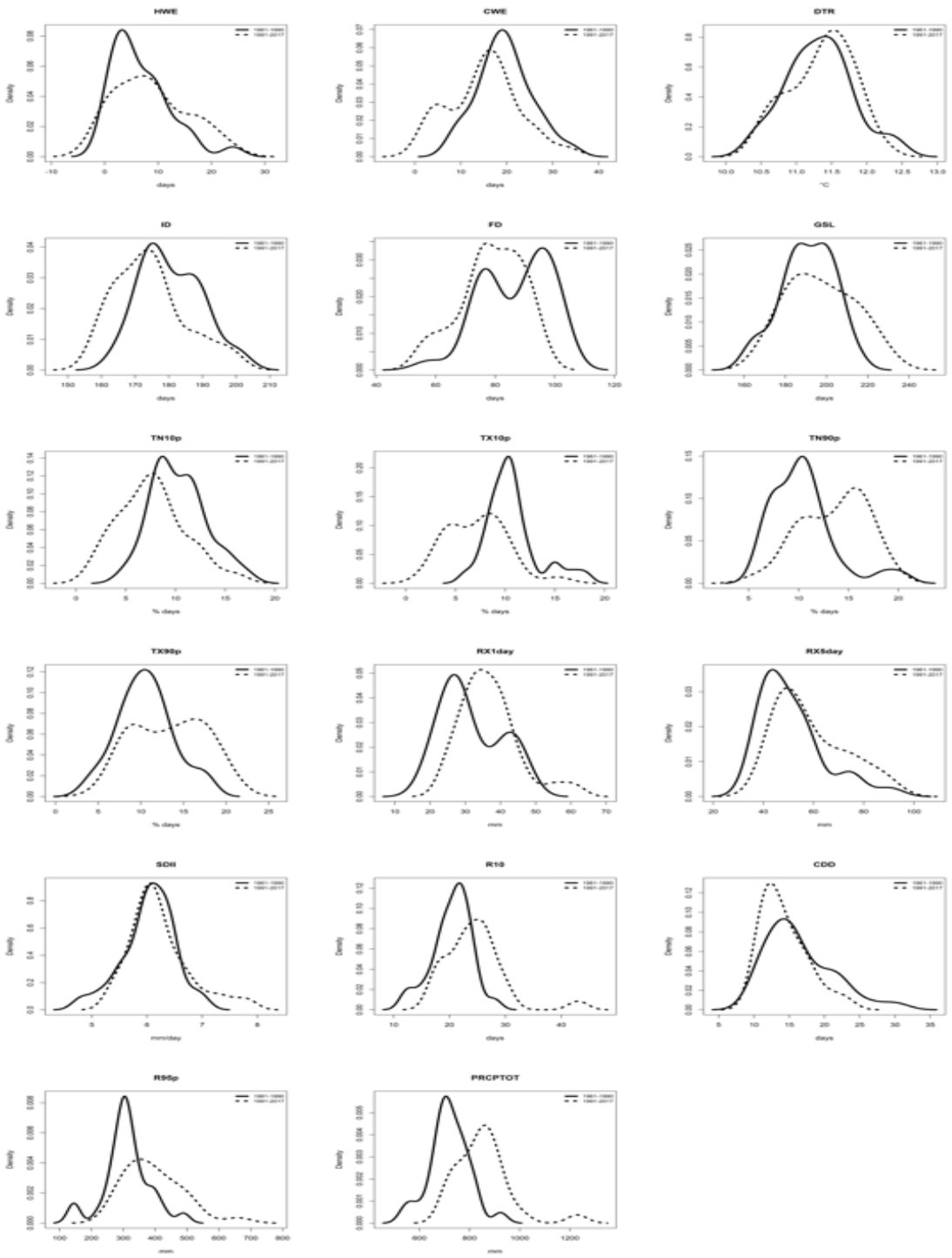


Figure 67: Annual probability density graphs for extreme weather events showing the temporal changes in annual probability distributions of extreme event indices in southern Ontario (averaged across southern Ontario townships).

4.3.3 Probability distributions of seasonal extreme weather event indices

In addition to analyses of the occurrence, frequency, and variability of annual extreme events, seasonal analyses were also conducted. Depending on the probability distribution graphs for the PS (Figure 68) there is a decrease in cool nights and cool days, while the diurnal temperature range (DTR) shows a slight increase, with more variability in the period from 1991 to 2017 compared to the base period. Furthermore, there has been a shift toward warmer nights (TN90p) and warmer days (TX90p). In addition, warm days (TX90p) have been shown to be more frequent in the period from 1991 to 2017.

Regarding precipitation events, we found a shift toward an increase in maximum 1-day precipitation amounts (RX1day), maximum 5-day precipitation amounts (RX5day), and the number of heavy precipitation days (R10). Simple daily precipitation intensity events (SDII), number of consecutive dry day events, number of very wet day events, and total precipitation have reflected a slight shift toward an increase.

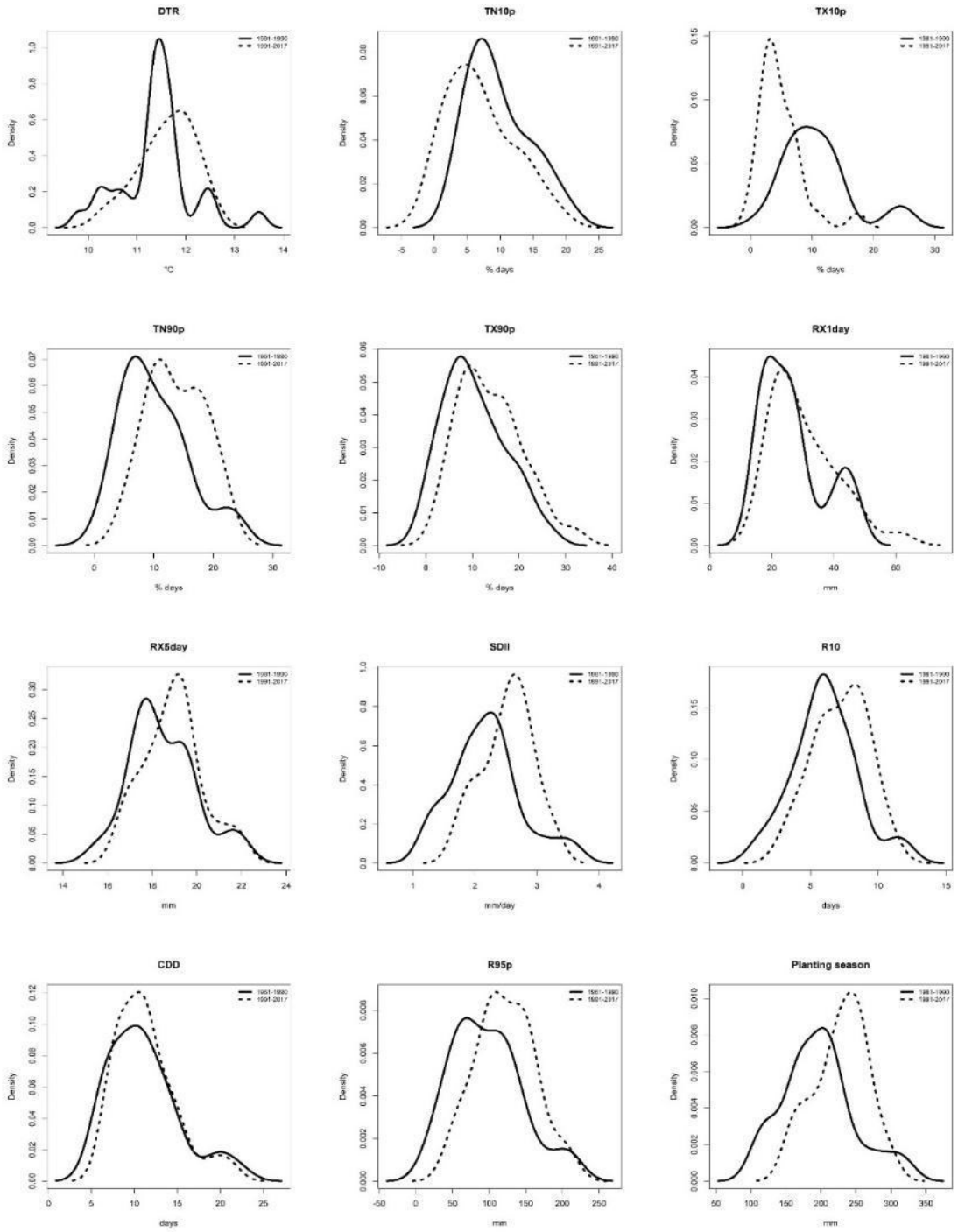


Figure 68: Probability density graphs for extreme weather events showing the temporal changes in probability distributions of extreme event indices in the PS (averaged across southern Ontario townships).

The dormancy season (Figure 69), diurnal temperature range (DTR), cool nights (TN10p), and cool days (TX10p) events have shown a decrease, while warm nights (TN90p) and warm days (TX90p) have shown an increase. This increase was more significant for the warm day events (TX90p). Warm days events' frequency increased considerably during the second period, 1991-2017. Regarding precipitation, the numbers of consecutive dry days and the maximum 5-day precipitation amounts (RX5day) showed a decrease, while maximum single-day precipitation amounts (RX1day), simple daily precipitation intensity (SDII) events, heavy precipitation days (R10), numbers of very wet days (R95p), and total amounts of precipitation showed an increase. The frequency of simple daily precipitation intensity (SDII) events, numbers of heavy precipitation days (R10), and numbers of very wet days (R95p) have demonstrated an increase. Moreover, there has been an increase in total wet-day precipitation (PRCPTOT) over the period 1991-2017. However, there is more variability in the very wet day (R95p) events and total wet-day precipitation (PRCPTOT).

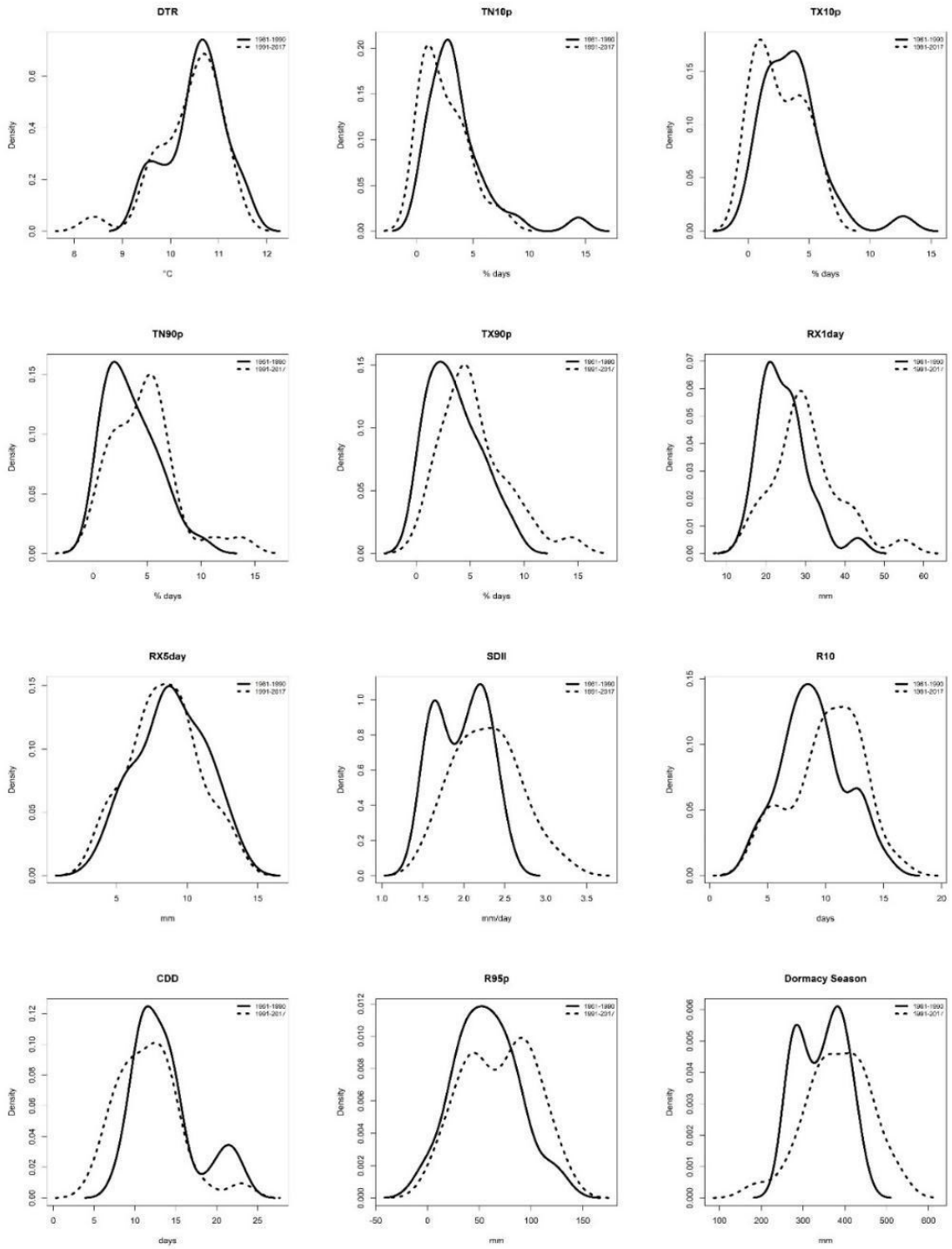


Figure 69: Probability density graphs for extreme weather events showing the temporal changes in probability distributions of extreme event indices in the DS (averaged across southern Ontario townships).

In the growing season (Figure 70), a decrease in the number of cool nights (TN10) and the number of cool days (TX10) has been noted. Nevertheless, there has been a shift toward an increase in the number of warm nights (TN90) and warm days (TX90). This increase was noticeable in the warm nights (TN90) events, in addition to more variability in warm nights (TN90) events, while the diurnal temperature range (DTR) showed a slight decrease.

Concerning precipitation, maximum 5-day precipitation amounts (RX5day) and maximum single-day precipitation amounts (RX1day), simple daily precipitation intensity (SDII) events, number of heavy precipitation days (R10), and number of very wet days (R95p) showed an increase. Furthermore, there was an increase in the occurrence of total wet-day precipitation (PRCPTOT). Thus, the number of consecutive dry days (CDD) has decreased.

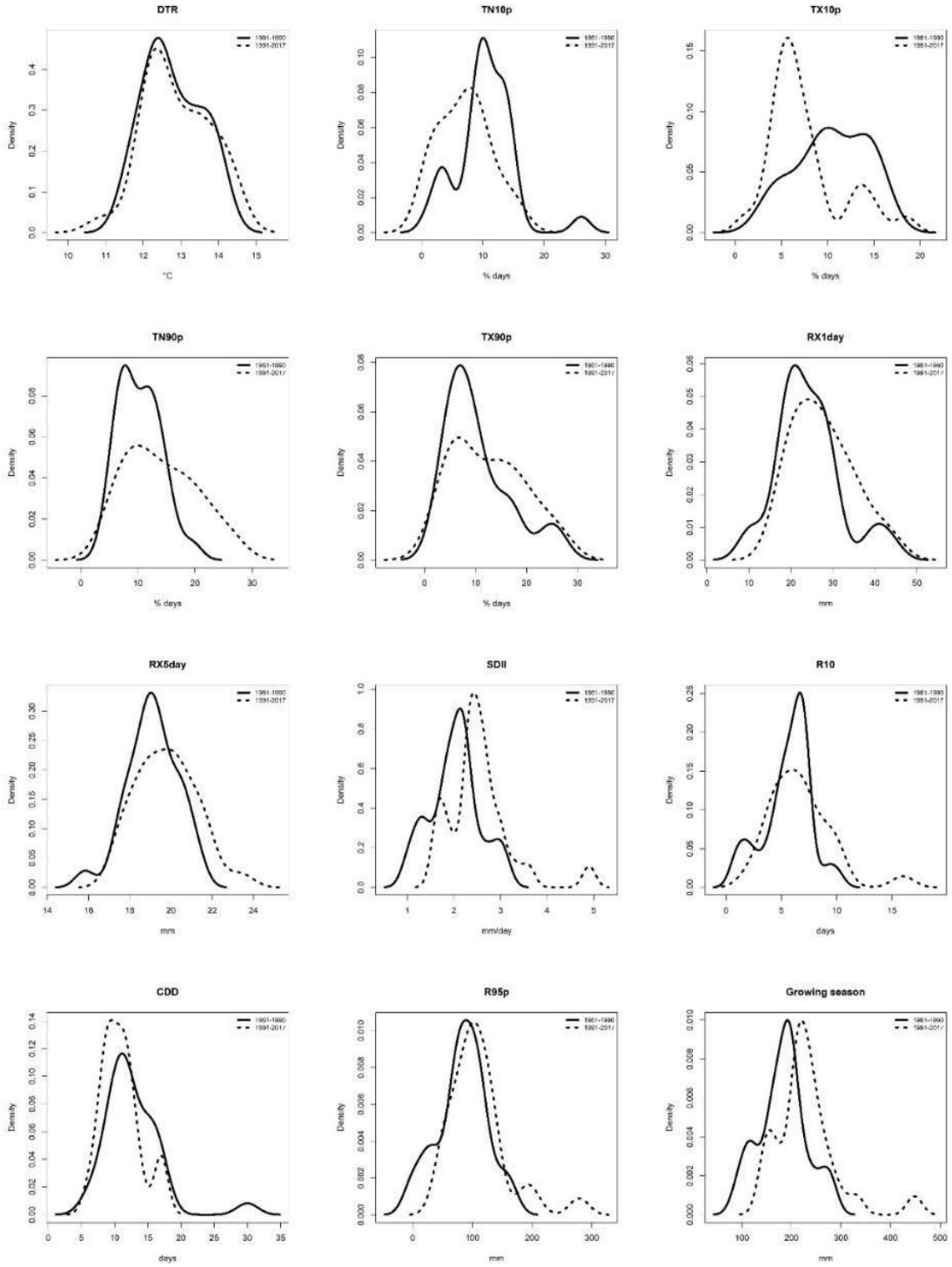

DTR
TN10p
TX10p
TN90p
TX90p
RX1day
RX5day
SDII
R10
CDD
R95p
Growing season
Density
°C
% days
mm
mm/day
days

Figure 70: Probability density graphs for extreme weather events in the showing the temporal changes in probability distributions of extreme event indices GS (averaged across southern Ontario townships).

The harvesting season (Figure 71) showed an increase in the diurnal temperature range (DTR) and numbers of warm nights (TN90) and warm days (TX90). The graphs confirm a higher occurrence of warm days (TX90). In contrast, the graphs also indicate a decrease in the number of cool nights (TN10) and the number of cool days (TX10). Maximum 5-day precipitation amounts (RX5day) and maximum single-day precipitation amounts (RX1day) showed a small increase, with a higher occurrence of single-day precipitation amounts (RX1day). The Simple daily precipitation intensity (SDII) events and the number of consecutive dry days (CDD) showed a small increase, while the numbers of heavy precipitation days (R10), numbers of very wet days (R95p), and total wet-day precipitation (PRCPTOT) tended to slightly increase in the period 1991 to 2017 (Figure 71).

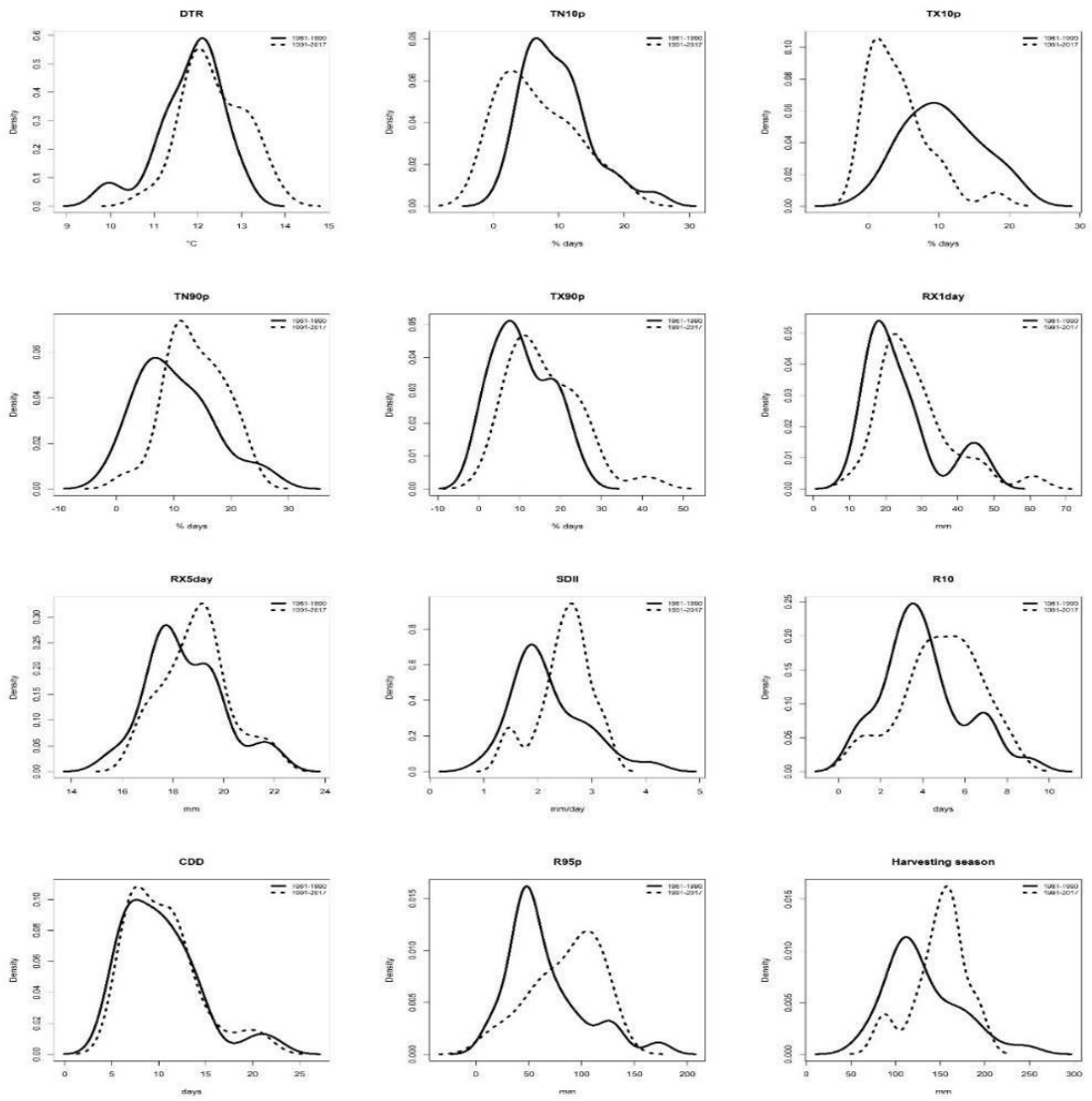


Figure 71: Probability density graphs for extreme weather events showing the temporal changes in probability distributions of extreme event indices in the HS (averaged across southern Ontario townships).

4.4 Trend analyses for crop-specific indices

Trends of crop-specific extreme weather indices for winter wheat and milling oats were also evaluated. Table 6 shows that for winter wheat there are increasing trends in winter warming index (WWI), precipitation amount in fall and spring (PAI) fall precipitation intensity (FPI), growing season length (GSL-Length), and growing degree days (GDDs) indices for the PS, the GS, and the HS. In contrast, there were decreasing trends in the indices related to cool weather in the growing season and in the jointing stages respectively (CWI and CWD), in addition to spring killing frost (SKF), and the two of the drought indices (Tillering- DI, Stem-Extension-DI while the Heading-Ripening-DI did not show a significant change). All of these trends were significant ($p < 0.05$ in most cases, $p < 0.1$ for WWI).

Concerning milling oats, growing degree days (GDDs) in the PS, the GS, and the HS, jointing and anthesis drought period (DP), precipitation amount index (PAI), precipitation intensity (PI), and heat waves- anthesis (HW) indices showed increasing trends (Table 7). The increasing trends were all statistically significant except the HW (0.12). The one decreasing trend was in the early frost (EF) index but this trend was not statistically significant.

Table 6: The trend (Sen's slope) in winter wheat-specific indices in southern Ontario (in days for most indices, but GDD for all those related to GDDs). Sig is the significance of the trends depending on the P-value, trends were considered significant when p-value < 0.05.

Indices	WWI	CWI	SKF	Tillering DI	Stem Extension DI	Heading Ripening DI	Fall PAI	Spring PAI	CWD	PS_GDD	GS_GDD	HS_GDD	GSL Length	FPI
Trend	0.13	-0.08	-0.10	-0.11	-0.15	-0.02	0.02	0.03	-0.09	3.06	2.98	2.44	0.29	0.01
Sig	0.06	0.03	0.01	0.01	0.00	0.44	0.05	0.01	0.00	0.00	0.00	0.00	0.00	0.02
Tau value	0.16	-0.18	-0.21	-0.22	-0.32	-0.06	0.17	0.21	-0.24	0.29	0.33	0.31	0.30	0.19
Trend lower bound	-0.01	-0.15	-0.16	-0.20	-0.23	-0.08	0.00	0.01	-0.16	1.45	1.51	1.26	0.14	0.00
Trend upper bound	0.28	-0.01	-0.02	-0.04	-0.08	0.03	0.04	0.05	-0.03	4.71	4.33	3.52	0.44	0.02

Table 7: The trend (Sen's slope) in milling oat-specific indices in southern Ontario. Heat wave -Anthesis (HW), drought period- jointing and Anthesis (DP), early frost (EF), and precipitaion intensity (PI) (days/year), precipitation amount index (PAI) (mm), early floods (EFL) (yes/no), and growing degree days in the PS, GS, and the HS (GDD) (GDDs). Sig is the significance of the trends depending on the P-value, trends were considered significant when p-value < 0.05.

Indices	HW	PS_GDD	GS_GDD	HS_GDD	DP	EF	PI	PAI	EFL	GSL
Trend	0.09	1.63	2.98	2.25	0.03	-0.03	0.05	1.19	0.00	0.18
Sig	0.12	0.02	0.00	0.00	0.03	0.23	0.00	0.00	0.01	0.01
Tau value	0.13	0.20	0.33	0.32	0.18	-0.10	0.34	0.32	0.21	0.22
Trend lower bound	-0.02	0.28	1.51	1.12	0.00	-0.08	0.03	0.58	0.00	0.04
Trend upper bound	0.20	2.97	4.33	3.38	0.06	0.02	0.08	1.84	0.01	0.30

4.5 Univariate correlation and Random Forest (RF) regression analyses results

Pearson correlation tests and RF regressions were conducted to investigate how the indices related to winter wheat yield (since milling oat yield data were not available). The correlations between the dependant variable and each of the predictors are presented in Table 8. Average yield (AvgYield), fall precipitation intensity index (FPI), and spring precipitation amount index (PAI) were found to be positively correlated with standardized residual yield, while winter warming index (WWI) and stem extension drought index (Stem_Extension_DI) were found to be negatively correlated and this correlation was found to be at a low level for all crop specific indices.

Table 8: Pearson correlation coefficients (r) between crop specific indices and standardized residual yield.

Crop specific indices	Correlation
FPI	0.06
WWI	-0.11
CWI	0.00
SKF	0.01
Tillering_DI	0.01
Stem_Extension_DI	-0.11
Heading_Ripening_DI	0.03
Fall_PAI	-0.01
Spring_PAI	0.06
CWD	0.02
PS_GDD	0.01
GS_GDD	-0.05
HS_GDD	0.03
GSL_Length	-0.06
AvgYield	0.21

Combining the observations of significant trends with yield correlations allows us to identify which trends are most likely to be of concern to wheat producers. Growing season length (GSL_Length) and growing degree days (GDDs) available in the PS, GS, HS are all indicative of the energy available for plant growth, and their trends were all significantly increasing. However, the growing season length (GSL_Length) was found to be negatively correlated with standardized residual yield (r = -0.06), and correlations with degree days were lower and inconsistent in direction, Winter warming index (WWI) is increasing by 0.1 days/year and is associated with decreasing yield (r = -0.11). Likewise, Tillering DI was significantly deceasing (-0.11 days/year), but it had very weak correlation with winter wheat yield (0.01). On the other hand, some indices showed positive impacts on crop growth; such as stem extension drought (Stem_Extension_DI), which had a negative relationship with standardized residuals (r = -0.11) but it is decreasing in frequency (-0.15 days/year). Finally, precipitation indices FPI, spring PAI, and Fall PAI with FPI and spring PAI (r = 0.06 for both), but had very little response to fall PAI (r = -0.01) (Table 8).

Random forest analyses were run four times using different sets of variables as previously described in Section 3.6. Depending on the first run that included all the pertinent predictors, the RF model explained 41% of the variance. In the second run that eliminated crop-specific indices, it was found that the RF model explained 33% of the variance. In the third run and after removing extreme weather indices, it was found that the RF model explained 41% of the variance. The soil texture did not seem to have much impact on winter wheat variance in the developed model, therefore the soil texture was removed from the model. The fourth run was only based on crop-specific indices, and it was found that the model explained 40% of yield variance in the region.

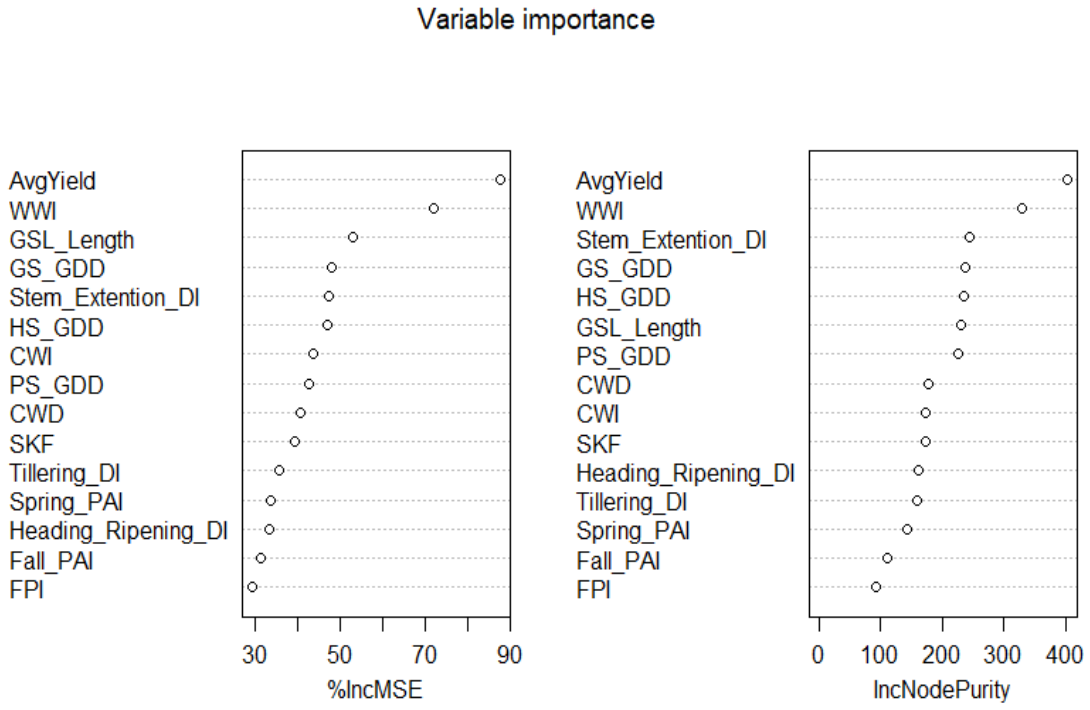


Figure 72: Variable importance. The graphs show the ranked variable importance depending on the increased mean square error (%IncMSE), the predictors are ranked from high importance at the top of the graph to the least important at the bottom of the graph and no negative importaces have been detected.

Variable importance analysis was based on the fourth run since extreme weather indices and soil texture provided very little improvement (1%), which can not justify adding multiple, possibly correlated variables, and it was found that crop-specific indices alone were more useful in explaining winter wheat yield variance based on the RF variance explained (Figure 72). The average yield (averaged in each township over the available record), which was found to be positively and highly correlated with the standardized residual yield, has considerable importance in the model with an increase in mean square error of 82% (IncMSE) when removed. Interestingly, the winter warming index (WWI) was the most important index in the RF model, linked to a 72% IncMSE% when removed, followed by the growing season length index (GSL_Length) with 53%, the growing degree days available in the growing season index (GS_GDD) with 48%, and the stem extension drought index (Stem_Extension_DI) with 47% (Figure 72).

Chapter 5. Discussion

This study provides a comprehensive analysis of weather extreme events at a local spatial scale (townships) and evaluates the importance of using crop-specific indices to assess the impacts of extreme events on crop yields. This section revisits and summarizes the most important results that are most likely to impact winter wheat and milling oats in the study region, then the discussion will be founded on these results. The trends were calculated and evaluated for their significance on climate variables (daily minimum temperature, daily maximum temperature, and daily precipitation). This analysis provided information about frequency, intensity, and magnitude of extreme temperature and precipitation events during the study period, and these results were comparable to the related analyses reported in prior

studies. Increasing trends in annual minimum temperature, annual maximum temperature, and annual total precipitation were observed in the southern Ontario. The increase in minimum temperatures was found to be faster and more spatially significant than the increase in maximum temperatures across most of the townships in southern Ontario(Figure 11), which leads to a decrease in the diurnal temperature range (Qian et al., 2010) (Figure 28).

Trends were also evaluated on extreme weather indices. In agreement with national and regional studies Wazneh et al. (2020) and Wazneh et al. (2017), cold extremes experienced a decrease in the whole study region (Figure 26), while hot extremes (HWE) did not show a significant increase and were not very common in all the townships during the period of study. Annual warm nights (TN90p) and annual warm days (TX90p) showed a significant increase across the townships. However, the increase in warm nights (TN90p) was spatially more important than the increase in warm days (TX90p) since warm nights (TN90p) showed a significant upward trend across southern Ontario (Figure 25), while some townships around Barrie and the very southern region showed no significant trends regarding warm days TX90p (Figure 24). Annual cool days (TX10P) and annual cool nights (TN10p) were shown to be significantly decreasing across all the townships (Figures 26 and 27). Similarly, annual frost days and annual icing days (IDs) have been decreasing, but the most significant decrease across the region was shown for annual icing days (ID) (Figure 29). The growing season was becoming longer, but this was more statistically significant in the southern part of southern Ontario, where winter wheat is mostly cultivated. Regarding precipitation indices, there was an increase in all the annual indices. The most significant increase was observed for heavy precipitation days (R10), indicating

more heavy precipitation events across the region except the townships at the west shores of Lake Ontario and Lake Erie (Figure 31).

At the seasonal time scale, there was a statistically significant increase in average minimum temperatures in the DS. This increase was found to be more significant in the northern and the snow belt areas which is expected to impact snow cover in extent and depth (Figure 15).

Consistently with previous regional studies Bush et al., (2019), warm days (TX90p), showed a significant upward trend in all seasons. The most important increase was observed in the GS across the whole region (Figure 34) and the DS but with less spatial extent (Figure 33), while warm nights (TN90P) showed significant upward trends in the PS, GS, and the HS across the townships (Figures 36, 37, and 38). The increase in warm days (TX90p) was observed more in the DS than the increase in warm nights (TN90P) across southern Ontario. Cool days (TX10P) and cool nights (TN10P) decreased in all seasons, particularly in the PS, GS, and HS across the townships. Finally, 5-day precipitation events (RX5) were found to be significantly increased in the PS, GS, and HS across all the townships which are known to impact the seeding and harvesting of winter wheat. Moreover, heavy precipitation events (R10) were found to have the most statistically significant increase in the GS and the DS more specifically in northern, eastern, and Bruce Peninsula townships (Figures 59 and 62).

In terms of frequency and variability of extreme weather events, this study presents results that are also consistent with previous studies reported in the literature for southern Ontario (Wazneh et al., 2020, Bush et al., 2019, Wazneh et al., 2017). In addition, it provides

detailed information about temporal (seasonal) and spatial (township) trends in temperature and precipitation variables. Overall, warm day events (TX90P) were more frequent in the GS across all the townships, with less extent in the DS and the HS, while warm night events (TN90P) tended to be more frequent in the GS and the DS across the study area. Precipitation events such as very wet days (R95p), total wet-day precipitation (PRCPTOT), 5-day precipitation amounts (Rx5day), heavy precipitation days (R10), and simple daily intensity (SDII) were more frequent in the GS during the period between 1990 to 2017 compared to the base period, while total wet-day precipitation (PRCPTOT), heavy precipitation days (R10), simple daily intensity (SDII), and 1-day precipitation amounts (Rx1day) tended to be more frequent in the DS during the period from 1990 to 2017.

For cereal farming, the warming weather and the increase in total precipitation sound promising, however, the increase in extreme weather events and the increase in the year-to-year and seasonal variability of these events put cereal production at risk. Total precipitation in the planting season has been increasing in the eastern townships and in the Bruce Peninsula region, which is expected to have negative impacts on winter wheat seeding. Delaying winter wheat seeding in these townships could potentially impact winter wheat yields as discussed in Section 2.2 (Figure 21). Heavy precipitation events have seen increased frequency and variability in the DS and the GS, and these events are not favorable for winter wheat and milling oat crops.

In this region, winter is warming up, in that the average minimum temperatures and the average maximum temperatures are increasing in the DS. A statistically high significant increase was noticed in the average minimum temperatures index specifically in the northern and the snow belt areas. This may be attributable to the progressive loss of snow

cover which means that solar radiation is being absorbed rather than reflected. In addition to the warming, there is an increase in precipitation events and amounts in the northern, eastern, and the snow belt townships of southern Ontario (most likely in form of rain) (Figure 22) which could be related again to the warming that favours evaporation from Lake Huron, driving high humidity and heavy rain and storms in these areas. Trend analyses of crop-specific indices revealed that there is warming in the DS since WWI was increasing by 0.1 days/year (Table 6). Growing season length (GSL_Length) and growing degree days (GDDs) available in the PS, GS, and HS were significantly increasing during the period of study (0.29, 3.06, 2.98, 2.44 days/year respectively) (Table 6). However, this increase does not necessarily benefit the crop since it accelerates crop development which makes the crop vulnerable to early frost events, winter kills and diseases, destabilizing the hardening process, resulting in less chance of surviving winter conditions (as discussed in Section 2.2). In terms of the relationship between yields and the studied predictors Pearson analyses show that standardized residuals are negatively correlated with WWI (-0.06) and with the increase in GDD-GS (-0.05), however, correlations with degree days were inconsistent in direction and low in the PS and the HS. On the other hand, stem extension drought (Stem_Extension_DI) showed a negative relationship with standardized residuals (-0.11) based on bivariate Pearson analyses, but it was found to have a significant decreasing trend (-0.15 days/year) which is considered a positive sign for the crop in southern Ontario.

The RF analysis revealed that the most important variables impacting deviations from long-term yields were average yield (AveYield), winter warming index (WWI), growing season length (GSL), growing degree days in the growing season GS_GDD, and stem extension

drought (Stem_Extension_DI). The possible implications of each of these are outlined in the following paragraphs.

Increasing WWI implies milder winters and a higher frequency of freeze-thaw cycles in the DS. This warming is projected to decrease snow cover in the region. The increase in growing degree days, particularly in the GS, could benefit the crop, yet the warming in the DS could be critical since the crop loses its hardening stage earlier and develops at a quicker rate, which affects crop maturity and reduces yield quality (Mukherjee et al., 2019). It was previously discussed that winter wheat can respond negatively to increases in the GDD since winter wheat survival is related to frost-free periods and frost events, unlike summer crops (Kukal and Irmak, 2018).

Likewise, the increased length of the growing season has consequences for the crop, since the growing season starts earlier and ends later. However, planting the crop early makes the crop vulnerable to snow mold and barley yellow dwarf virus (BYDV) infection (OMAFRA, 2017a), whereas planting later than the optimum seeding dates does not offer the crop enough growing degree days to enable the wheat to get well established and prepared for the hardening stage, and by consequence, increases the risk of early frost-kill (OMAFRA, 2017a). These risks, combined with the demonstrated negative impacts of the winter warming trend, show that assuming these trends continue with existing crops and practices in southern Ontario the increased risks from climate change could outweigh the benefits of climate change to winter wheat cultivation. Research at finer spatial scales with more detailed, sustained yield data could further refine the susceptibility of winter wheat to specific extreme weather events.

Precipitation events have increased in frequency and amounts across the region, especially in the GS. Also, drought indices (Tillering- DI, Stem-Extension-DI) showed decreasing trends, especially in the GS. Yet the patterns of spatial (across the townships) and the temporal variabilities of precipitation events could be critical and problematic, especially with the increase in warm conditions across the townships. Winter wheat exposure to heatwaves and drought periods in specific pheno-phase periods such as the stem extension stage (Figure 72) leads to negative impacts on yield potential and grain quality (Hlaváčová et al., 2018; Liu et al., 2020; Roberts et al., 2012).

Overall and from an agricultural perspective, the shift toward warming conditions, the increase in the GSL, and the increase in precipitation amounts could bring a potential benefit to the region's agricultural production in the region (Qian et al., 2010); however, the warming pattern in the GS presented in this study, accompanied by the increase in precipitation events (R95p, PRCPTOT, Rx5day, R10, and SDII), creates more risks to winter wheat crops, since these conditions are more favorable for fusarium and disease infections (Reid et al., 2007a). Additionally, these new climate conditions favor the migration of certain insects to the region that can cause many diseases in the studied crops (Reid et al., 2007a). Moreover, the increase in warm conditions during the DS could lead to mild winters with more freeze-thaw cycles; this leads to a process called deacclimation, which in this case means that winter wheat loses its freezing tolerance, reducing the plant's survival potential under adversely low temperatures (Vítámvás et al., 2019; Hayhoe et al., 2003a). As well, losing snow cover (extent and depth) due to warming increases wheat winter-kill since snow cover helps protect the crop against extreme cold air and sub-zero temperatures until spring (Hayhoe et al., 2003a). In addition, the variabilities in wet (RX1

and RX5) and warm events in the GS, could be problematic for winter wheat crop, especially, in stem-extension growth stages as discussed previously since it impacts yields and grain quality and knowing that most of winter wheat crop is planted in non irrigated areas.

Looking at the pattern of warming and increased precipitation amounts received in the northern and eastern parts of southern Ontario in the GS, it is worthwhile to mention that these conditions are favorable for milling oats expansion in these areas because milling oats can tolerate low temperature, high moisture and could be grown successfully under a variety of soil types as discussed by Derick (2002). Crop-specific indices were also designed and calculated for milling oats, based on their phenological stages following Zadock's growth scale for cereal crops. Although their relationship with yield could not be directly assessed, based on the trend analysis on milling oats-specific indices (Table 7), early killing frost (EF) is not projected to have a major impact on yield. Milling oats trend analyses also show that there is an increase in growing season length and the growing degree days available for milling oats. However, early planting as a result of the lengthening of the growing season length could make the plant more vulnerable to flood events, which decreases the seed quality at harvest time. Drought events (DP) increased significantly by 0.03 days/year (Table 7). Combining these with the variability in precipitation and temperature events during the growing season, which has been observed in the area, is projected to have negative impacts on milling oats yields especially when the crop is planted late, and this is consistent with observations made by Statistics Canada (2021).

Since milling oats are sown in early spring, the increase in precipitation intensity (PI) and the precipitation amounts (PAI) events in this period could significantly affect the seeding process leading to lower yield. Excess rain and water in the growing season and water plot were observed to have impacts on crop growth during the growing season as suggested by (May et al., 2004; McLeod, 1982), and increased rates of diseases and fusarium (Ziesman et al, 2010). In addition, these wet conditions are projected to have negative impacts on crop yields, since the crop is sensitive to excess water at the tillering stage, which affects crop yields (Ghobadi et al., 2017). Oat grain yield decreases due to excess water at the tillering stage by 42% and this causes a significant decrease in grain numbers per spike and spike numbers per plant (Ghobadi et al., 2017).

The combination of observations from the literature, the observed trends in oat-specific indices, and the known links between the winter wheat indices and reported yields provides evidence that there are also climate change-induced risks impacting oat production in southern Ontario. Further research is needed to confirm and better assess specific relationships between extreme weather indices and oat yield variability in the region, and that would benefit from active monitoring of those yields.

In accordance with Wazneh et al. (2017), this research confirms the increase in warm extreme (warm days and warm nights) and precipitation extreme events in southern Ontario, and this has been linked to the decreased area under agricultural production and changes in the suitability of specific crops and varieties (Comer et al., 2017). Southern Ontario conditions are projected to have negative impacts on winter wheat and milling oat yields and potentially increase yield variance, as suggested by Cabas et al. (2010). Adaptive plans and practices should be considered in future agricultural planning in the study region.

For instance, changing varieties of cultivars to more adaptive genotypes that resist hot and humid weather conditions for winter wheat is likely beneficial. Additionally, changing agricultural practices for milling oats including considering frost sowing (a technique that could overcome the seeding delays related to excessive soil moisture) (OMAFRA, 2017) and irrigation during the growing season should be also considered.

This present research shows that the frequency and the magnitude of warm and precipitation extremes are increasing, especially in northern parts of southern Ontario. The increase in the frequency, magnitude, and pattern of these extremes is projected to have negative impacts on winter wheat and oat yields, therefore, crop management and adaptation plans are needed to better support and improve the cereal crop system in the region.

Pearson correlation analysis only found low correlations for all crop-specific indices. Giving the limitation of parametric techniques and possible violations of parametric assumptions in these data, nonparametric correlation techniques such as Spearman analysis should be explored in future work.

In addition, Average yield (AvgYield) showed considerable importance in explaining yield variance. This may be due to the sensitivity of high-performing farms to negative effects of unfavorable extreme weather events, or changes in area planted, so further study is needed to describe the role of the average yield data in the RF model. It is possible that there are other confounding correlations, but the use of standardized yield residuals as the dependent variable should account for the impacts of general technological improvements leading to higher yields (Cabas et al., 2010).

Likewise, although soil texture did not have particularly strong impacts in the modelling reported here, soil quality more generally could potentially explain inconsistent relationships between weather indices and yields, especially with respect to indices related to precipitation variables, and possibly during specific growth stages, especially since the majority of grain and cereal farms in Ontario are not irrigated (Statistics Canada, 2011). More analyses and investigations would be needed to better integrate variable soil conditions in this type of modelling.

Excluding crop-specific indices considerably (by 8%) reduces the explained variance in the RF model, whereas removing the generic extreme weather indices did not. Crop-specific indices already incorporate the weather data and have the additional advantage of being tuned to reflect that crop's tolerance and thresholds.

Chapter 6. Conclusion

Climate indices have been widely used to monitor climate change worldwide, but many of these indices are not intended to address the specific needs of an agricultural system and are not necessarily relevant to agricultural production. This research has provided a comprehensive study of extreme weather events annually and seasonally at a local spatial scale (townships) from 1950 to 2017. Increases in average annual minimum, maximum, and sum precipitation have been observed. Seasonally, there was a decrease in cold extremes and an increase in intensity, duration, and magnitude in warm extremes (warm days and warm nights), and precipitation extremes. In addition, variability was observed in warm days (TX90P), warm nights (TN90P), 5-day precipitation events (RX5), and heavy precipitation events in the GS, in addition to variabilities in heavy precipitation events (R10) and very wet days event (R95P) in the HS. Furthermore, the region has been experiencing milder winters which lead to an increase in the freeze-thaw cycle process, a major risk for winter wheat yields in the region.

Crop-specific indices have been found efficient tools to investigate the relationship between weather extremes events and yield variance. The winter warming index, stem-extension drought index, and GSL length reflect the most significant impacts on winter wheat yields, and these indices were shown to be negatively correlated with crop yields. Changes in Ontario conditions especially the warming in the DS and the increase in the freeze-thaw cycles in southern Ontario could cause high and major risks to winter wheat, especially in the northern, eastern, and snow belt townships. In addition, the increase in warm conditions in the GS accompanied by an increase in wet conditions (precipitation) make the crop vulnerable to diseases and insect infestations over the whole region. The

prolonged drought events in the GS more specifically in the stem-extension growth periods as a result of variability in precipitation events in the GS pose risk to winter wheat yields and grain quality.

Due to warming and the increase in total precipitation across the townships, milling oats have big potential in the area, especially in northern and eastern townships. The increase in precipitation intensity (PI) events and the precipitation amounts index (PAI) in early spring can have an important impact on milling oats since these indices could lead to floods and water excess. These conditions are known to have negative impacts on milling oats yields by delaying the seeding process and damaging the crop roots in further growth stages. Moreover, the increase in the variability in precipitation events during the growing season could lead to longer drought periods during important growth stages such as jointing and anthesis stages for milling oat. These conditions could significantly impact milling oat yields. These changes in weather conditions in southern Ontario are projected to have negative impacts on winter wheat and milling oat farming. Adaptive plans and changing varieties and practices should be considered in future agriculture management.

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Appendix 1. R scripts

1.1 Extracting the gridded weather data values of all the points for each township

```
####Estimated variables values for townships centroid in southern Ontario region ####

library(raster)
library(rgdal)
library(sp)
library(maptools)
library(rgeos)
library(magrittr)
library(ggplot2)
library(gridExtra)
library(rasterVis)
library(sf)
library(gtools)

#### Data preparations ####

outputfolder<- as.character("C:/Users/walaa/Documents/Wheat project/Townships
        centroid variables estimated values")

inputfolder<- as.character ("C:/Users/walaa/Documents/Wheat project/")

setwd(inputfolder)

# this is a code to read Ontario Township polygons csv file in R
ONtown <- read.csv(paste(inputfolder,"S_ON townships cent1.csv", sep=""),header = T,
        stringsAsFactors = FALSE)

# this code is to read the third column of the csv file which contains the names of the
        townships
townnames<- ONtown[2]

Uniqtownnames<- unique(townnames)

studytownships<- c(1:614)

#Preparing the data frame elements to save the daily parameters (i.e. "TempMin",
        "TempMax", "Precipitation") that will be extracted in the following loops
listst1<- Uniqtownnames

listst2<- list( "Date")
```

```
for(i in 1:length(studytownships)) {nam1 <- listst1[i,]
for (ii in 1:1) {nam2 <- paste(nam1, listst2[ii],  sep = "_")
assign(nam2, list())
}}

# Preparing the data frame elements to save the daily parameters (i.e. "TempMin",
        "TempMax", "Precipitation") that will be extracted in the following loops
listst0<- unlist(Uniqtownnames)

listst1<- Uniqtownnames

listst2<- list("TempMinON", "TempMaxON", "PrecipitationON")

listst3<- list ("Cent")

for(i in studytownships) {nam1 <- paste((listst1[i,1]),  sep = ".")
for (ii in 1:3) {nam2 <- paste(nam1, listst2[ii],  sep = "_")
for (iii in 1:1){nam3 <- paste(nam2, listst3[iii],  sep = "_")
assign(nam3, list())
}}}

### Loop to work on the raster files in the different folder namely "TempMin ON",
        "TempMax ON", "Precipitation ON" (all the raster files related to each parameter
        should be in one folder without gaps in or repetition, those rasters are for Ontario
        area and taken form the original Canada rasters of gridded data)

folderlist <- listst2

for (reptpar in 1: length(folderlist)) { folder <- folderlist[reptpar]
rasValueall<- matrix( nrow = 614, ncol =24837)
Gridded_data_path<-paste(inputfolder, folder, sep="")
all_Gridded_Data<- list.files(Gridded_data_path,full.names = TRUE,pattern = ".asc$")
all_Gridded_Data2<- list.files(Gridded_data_path,full.names = F,pattern = ".asc$")

# Preparing the raster files
all_Gridded_Data<- mixedsort(all_Gridded_Data) # this is a code to reorganize the files
all_Gridded_Data2<- mixedsort(all_Gridded_Data2)

# Loop for the three variables "TempMin", "TempMax", "Precipitation"
for (reptfile in 1:length(all_Gridded_Data) ) {
 rasterfile<- all_Gridded_Data[reptfile]
 rasterfile2<- all_Gridded_Data2[reptfile]
 print(reptpar)
 print(reptfile)

 r <- raster(rasterfile)
```

```
 crs(r)<-("+proj=longlat +ellps=GRS80 +datum=NAD83 +no_defs ")

#### Extracting the estimated values for Ontario and calculating centroids of the
          polygons

# This code is to read the columns 8 and 9 as spatial points
 index<- (as.matrix(((ONtown [,c(8,9)]))))
 index<-SpatialPoints(index)

  # Extracting the estimated values for the centroid special points (countysp)
 rasValue<-extract(r, index)

 rasValueall[,reptfile]<-rasValue

 if (folder== "TempMinON")for (i in studytownships) {{ d<-as.numeric(reptfile-1)
 date<- as.Date(d, origin = "1950-01-01")
 nam <- paste(Uniqtownnames[i,],"Date",  sep = "_")
 assign ( nam, c(get(nam), as.character(date)))}}
  }

for (i in studytownships) {
 nam4 <- paste(Uniqtownnames[i,],folder,"Cent",  sep = "_")
 assign ( nam4, append (get(nam4), rasValueall[i,]))}

assign ( paste(folder,"Cent",  sep = "_"), rasValueall)
save.image(paste(outputfolder,folder, ".RData",sep = ""))
}

list2<- list("TempMinON", "TempMaxON", "PrecipitationON","Date")

for(i in studytownships) { for (ii in 1:4){
 c1 <- paste(Uniqtownnames[i,],list2[1],"Cent",  sep = "_")
 c2 <- paste(Uniqtownnames[i,],list2[2],"Cent",  sep = "_")
 c3 <- paste(Uniqtownnames[i,],list2[3],"Cent",  sep = "_")
 c4 <- paste(Uniqtownnames[i,],list2[4],  sep = "_")

 TempMinON<- get (c1)
 TempMaxON<- get (c2)
 PrecipitationON<- get (c3)
 Date<- get (c4)

 allcvalues<- cbind(TempMinON, TempMaxON, PrecipitationON,Date)

 write.csv(allcvalues,paste(outputfolder,"/" ,Uniqtownnames[i,], "extracted-
          cent",".csv",sep=""), row.names = FALSE)
```

```
}}

save.image("/home/walaa/output/Townships centroid.RData")


#### End of the script ####
```

1.2. Winter wheat-specific indices calculations

```
# This script calculates winter wheat-specific indices

outputfolder<- as.character("C:/Users/walaa/Documents/Wheat project/Winter wheat
indices")

inputfolder<- as.character ("C:/Users/walaa/Documents/Wheat project/")

setwd(inputfolder)


file_list<- list.files(path="C:/Users/walaa/Documents/Wheat project/Townships centroid
variables estimated values")

base_path<-"C:/Users/walaa/Documents/Wheat project"

monthNames<-c("January", "February", "March", "April", "May", "June", "July",
"August", "September", "October", "November", "December")

out_csv_dir<-paste0(base_path,"/Winter wheat indices/")

options(stringsAsFactors = FALSE)


PlantingSeason <- 8:10

DormacySeason<- c(11,12,1,2,3,4)

GrowingSeason <- 5:7

HarvestingSeason <- 8:9


periods <- list(1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, PlantingSeason,DormacySeason,
GrowingSeason, HarvestingSeason)

seasonPeriods <- list(PlantingSeason, GrowingSeason, HarvestingSeason)

getName <- function(period) {

 if (length(period) == 1) {
```

```
 return (monthNames[period])
 } else if (all(period == PlantingSeason)) {
 return ("PS")
 } else if (all(period == Dormacyseason)) {
 return ("DS")
 } else if (period == GrowingSeason) {
 return ("GS")
 } else if (period == HarvestingSeason) {
 return ("HS")
 }
 return ("ERROR - PERIOD")
}

#Settings for quality control
NARM <- TRUE
ROUNDDIGITS <- 1

first_year<- 1950
last_year<- 2017

# Define function for calculating winter wheat Seeding Date for each year using GDD
and optimal date
calculatewheatSeedingDate <- function(InputTable, first_year, last_year) {
# Find seeding date for each year and fill hashtable: year -> seeding date
 print("Prepare wheat seeding dates")
 seedingDates <- vector()
 seedingDatesdaynumber <- vector()
 frostDates<-vector()
 i<-1
```

```
for (y in first_year:last_year) {
ySeedingDate <- NA
startperiod <- as.Date(paste0(y, "-8-1"))
endperiod <- as.Date(paste0(y, "-12-31"))
dayTableTrim<-InputTable[as.Date(InputTable$Date,"%Y-%m-%d") >= startperiod &
                    as.Date(InputTable$Date,"%Y-%m-%d") <=  endperiod,]
daymintemp<- dayTableTrim$TempMinON
frostdayindex<-which (daymintemp<=-2)[1]
yfirstfrostDate <- startperiod  + frostdayindex
G<- (dayTableTrim$TempMinON+dayTableTrim$TempMaxON/2)-5
G<-G[1:frostdayindex ]
GDD<-0
for (ii in 1:frostdayindex){
GDD<- GDD+ G[frostdayindex+1-ii]
if (GDD>130){ySeedingDate<-yfirstfrostDate - ii
break
}
}
frostDates[i]<- as.character(yfirstfrostDate)
seedingDates[i]<- as.character(ySeedingDate)
seedingDatesdaynumber[i]<- frostdayindex
i<-i+1
   }
optiseedingDate<- median(seedingDatesdaynumber)
seedfrostDatesData<- list(seedingDates,frostDates,optiseedingDate)
return (seedfrostDatesData)
}
```

```
#Calculate growing season length

calculateGSL <- function(InputTable, first_year, last_year) {
 print("GSL")
 GSLV<-vector()
 startseasonv<- vector()
 endseasonv<- vector()
 ind<-1
 yn<- last_year-first_year
 for (y in first_year:last_year){
 GSL<-0
 startperiod <- as.Date(paste0(y, "-3-1"))
 endperiod <- as.Date(paste0(y, "-11-1"))
 dayTableTrim<-InputTable[as.Date(InputTable$Date,"%Y-%m-%d") >= startperiod &
                        as.Date(InputTable$Date,"%Y-%m-%d") <=  endperiod,]
 z<- dayTableTrim$TempMinON >= 5
 zz<- dayTableTrim$TempMinON <= 5

 for (i in 1:120) { if (all(z[c(i,i+1,i+2,i+3,i+4)])){
 startseason=startperiod+i
 istart<-i+60
 break
 }}
 for (ii in istart:306 ){if (all(z[c(ii,ii+1,ii+2,ii+3,ii+4)])){
 endseason=startperiod+ii
 break
 }}
 GSL<- ii-i
```

```
 GSLV[ind]<-GSL
 startseasonv[ind]<- startseason
 endseasonv[ind]<- endseason
 ind<- ind+1
 }
 GSLVDATA<-list(startseasonv,endseasonv,GSLV)
 return(GSLVDATA)
}

#Calculate GROWING DEGREE-DAYS
calculateGDD <- function(InputTable, first_year, last_year) {
 print("GDD")
 GDDSeasonsV<-list()
 ii<-1
 for (m in seasonPeriods) {
 m<-unlist(m)
 InputTableSeasonTrim<-
InputTable[as.numeric(format(as.Date(InputTable$Date,"%Y-%m-%d"),format="%m"))
%in% m,]
 i<-1
 GDDV<-vector()
 for (y in first_year:last_year) {
 InputTableYearTrim <-
InputTableSeasonTrim[as.numeric(format(as.Date(InputTableSeasonTrim$Date,"%Y-%
m-%d"),format="%Y")) %in% y, ]
 G<- (InputTableYearTrim$TempMinON+InputTableYearTrim$TempMaxON/2)-5
 GDD<-sum(G)
 GDDV[i]<- GDD
 i <- i + 1
 }
```

```
 GDDSeasonsV[[ii]]<-GDDV
 ii<-ii+1
 }
 return(GDDSeasonsV)
}

# Calculate FALL PRECIPITATION INTENSITY
calculateFPI <- function(InputTable,seedfrostDatesData, first_year, last_year) {
 print("FPI")
 FPIV<-vector()
 yn<- last_year-first_year
 for (i in 1:yn+1){
 FPI<-0
 seedingday <- seedfrostDatesData[[1]][i]
 frostday <- seedfrostDatesData[[2]][i]

 dayTableTrim<-InputTable[as.Date(InputTable$Date,"%Y-%m-%d") >= seedingday &
as.Date(InputTable$Date,"%Y-%m-%d") <= frostday,]
 z<- dayTableTrim$PrecipitationON >10
 FPI<-sum(z)
 FPIV[i]<- FPI

  }
  return(FPIV)
}

# WINTER WARMING INDEX (WWI)
calculateWWI <- function(InputTable, first_year, last_year) {
 print("WWI")
```

```
 WWIV<-vector()
 i<-1
 for (y in first_year:last_year){
 WWI<-0
 startperiod <- as.Date(paste0(y, "-11-1"))
 endperiod <- as.Date(paste0(y+1, "-5-1"))
   dayTableTrim<-InputTable[as.Date(InputTable$Date,"%Y-%m-%d") >= startperiod &
                        as.Date(InputTable$Date,"%Y-%m-%d") <=  endperiod,]
 z<- dayTableTrim$TempMaxON >= 5
 WWI<-sum(z)
 WWIV[i]<- WWI
 i<-i+1
    }
  return(WWIV)
}

# COOL WAVE INDEX
calculateCWI <- function(InputTable, first_year, last_year) {
 print("CWI")
 CWIV<-vector()
 i<-1
 for (y in first_year:last_year){
 CWI<-0
 startperiod <- as.Date(paste0(y, "-3-1"))
 endperiod <- as.Date(paste0(y, "-7-1"))
 dayTableTrim<-InputTable[as.Date(InputTable$Date,"%Y-%m-%d") >= startperiod &
                        as.Date(InputTable$Date,"%Y-%m-%d") <=  endperiod,]
 z<- dayTableTrim$TempMaxON < 5
```

```
 CWI<-sum(z)
 CWIV[i]<- CWI
 i<-i+1
 }
 return(CWIV)
}

# SPRING KILLING FROST
calculateSKF <- function(InputTable, first_year, last_year) {
 print("SKF")
SKFV<-vector()
 i<-1
 for (y in first_year:last_year){
 SKF<-0
 startperiod <- as.Date(paste0(y, "-3-1"))
 endperiod <- as.Date(paste0(y, "-6-1"))
 dayTableTrim<-InputTable[as.Date(InputTable$Date,"%Y-%m-%d") >= startperiod &
                          as.Date(InputTable$Date,"%Y-%m-%d") <=  endperiod,]
 z<- dayTableTrim$TempMinON <= -2
 SKF<-sum(z)
 SKFV[i]<- SKF
 i<-i+1
 }
 return(SKFV)
}

# Calculating heading, flowering, and grain filling DROUGHT INDEX (Seasonally)
calculateDI <- function(InputTable, first_year, last_year) {
```

```
 print("DI")
 DISeasonsV<-list()
 ii<-1
 for (m in seasonPeriods) {
 m<-unlist(m)
 InputTableSeasonTrim<-
InputTable[as.numeric(format(as.Date(InputTable$Date,"%Y-%m-%d"),format="%m"))
%in% m,]
 i<-1
 DIV<-vector()
 for (y in first_year:last_year) {
 InputTableYearTrim <-
InputTableSeasonTrim[as.numeric(format(as.Date(InputTableSeasonTrim$Date,"%Y-%
m-%d"),format="%Y")) %in% y, ]
 z<- InputTableYearTrim$PrecipitationON == 0
 DI<-sum(z)
 DIV[i]<- DI
 i <- i + 1
 }
 DISeasonsV[[ii]]<-DIV
 ii<-ii+1
 }
 return(DISeasonsV)
}

# Calculating Fall and spring PRECIPITATION AMOUNT INDEX
PAIPeriods<- list(c(8,9,10), c(3,4,5))
calculatePAI <- function(InputTable, first_year, last_year) {
 print("PAI")
 PAIPeriodsV<-list()
```

```
 ii<-1
 for (m in PAIPeriods) {
 m<-unlist(m)
 InputTableSeasonTrim<-
InputTable[as.numeric(format(as.Date(InputTable$Date,"%Y-%m-%d"),format="%m"))
%in% m,]
 i<-1
 PAIV<-vector()
 for (y in first_year:last_year) {
 InputTableYearTrim <-
InputTableSeasonTrim[as.numeric(format(as.Date(InputTableSeasonTrim$Date,"%Y-%
m-%d"),format="%Y")) %in% y, ]
 z<- InputTableYearTrim$PrecipitationON >=10
 PAI<-sum(z)
 PAIV[i]<- PAI
 i <- i + 1
 }
 PAIPeriodsV[[ii]]<-PAIV
 ii<-ii+1
 }
  return(PAIPeriodsV)
}

# Calculating COOL WAVE DAYS (CWD)
calculateCWD <- function(InputTable, first_year, last_year) {
  print("CWD")
  CWDV<-vector()
  i<-1
  for (y in first_year:last_year){
 CWD<-0
```

```
 startperiod <- as.Date(paste0(y, "-3-1"))
 endperiod <- as.Date(paste0(y, "-6-1"))
 dayTableTrim<-InputTable[as.Date(InputTable$Date,"%Y-%m-%d") >= startperiod &
                          as.Date(InputTable$Date,"%Y-%m-%d") <=  endperiod,]
 z<- dayTableTrim$TempMinON < 5
 CWD<-sum(z)
 CWDV[i]<- CWD
 i<-i+1
 }
 return(CWDV)
}

for(file_name in file_list[1]) {

 setwd(base_path)
 in_csv_path<-paste0(base_path, "/Townships centroide variables estimated values/",
file_name)

 print(paste0("Processing ",in_csv_path))
 InputTable <- read.csv(in_csv_path)
 first_year<-
as.numeric(format(as.Date(InputTable[1,"Date"],"%Y-%m-%d"),format="%Y"))
 last_year<-
as.numeric(format(as.Date(InputTable[nrow(InputTable),"Date"],"%Y-%m-%d"),format
="%Y"))

 dir.create(out_csv_dir, showWarnings=FALSE)
 seedfrostDatesData <- calculatewheatSeedingDate(InputTable, first_year, last_year)

 Period<-(c(first_year:last_year))
```

```
 FPI <- calculateFPI(InputTable,seedfrostDatesData, first_year, last_year)
 WWI <- calculateWWI(InputTable, first_year, last_year)
 CWI <- calculateCWI(InputTable, first_year, last_year)
 SKF <- calculateSKF(InputTable, first_year, last_year)
 DI<-calculateDI(InputTable, first_year, last_year)
 TilleringDI <- unlist(DI[1])
 StemExtensionDI <- unlist(DI[2])
 Heading_RipeningDI  <- unlist(DI[3])
 PAI <- calculatePAI(InputTable, first_year, last_year)
 FallPAI <- unlist(PAI[1])
 SpringPAI<- unlist(PAI[2])
 CWD <- calculateCWD(InputTable, first_year, last_year)
 GDD <- calculateGDD(InputTable, first_year, last_year)
 PS_GDD <- unlist(GDD[1])
 GS_GDD <- unlist(GDD[2])
 HS_GDD <- unlist(GDD[3])
 GSL <- calculateGSL(InputTable, first_year, last_year)
 GSL_length <- unlist(GSL[3])
 seedingDates <-unlist(seedfrostDatesData[1])
 frostDates <-unlist(seedfrostDatesData[2])


 result<-
cbind(Period,FPI,WWI,CWI,SKF,TilleringDI,StemExtensionDI,Heading_RipeningDI,Fa
llPAI , SpringPAI, CWD,PS_GDD,GS_GDD,
HS_GDD,GSL_length,seedingDates,frostDates)
 out_csv_path <- paste0(out_csv_dir, file_name)
 write.csv(result,out_csv_path,row.names=FALSE)
}
#### End of script ####
```

1.3. Winter wheat agroclimatic indices

```
outputfolder<- as.character("C:/Users/walaa/Documents/Wheat project/Winter wheat indices")

inputfolder<- as.character ("C:/Users/walaa/Documents/Wheat project/")


setwd(inputfolder)

# This script calculates agroclimatic and wheat-specific extreme event indices


file_list<- list.files(path="C:/Users/walaa/Documents/Wheat project/Townships centroide variables estimated values")

base_path<-"C:/Users/walaa/Documents/Wheat project"

monthNames<-c("January", "February", "March", "April", "May", "June", "July", "August", "September", "October", "November", "December")

out_csv_dir<-paste0(base_path,"/Winter wheat indices/")

options(stringsAsFactors = FALSE)


PlantingSeason <- 8:10

DormacySeason<- c(11,12,1,2,3,4)

GrowingSeason <- 5:7

HarvestingSeason <- 8:9


periods <- list(1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, PlantingSeason,DormacySeason, GrowingSeason, HarvestingSeason)

seasonPeriods <- list(PlantingSeason, GrowingSeason, HarvestingSeason)

getName <- function(period) {

 if (length(period) == 1) {

 return (monthNames[period])

 } else if (all(period == PlantingSeason)) {

 return ("PS")
```

```
 } else if (all(period == Dormacyseason)) {
 return ("DS")
 } else if (period == GrowingSeason) {
 return ("GS")
 } else if (period == HarvestingSeason) {
 return ("HS")
 }
 return ("ERROR - PERIOD")
}

#Settings for quality control
NARM <- TRUE
ROUNDDIGITS <- 1

first_year<- 1950
last_year<- 2017

# Define function for calculating winter wheat Seeding Date for each year using GDD
and optimal date
calculateGSL <- function(InputTable, first_year, last_year) {
 print("GSL")
 GSLV<-vector()
 startseasonv<- data.frame()
 endseasonv<- data.frame()
 ind<-1
 yn<- last_year-first_year
 for (y in first_year:last_year){
 GSL<-0
 startperiod <- as.Date(paste0(y, "-3-1"))
```

```
  endperiod <- as.Date(paste0(y, "-12-31"))
dayTableTrim<-InputTable[as.Date(InputTable$Date,"%Y-%m-%d") >= startperiod &
                         as.Date(InputTable$Date,"%Y-%m-%d") <=  endperiod,]
z<- dayTableTrim$TempMinON >= 5
zz<- dayTableTrim$TempMinON <= 5

for (i in 1:120) { if (all(z[c(i,i+1,i+2,i+3,i+4)])){
startseason=startperiod+i
istart<-i+60
break
}}
for (ii in istart:306 ){if (all(zz[c(ii,ii+1,ii+2,ii+3,ii+4)])){
endseason=startperiod+ii
break
}}
GSL<- ii-i
GSLV[ind]<-GSL
startseasonv[ind,1]<- as.character(startseason)
endseasonv[ind,1]<- as.character(endseason)
ind<- ind+1
}
GSLVDATA<-list(startseasonv,endseasonv,GSLV)
return(GSLVDATA)
}

for(file_name in file_list) {

setwd(base_path)
```

```
 in_csv_path<-paste0(base_path, "/Townships centroide variables estimated values/",
file_name)

 in_csv_path0<-paste0(base_path, "/Winter wheat indices/", file_name)

 print(paste0("Processing ",in_csv_path))

 InputTable <- read.csv(in_csv_path)

 result0 <- read.csv(in_csv_path0)


 first_year<-
as.numeric(format(as.Date(InputTable[1,"Date"],"%Y-%m-%d"),format="%Y"))

 last_year<-
as.numeric(format(as.Date(InputTable[nrow(InputTable),"Date"],"%Y-%m-%d"),format
="%Y"))


 GSL <- calculateGSL(InputTable, first_year, last_year)

 GSS <- unlist(GSL[1])

 GSE <- unlist(GSL[2])

 GSLen <- unlist(GSL[3])


 result0[,15]<- GSLen

 result<-cbind(result0,GSS,GSE )

 #out_csv_path <- paste0(out_csv_dir,"Winter wheat indices all/", file_name)

 #write.csv(result,out_csv_path,row.names=FALSE)

}

#### End of the script ####
```

1.4. Milling oats agroclimatic and phenological indices calculation

```
# This script calculates agroclimatic and milling oats phenological indices


file_list<- list.files(path="C:/Users/walaa/Documents/Wheat project/Townships centroide
variables estimated values")
```

```
base_path<-"C:/Users/walaa/Documents/Wheat project"
out_csv_dir<-paste0(base_path,"/oat indices/")
options(stringsAsFactors = FALSE)

first_year<- 1950
last_year<- 2017



PlantingSeason <- 4:5
GrowingSeason <- 5:7
HarvestingSeason <- 7:8
periods <- list(1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, PlantingSeason, GrowingSeason,
HarvestingSeason)

seasonPeriods <- list(PlantingSeason, GrowingSeason, HarvestingSeason)

# Calculate growing season length

calculateGSL <- function(InputTable, first_year, last_year) {
  print("GSL")
  GSLV<-vector()
  startseasonv<- vector()
  endseasonv<- vector()
  ind<-1
  for (y in first_year:last_year){
    GSL<-0
    startperiod <- as.Date(paste0(y, "-04-1"))
    endperiod <- as.Date(paste0(y, "-12-31"))
    endseason<-as.character(endperiod)
```

```
    dayTableTrim<-InputTable[as.Date(InputTable$Date,"%Y-%m-%d") >= startperiod &
                              as.Date(InputTable$Date,"%Y-%m-%d") <=  endperiod,]
    z<- dayTableTrim$TempMinON >= 0
    zz<- dayTableTrim$TempMinON <= 0

    for (i in 1:120) { if (all(z[c(i,i+1,i+2,i+3,i+4)])){
      startseason=startperiod+i
      istart<-i+90
      break
    }}
    for (ii in istart:271 ){if (all(zz[c(ii,ii+1,ii+2,ii+3,ii+4)])){
      endseason=startperiod+ii
      break
    }}
    GSL<- ii-i
    GSLV[ind]<-GSL
    startseasonv[ind]<- as.character(startseason)
    endseasonv[ind]<- as.character(endseason)

    ind<- ind+1
  }
  GSLVDATA<-list(startseasonv,endseasonv,GSLV)
  return(GSLVDATA)
}



# Calculate GROWING DEGREE-DAYS
calculateGDD <- function(InputTable, first_year, last_year) {
```

```
  print("GDD")
  GDDSeasonsV<-list()
  ii<-1
  for (m in seasonPeriods) {
    m<-unlist(m)
    InputTableSeasonTrim<-
InputTable[as.numeric(format(as.Date(InputTable$Date,"%Y-%m-%d"),format="%m"))
%in% m,]
    i<-1
    GDDV<-vector()
    for (y in first_year:last_year) {
      InputTableYearTrim <-
InputTableSeasonTrim[as.numeric(format(as.Date(InputTableSeasonTrim$Date,"%Y-%
m-%d"),format="%Y")) %in% y, ]
      G<- (InputTableYearTrim$TempMinON+InputTableYearTrim$TempMaxON/2)-0
      GDD<-sum(G)
      GDDV[i]<- GDD
      i <- i + 1
    }
    GDDSeasonsV[[ii]]<-GDDV
    ii<-ii+1
  }
  return(GDDSeasonsV)
}



# Calculate  PRECIPITATION Inten


calculatePI <- function(InputTable, first_year, last_year) {
  print("PI")
```

```
  PIV<-vector()

  i<-1
  for (y in  first_year:last_year){
    PI<-0
    startperiod <- as.Date(paste0(y, "-04-1"))
    endperiod <- as.Date(paste0(y, "-07-31"))

    dayTableTrim<-InputTable[as.Date(InputTable$Date,"%Y-%m-%d") >= startperiod &
                             as.Date(InputTable$Date,"%Y-%m-%d") <= endperiod,]
    z<- dayTableTrim$PrecipitationON >10
    PI<-sum(z)
    PIV[i]<- PI
    i<-i+1

  }
  return(PIV)
}


# Oat HEAT WAVES (HW)
calculateHW <- function(InputTable, first_year, last_year) {
  print("HW")
  HWV<-vector()
  i<-1
  for (y in first_year:last_year){
    HW<-0
```

```
    startperiod <- as.Date(paste0(y, "-05-1"))
    endperiod <- as.Date(paste0(y, "-08-1"))
    dayTableTrim<-InputTable[as.Date(InputTable$Date,"%Y-%m-%d") >= startperiod &
                             as.Date(InputTable$Date,"%Y-%m-%d") <=  endperiod,]
    z<- dayTableTrim$TempMaxON >= 25
    HW<-sum(z)
    HWV[i]<- HW
    i<-i+1
  }
  return(HWV)
}
# Oat Early FROST(EF)
calculateEF <- function(InputTable, first_year, last_year) {
  print("EF")
  EFV<-vector()
  i<-1
  for (y in first_year:last_year){
    EF<-0
    startperiod <- as.Date(paste0(y, "-04-1"))
    endperiod <- as.Date(paste0(y, "-05-31"))
    dayTableTrim<-InputTable[as.Date(InputTable$Date,"%Y-%m-%d") >= startperiod &
                             as.Date(InputTable$Date,"%Y-%m-%d") <=  endperiod,]
    z<- dayTableTrim$TempMinON <= -2
    EF<-sum(z)
    EFV[i]<- EF
    i<-i+1
  }
  return(EFV)
```

```
}

# Oat jointing and anthesis DROUGHT period (DP)
calculateDP <- function(InputTable, first_year, last_year) {
  print("DP")
  DPV<-vector()
  i<-1
  for (y in first_year:last_year){
    DP<-0
    startperiod <- as.Date(paste0(y, "-4-1"))
    endperiod <- as.Date(paste0(y, "-6-1"))
    dayTableTrim<-InputTable[as.Date(InputTable$Date,"%Y-%m-%d") >= startperiod &
                             as.Date(InputTable$Date,"%Y-%m-%d") <=  endperiod,]
    dayTableTrim<- dayTableTrim[dayTableTrim$PrecipitationON <=0,]
    z<-dayTableTrim$TempMaxON>25
    DP<-sum(z)
    DPV[i]<- DP
    i<-i+1
  }
  return(DPV)
}
# Calculating PRECIPITATION AMOUNT INDEX
calculatePAI <- function(InputTable, first_year, last_year) {
  print("PAI")
   PAIV<-vector()
    i<-1
    for (y in first_year:last_year) {
        startperiod <- as.Date(paste0(y, "-4-1"))
```

```
      endperiod <- as.Date(paste0(y, "-7-31"))
       dayTableTrim<-InputTable[as.Date(InputTable$Date,"%Y-%m-%d") >=
startperiod &
                        as.Date(InputTable$Date,"%Y-%m-%d") <=  endperiod,]
     z<- dayTableTrim$PrecipitationON
     PAI<-sum(z)
     PAIV[i]<- PAI
     i <- i + 1
}
  return(PAIV)
}

# Calculating EARLY FLOODS
calculateEFL <- function(InputTable, first_year, last_year) {
  print("EFL")
  EFLV<-vector()
  i<-1
  for (y in first_year:last_year) {
    startperiod <- as.Date(paste0(y, "-4-1"))
    endperiod <- as.Date(paste0(y, "-5-31"))
    dayTableTrim<-InputTable[as.Date(InputTable$Date,"%Y-%m-%d") >= startperiod &
                        as.Date(InputTable$Date,"%Y-%m-%d") <=  endperiod,]
    z<- dayTableTrim$PrecipitationON
    EFL<-sum(z)
    if (EFL>125){EFLV[i]<- 1}else{EFLV[i]<- 0}
      i <- i + 1
  }
  return(EFLV)
}
```

```
for(file_name in file_list) {
  setwd(base_path)
  in_csv_path<-paste0(base_path, "/Townships centroide variables estimated values/",
file_name)
  print(paste0("Processing ",in_csv_path))
  InputTable <- read.csv(in_csv_path)
  Period<-(c(first_year:last_year))
  HW <- calculateHW(InputTable, first_year, last_year)
  GDD <- calculateGDD(InputTable, first_year, last_year)
  PS_GDD <- unlist(GDD[1])
  GS_GDD <- unlist(GDD[2])
  HS_GDD <- unlist(GDD[3])
  DP<-calculateDP(InputTable, first_year, last_year)
  EF<-calculateEF(InputTable, first_year, last_year)
  PI<-  calculatePI(InputTable, first_year, last_year)
  PAI<-  calculatePAI(InputTable, first_year, last_year)
  EFL<-calculateEFL(InputTable, first_year, last_year)
  GSL <- calculateGSL(InputTable, first_year, last_year)
  GSS <- unlist(GSL[1])
  GSE <- unlist(GSL[2])
  GSLen <- unlist(GSL[3])
     result<-cbind(Period,HW,PS_GDD,GS_GDD, HS_GDD, DP,EF, PI,PAI,EFL,
GSS ,GSE,GSLen)
  out_csv_path <- paste0(out_csv_dir, file_name, ".csv")
  write.csv(result,out_csv_path,row.names=FALSE)
}
#### End of the script ####
```

1.5. Soil data extracting from GEE Geotiff image using R scripts

```
library(tiff)
library(raster)
library(rgdal)
library(sp)
library(rgee)
library(ggplot2)
library(sf)

#### Data preparations  ####

file_list<- list.files(path="C:/Users/walaa/Documents/Wheat project/Townships
centroid variables estimated values")

outputfolder<- as.character("C:/Users/walaa/Documents/R")
inputfolder<- as.character ("C:/Users/walaa/Documents/Wheat project/")
base_path<-"C:/Users/walaa/Documents/Wheat project"
out_csv_dir<-paste0(base_path,"/townsips soil median/")
options(stringsAsFactors = FALSE)

img <- readGDAL("C:/Users/walaa/Documents/soiltexture1/exportsoiltableimage.tif")

rasterimage<- raster(img)
rasterimageb1<- raster(img[1])
rasterimageb2<- raster(img[2])
rasterimageb3<- raster(img[3])
rasterimageb4<- raster(img[4])
```

```
studytownships<- c(1:614)

data.shape<-
readOGR(dsn="C:/Users/walaa/Documents/ArcGIS/Projects/Township1/SOntario
polygons townships reprojected.shp")

#plot(data.shape)

setwd(inputfolder)

# This is a code to read Ontario counties' polygons csv file in R

ONtownp1 <- read.csv(paste(inputfolder,"townships boundaries
xy_TableToExcel_3.csv", sep=""),header = T, fileEncoding="UTF-8-BOM")

ONtownp2 <- read.csv(paste(inputfolder,"townships boundaries
xy_TableToExcel_3p2.csv", sep=""),header = T, fileEncoding="UTF-8-BOM")

ONtown<- rbind(ONtownp1, ONtownp2)

ONtown_CRS <- st_crs(rasterimage)

townnames<- ONtown[2] # this code is to read the third column of the csv file which
contains the names of the townships

Uniqtownnames<- unique(townnames)

Townshmedian <- data.frame()

for (i in 1:613) {namc<-Uniqtownnames[i,]

index<- as.matrix(ONtown[2])==namc

Townsh<-(subset(ONtown,index, select= c(POINT_X, POINT_Y)))

# Transfer polygON coordinate matrix to spacial point to create spacial object as input for
the crop function (crop function needs the extent information)

Townsh<- as.matrix(Townsh)

Townshsp<- spPolygons(Townsh)
```

```
#Extracting the estimated values for the counties special points (Townshsp)
rasValue1=extract(rasterimageb1, Townsh)
rasValue2=extract(rasterimageb2, Townsh)
rasValue3=extract(rasterimageb3, Townsh)
rasValue4=extract(rasterimageb4, Townsh)

# For calculating the median of the rastelayers
B1median<- median(rasValue1[rasValue1>0],na.rm = TRUE)
B2median<- median(rasValue1[rasValue2>0],na.rm = TRUE)
B3median<- median(rasValue1[rasValue3>0],na.rm = TRUE)
B4median<- median(rasValue1[rasValue4>0],na.rm = TRUE)

# For calculating the centroid of the townships' polygons
Townshmedianline<-c(B1median,B2median,B3median,B4median)
Townshmedian<-rbind(Townshmedian,Townshmedianline)
}
Townshmedian<-cbind(Uniqtownnames,Townshmedian)
colnames(Townshmedian) <- c("Township", "B1median", "B2median",
"B3median","B4median")

write.csv(Townshmedian,paste(out_csv_dir, "median",".csv",sep=""), row.names =
FALSE)
save.image("/Users/walaa/Documents/Wheat project/R.RData")
#### End of the script ####
```

1.6. Random Forest regression analyses

```
#This script is to analyze the impact of extreme weather events and the soil texture on
        winter wheat yields using Randomforest model
```

```
library(randomForest)
library(tree)
library(randomForestExplainer)


pathind<- "C:/Users/walaa/Documents/Wheat project/Winter wheat indices/Winter wheat
        indices all/"
pathsoil<-"C:/Users/walaa/Documents/Wheat project/townsips soil median/"
pathyields<-"C:/Users/walaa/Documents/Wheat project/winter wheat yields/"
pathew<-"C:/Users/walaa/Documents/Wheat projectEWI-SOntario/"
pathout<-"C:/Users/walaa/Documents/Wheat project/random forest winter w/"

inddata <- read.csv(paste0(pathind,"all towns ind data.csv") ,header=TRUE)
soildata <- read.csv(paste0(pathsoil,"median.csv") ,header=TRUE)
yieldsdata<-read.csv(paste0(pathyields,"all towns resdatav2.csv") ,header=TRUE)
ewdata<-read.csv(paste0(pathew,"all towns EWI data.csv") ,header=TRUE)

for (i in 1: nrow(inddata)){inddata$Geotownship[i]<-
        tolower(substr(inddata$Geotownship[i], 1, 12))}
colnames(inddata)[4] <- "Year"
for (i in 1: nrow(yieldsdata)){yieldsdata$Geotownship[i]<-
        tolower(substr(yieldsdata$Geotownship[i], 1, 12))}
for (i in 1: nrow(soildata)){soildata$Township[i]<-tolower(substr(soildata$Township[i],
        1, 12))}
colnames(soildata)[1] <- "Geotownship"
for (i in 1: nrow(ewdata)){ewdata$Geotownship[i]<-
        tolower(substr(ewdata$Geotownship[i], 1, 12))}
colnames(ewdata)[4] <- "Year"

# This code is to read the first column of the csv file which contains the names of the
        townships
townnamesy<- yieldsdata$Geotownship

Uniqtownnamesy<- sort(unique(townnamesy))
dataall<- data.frame()

for (namc in Uniqtownnamesy){

 index<- as.matrix(inddata$Geotownship)==namc
 index<- which(index, arr.ind = FALSE, useNames = TRUE)
 dataind<- inddata [index,]

 index<- as.matrix(soildata$Geotownship)==namc
 index<- which(index, arr.ind = FALSE, useNames = TRUE)
 datasoil<- soildata [index,]
```

```
 index<- as.matrix(yieldsdata$Geotownship)==namc
 index<- which(index, arr.ind = FALSE, useNames = TRUE)
 datay<- yieldsdata [index,]

 index<- as.matrix(ewdata$Geotownship)==namc
 index<- which(index, arr.ind = FALSE, useNames = TRUE)
 dataew<- ewdata [index,]

 data<-merge(dataind,datay,by="Year" )
 data<-merge(data,dataew, by="Year" )

 soilcolumns <-data.frame()
 add<-datasoil[2:5]
 soilcolumns[1:31,1:4]<-add
 data<- cbind(data,soilcolumns)

 dataall<-rbind(dataall,data)
}
dev.off()

# These codes perform different runs using different parameters, the irrelevant columns
        are deleted by -c

# In this code all meaningful predictors are kept
# dataall<-select (dataall,-c(  Year ,X.x , township.x, Geotownship.x, seedingDates,
        frostDates,  GSS, GSE, Geotownship.y,Eff.Acres, Yield..bu.ac.,  resid, X.y,
        township.y, Geotownship))

# In this code crop indices are removed
# dataall<-select (dataall,-c(Year ,X.x , township.x, Geotownship.x, seedingDates,
        frostDates,  GSS, GSE, Geotownship.y, Eff.Acres, Yield..bu.ac.,  resid, X.y,
        township.y, Geotownship, FPI, WWI, CWI, SKF, Tillering_DI,
        Stem_Extension_DI, Heading_Ripening_DI, Fall_PAI, Spring_PAI, CWD,
        PS_GDD, GS_GDD, HS_GDD, GSL_Length, AvgYield))

# In this code weather indices are removed
#dataall<-select (dataall,-c(  Year ,X.x , township.x, Geotownship.x, seedingDates,
        frostDates,  GSS, GSE, Geotownship.y,Eff.Acres, Yield..bu.ac.,  resid, X.y,
        township.y, Geotownship,  RX1 ,  RX5 ,CDD ,R10 ,SDII ,HWE ,CWE ,
        DTR ,GSL, AvgTempMin, AvgTempMax, SumPrecipitation ))

# In this code weather indices and soil data are removed
dataall<-select (dataall,-c(  Year ,X.x , township.x, Geotownship.x, seedingDates,
        frostDates,  GSS, GSE, Geotownship.y,Eff.Acres, Yield..bu.ac.,  resid, X.y,
        township.y, Geotownship,  RX1 ,  RX5 ,CDD ,R10 ,SDII ,HWE ,CWE ,
```

```
        DTR ,GSL, AvgTempMin, AvgTempMax, SumPrecipitation,  B1median,
        B2median, B3median, B4median))

# In this code weather indices and average yield are removed
# dataall<-select (dataall,-c( AvgYield, Year ,X.x , township.x, Geotownship.x,
        seedingDates, frostDates,  GSS, GSE, Geotownship.y,Eff.Acres, Yield..bu.ac.,
        resid, X.y,   township.y, Geotownship,  RX1 ,
        RX5 ,CDD ,R10 ,SDII ,HWE ,CWE , DTR ,GSL, AvgTempMin, AvgTempMax,
        SumPrecipitation ))

# In this code all meaningful are kept except soil ones
# dataall<-select (dataall,-c(  Year ,X.x , township.x, Geotownship.x, seedingDates,
        frostDates,  GSS, GSE, Geotownship.y,Eff.Acres, Yield..bu.ac.,  resid, X.y,
        township.y, Geotownship, B1median, B2median, B3median , B4median))


# in this code weather ind and average yield removed
# dataall<-select (dataall,-c( Year ,X.x , township.x, Geotownship.x, seedingDates,
        frostDates,  GSS, GSE, Geotownship.y,Eff.Acres, Yield..bu.ac.,  resid, X.y,
        township.y, Geotownship,  RX1 ,  RX5 ,CDD ,R10 ,SDII ,HWE ,CWE ,
        DTR ,GSL, AvgTempMin, AvgTempMax, SumPrecipitation ,  B1median,
        B2median, B3median, B4median  ))

summary(dataall)
# dataall<-dataall1
# removing NA data
dataall <- dataall[!(dataall$standardized_resid %in% c(NA)),]
dataall <- dataall[!(dataall$standardized_resid %in% c(NaN)),]
colSums(is.na(dataall))

# This code is to spliting the data set into training and testing data

sample = sample.split(dataall$standardized_resid, SplitRatio = 0.75)
train = subset(dataall, sample == TRUE)
test  = subset(dataall, sample == FALSE)
dim(train)
dim(test)

#This code is to run Random forest nomber of tree is 500 by default
set.seed(131)

regression.rf <- randomForest(standardized_resid ~ ., data=train,importance=TRUE,
        na.action=na.omit)

print(regression.rf)
plot(regression.rf, main= "Error rate vs. number of trees")
```

```
summary(regression.rf)
print(regression.rf)

#predict(model, newdata= df)
varImpPlot(regression.rf, main="Variable importance" )
varImp(regression.rf )

#### End of the script ####
```

Appendix 2. Flow chart shows the raw data, generated datasets, and the related analyses

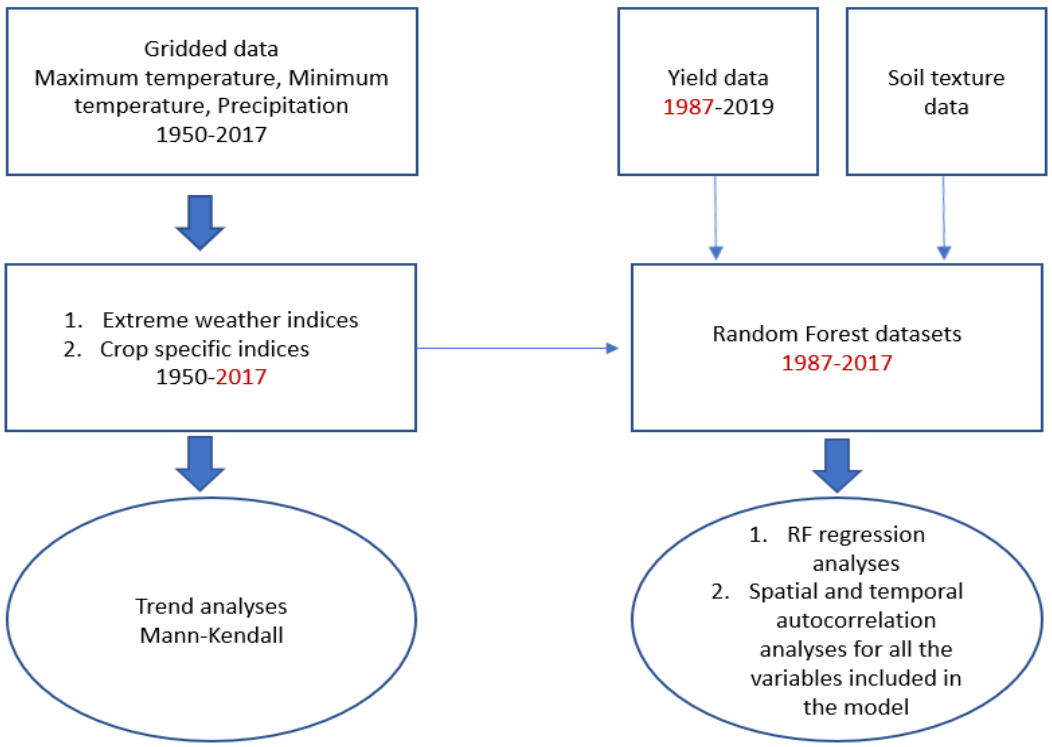

Figure1: Flow chart shows the raw data, generated datasets, and the related analyses.

Appendix 3. Figures of temporal and spatial changes in extreme weather indices

Maps of extreme weather indices that shows the least significant increase or decrease in trends southern Ontario region.

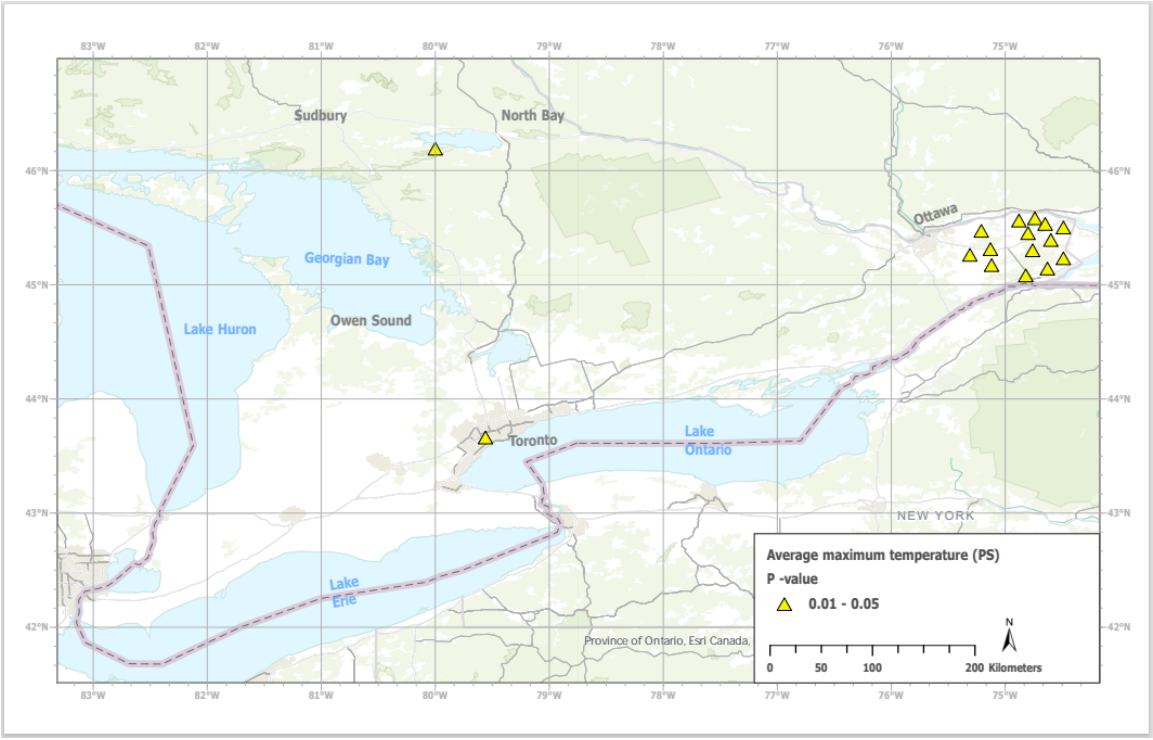

Figure 1: Map of trend significance for seasonal average maximum temperatures in southern Ontario townships for the PS. Yellow upright triangles represent significant upward trends (P-value from 0.01 to 0.05). Red upright triangles represent high-ranking significant upward trends (P-value less than 0.01), and empty spaces represent townships where the trends were not statistically significant

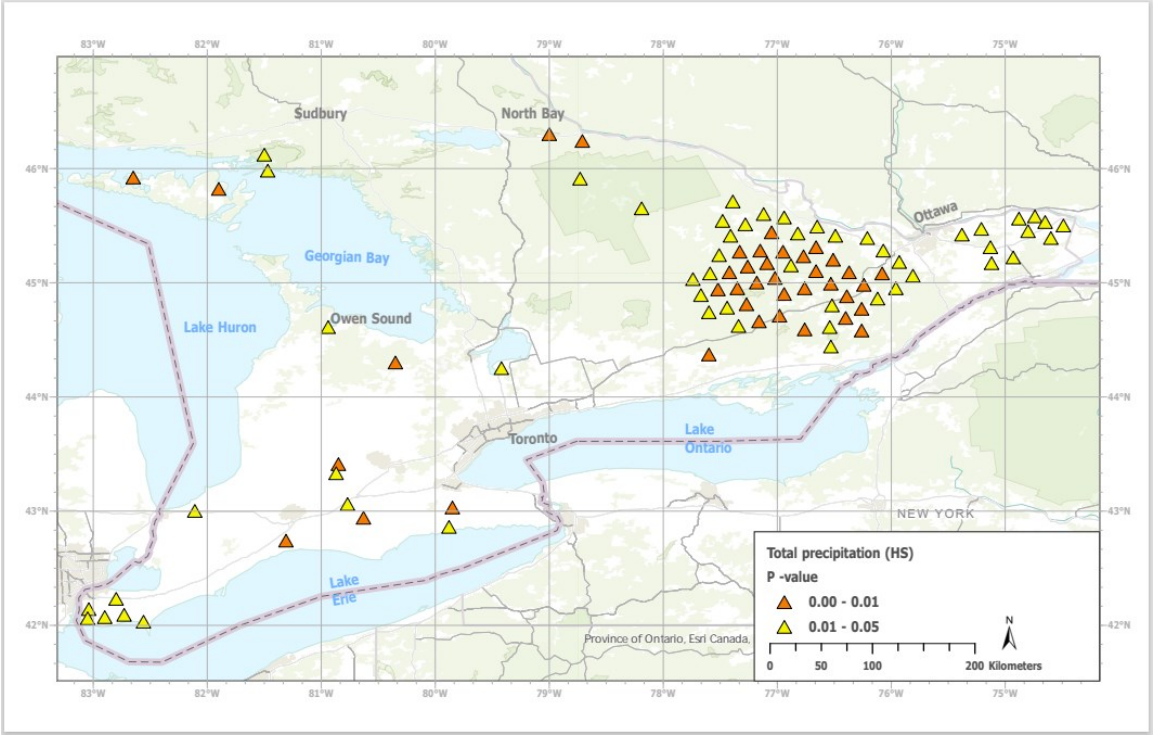

Figure 2: Map of trend significance for seasonal total precipitation in southern Ontario townships for the HS. Yellow upright triangles represent significant upward trends (P-value from 0.01 to 0.05). Red upright triangles represent high-ranking significant upward trends (P-value less than 0.01), and empty spaces represent the townships where the trends were not statistically significant.

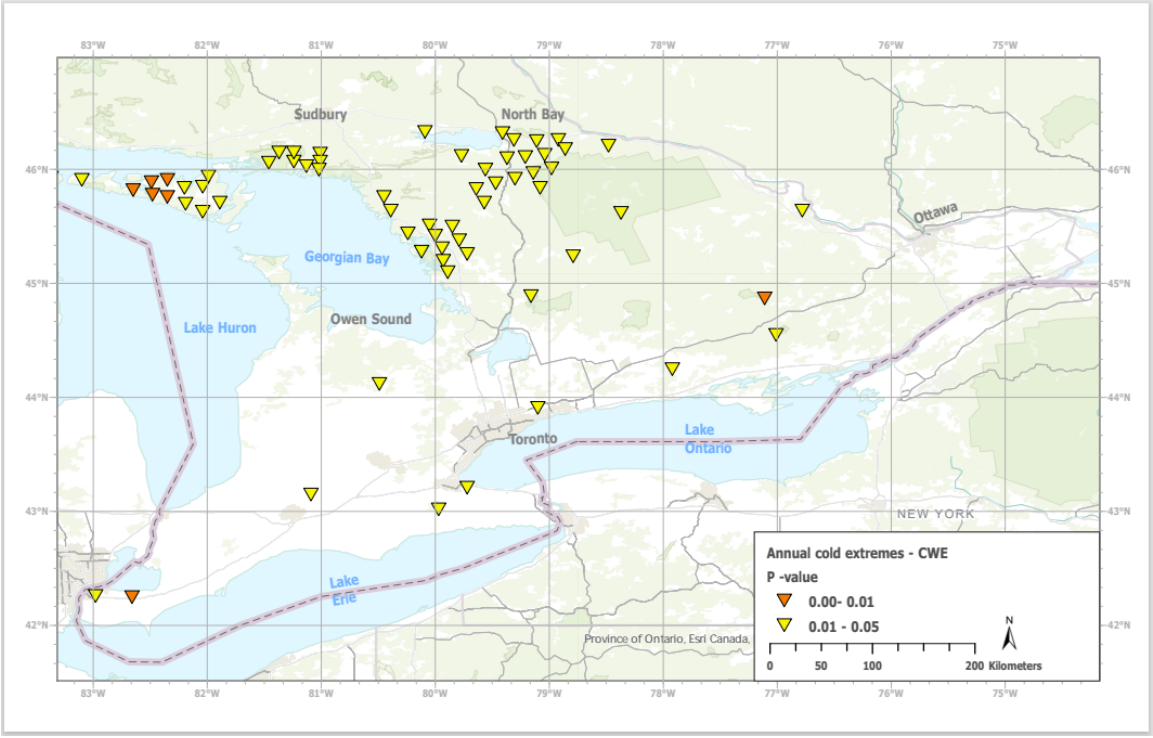

Figure 3: Map of trend significance for annual extreme weather indices of cold weather extremes (CWEs). Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant. Downward triangles indicate a downward trend.

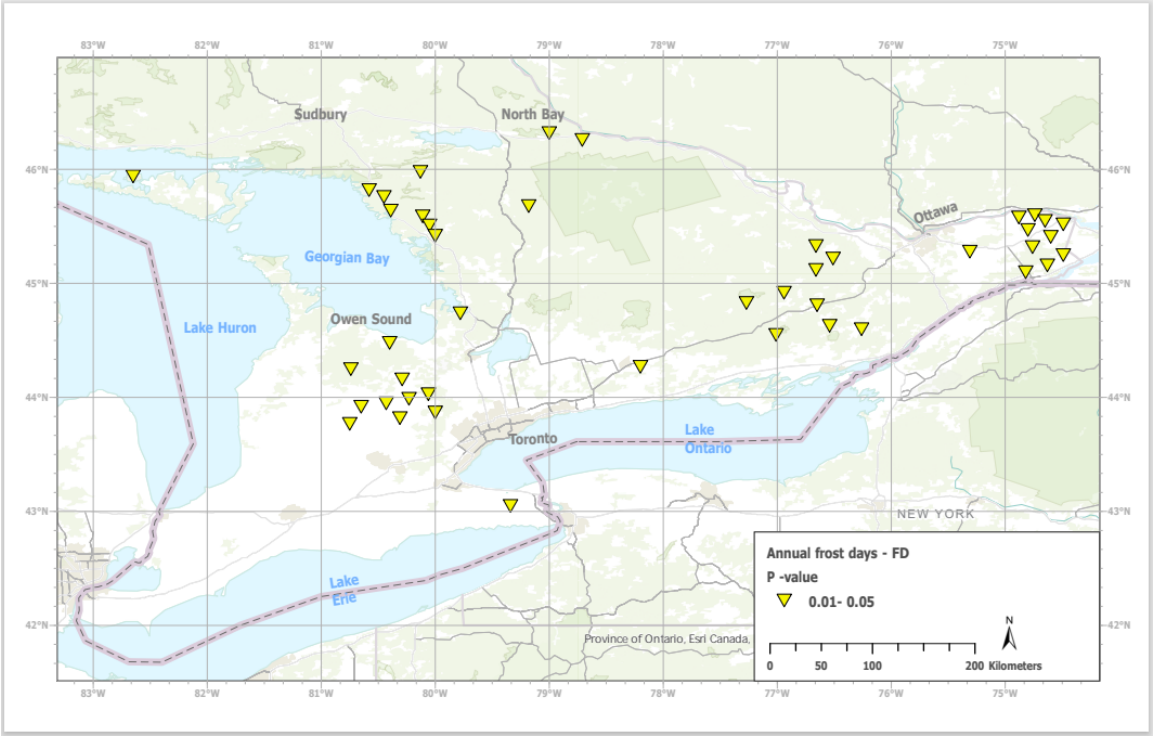

Figure 4: Map of trend significance for annual extreme weather indices: annual frost days (FDs). Yellow triangles represent significant trends (P-value from 0.01 to 0.05). The empty spaces represent townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend.

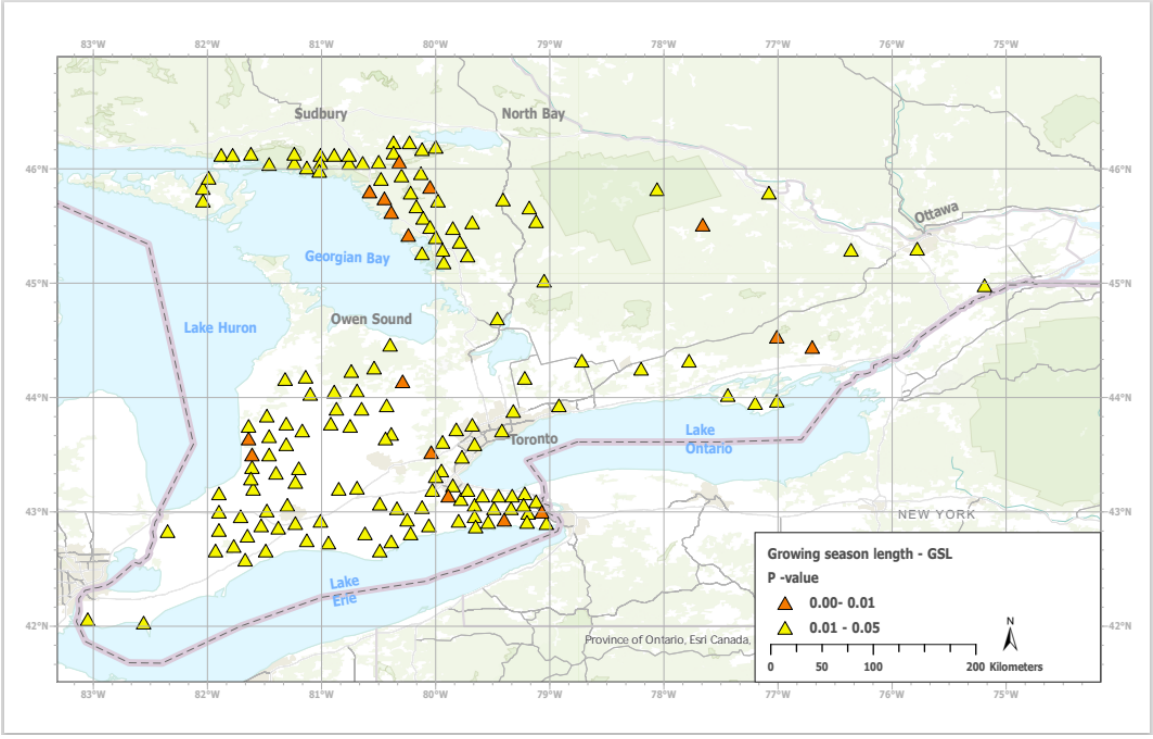

Figure 5: Map of trend significance for growing season length (GSL). Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend.

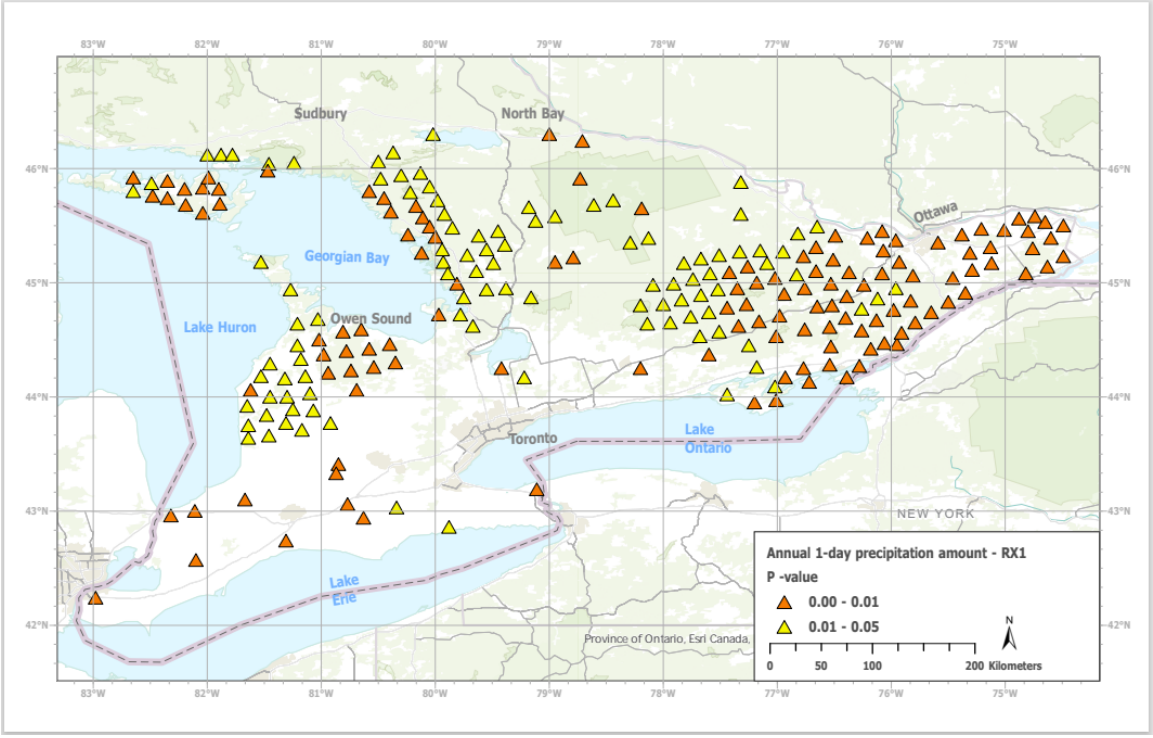

Figure 6: Map of trend significance for annual extreme weather indices: 1-day precipitation amounts (RX1). Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant. Upward triangles indicate an upward trend, while downward triangles indicate a downward trend.

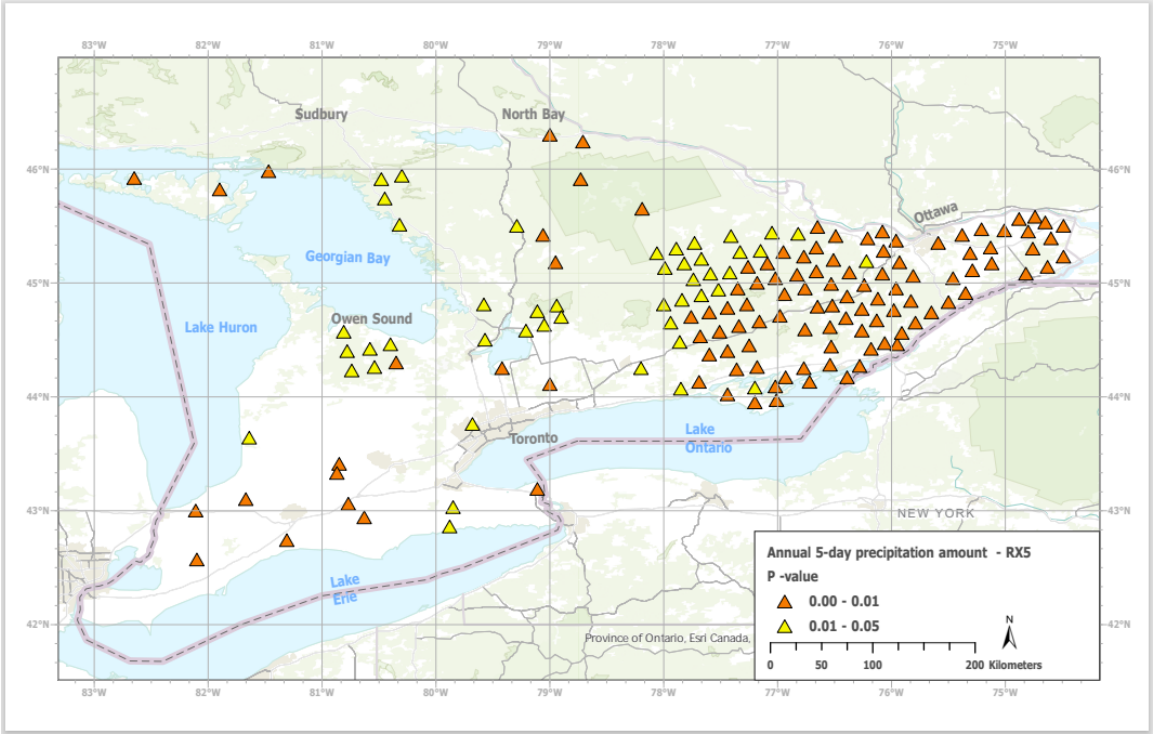

Figure 7: Map of trend significance for annual extreme weather indices: 5-day precipitation amounts (RX5). Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant. Upward triangles indicate an upward trend, while downward triangles indicate a downward trend.

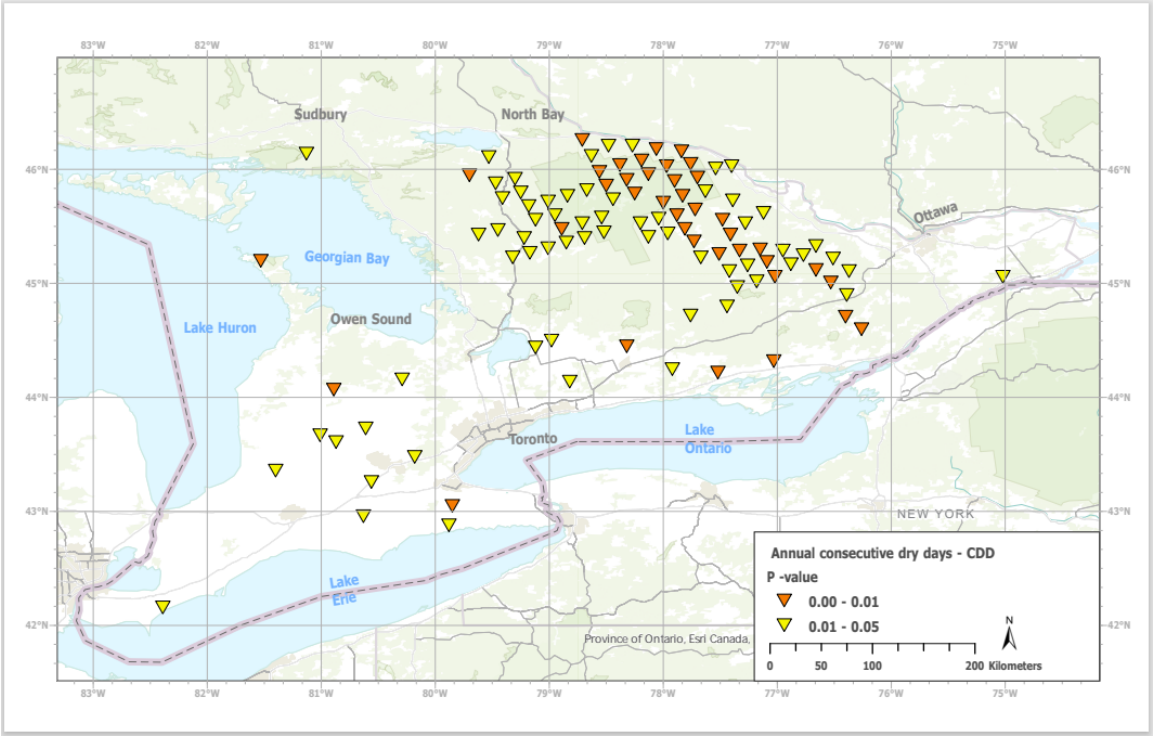

Figure 8: Map of trend significance for annual extreme weather indices: consecutive dry days (CDDs). Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant. Upward triangles indicate an upward trend, while downward triangles indicate a downward trend.

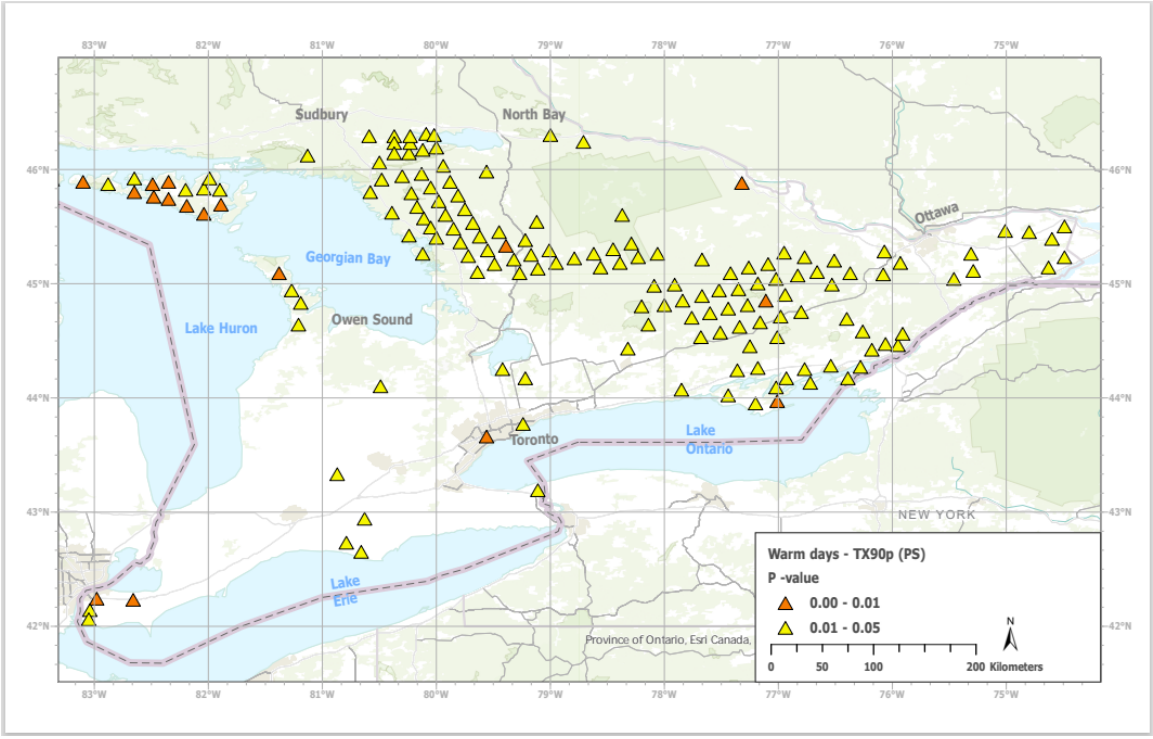

Figure 9: Maps of trend significance of seasonal warm days (TX90P) index for the PS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant. Upward triangles indicate an upward trend.

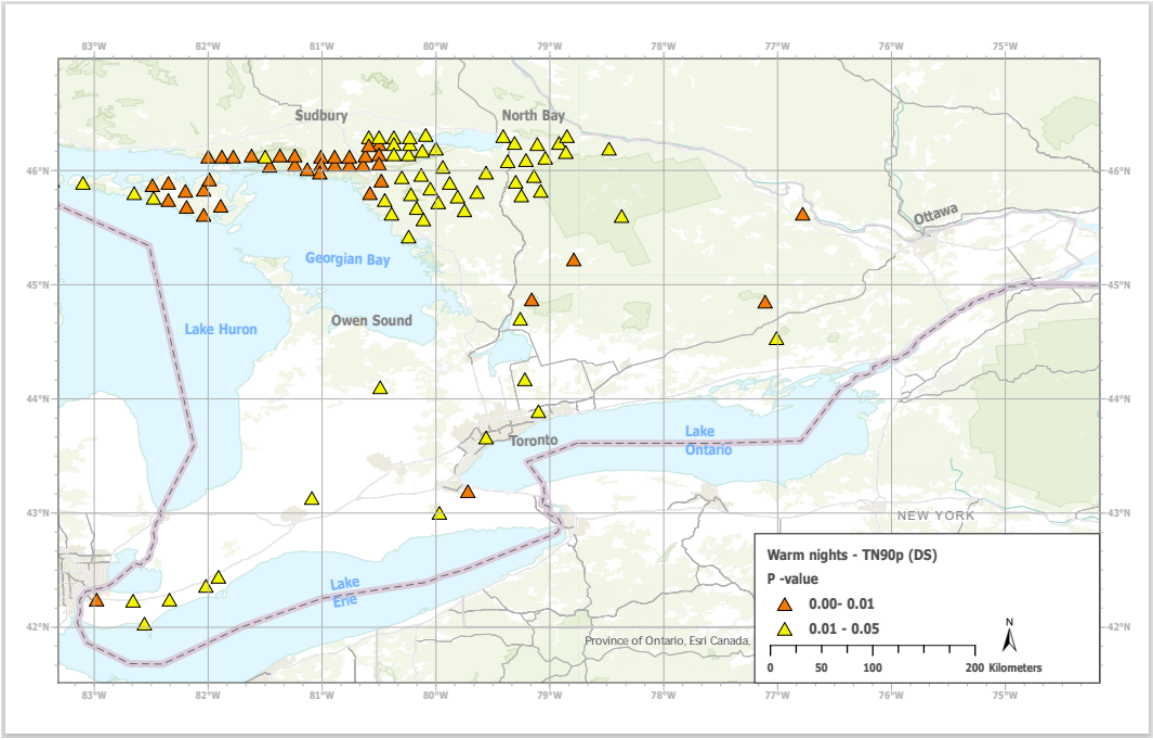

Figure 10: Maps of trend significance for seasonal warm nights (TN90P) for the DS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant.

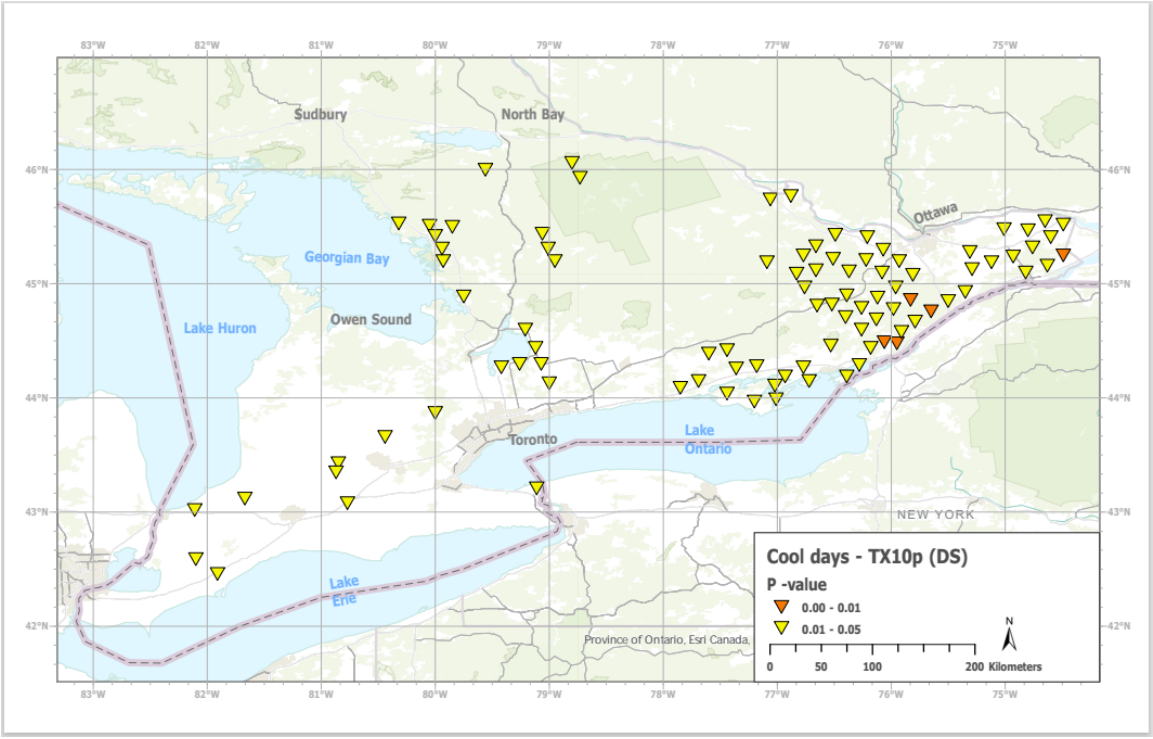

Figure 11: Maps of trend significance for the seasonal cool days index (TX10P) for the DS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty spaces represent townships where the trends were not statistically significant. Downward triangles indicate a downward trend.

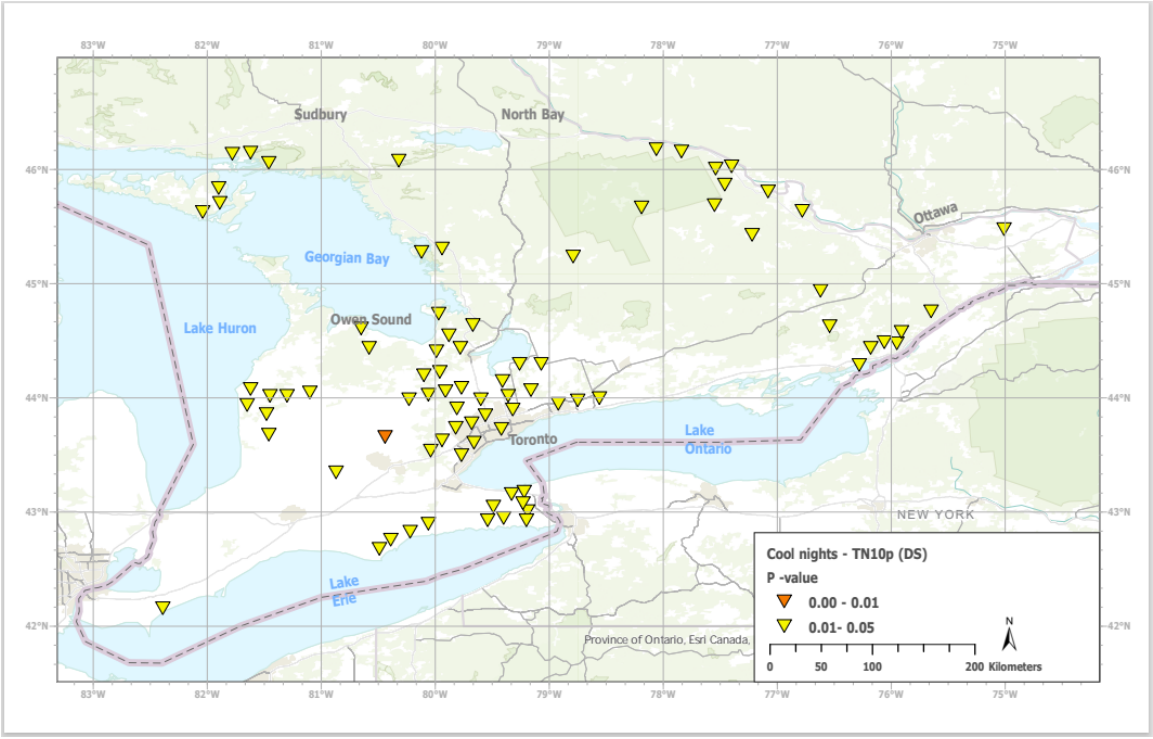

Figure 12: Maps of trend significance for seasonal cool nights (TN10P) index for the DS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05). The empty space represents townships where the trends were not statistically significant, and a downward triangle indicates a downward trend.

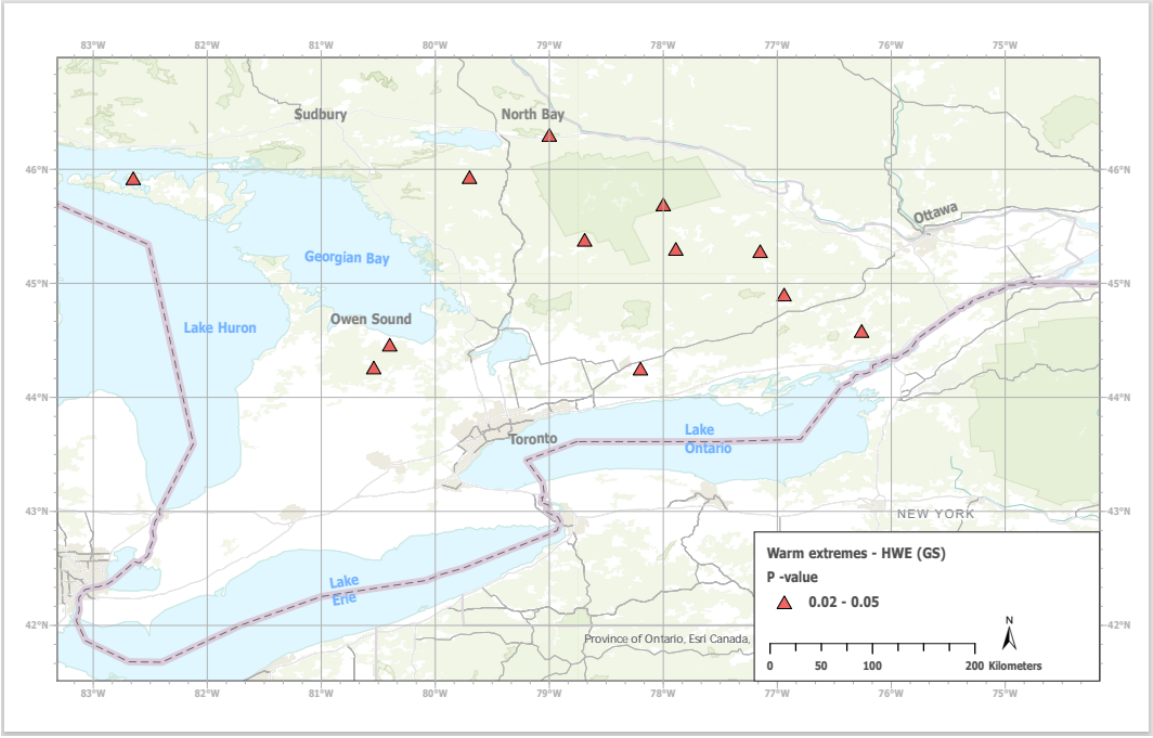

Figure 13: Maps of trend significance for seasonal hot extreme (HWE). Red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend.

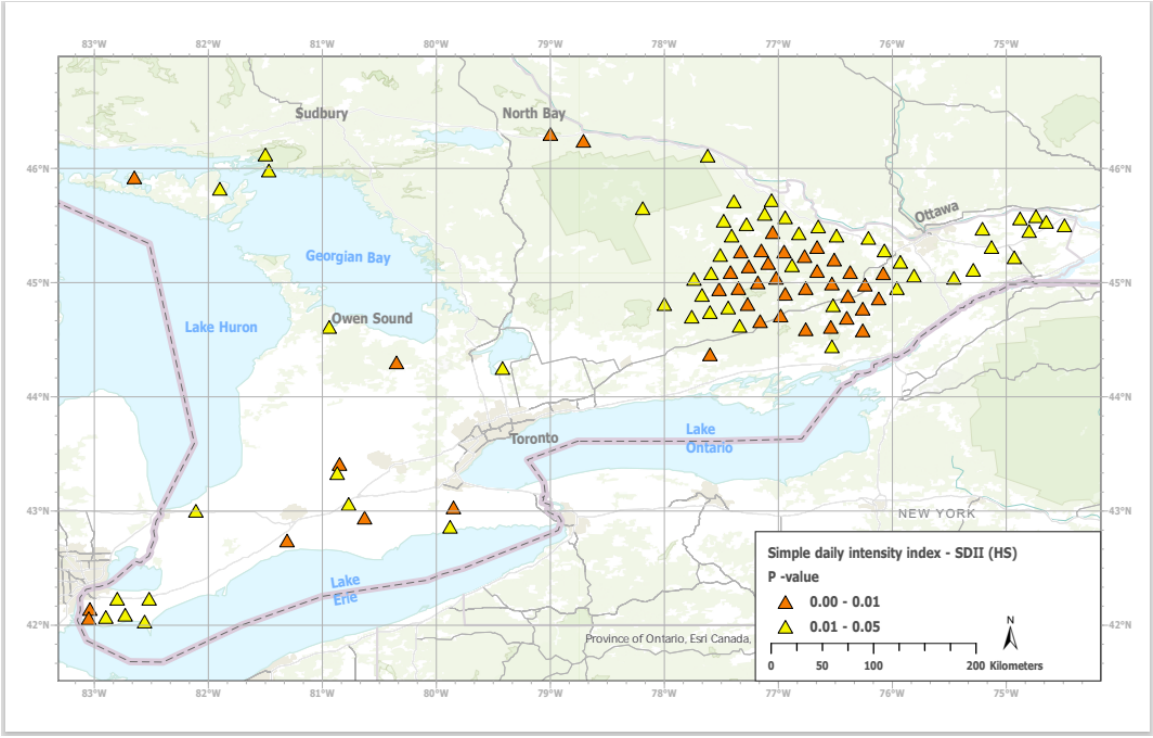

Figure 14: Map of trend significance for simple intensity index (SDII) in the PS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend

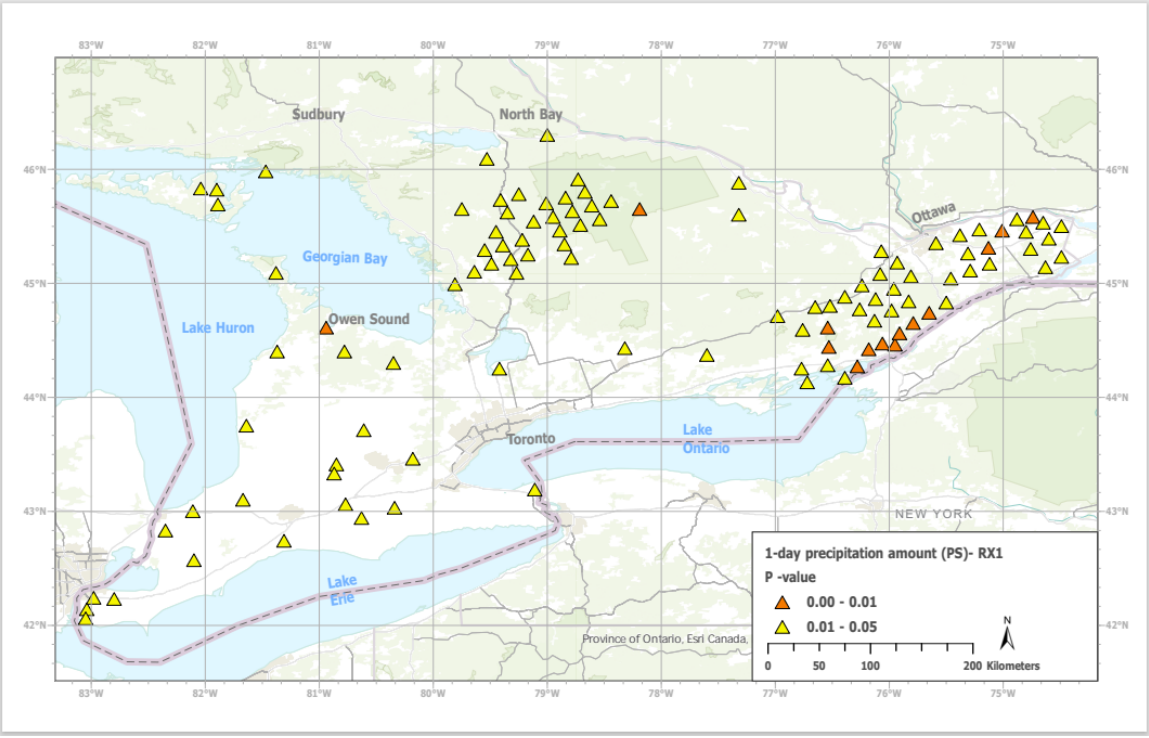

Figure 15: Map of trend significance for 1- day precipitation amount (RX1) in the PS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend

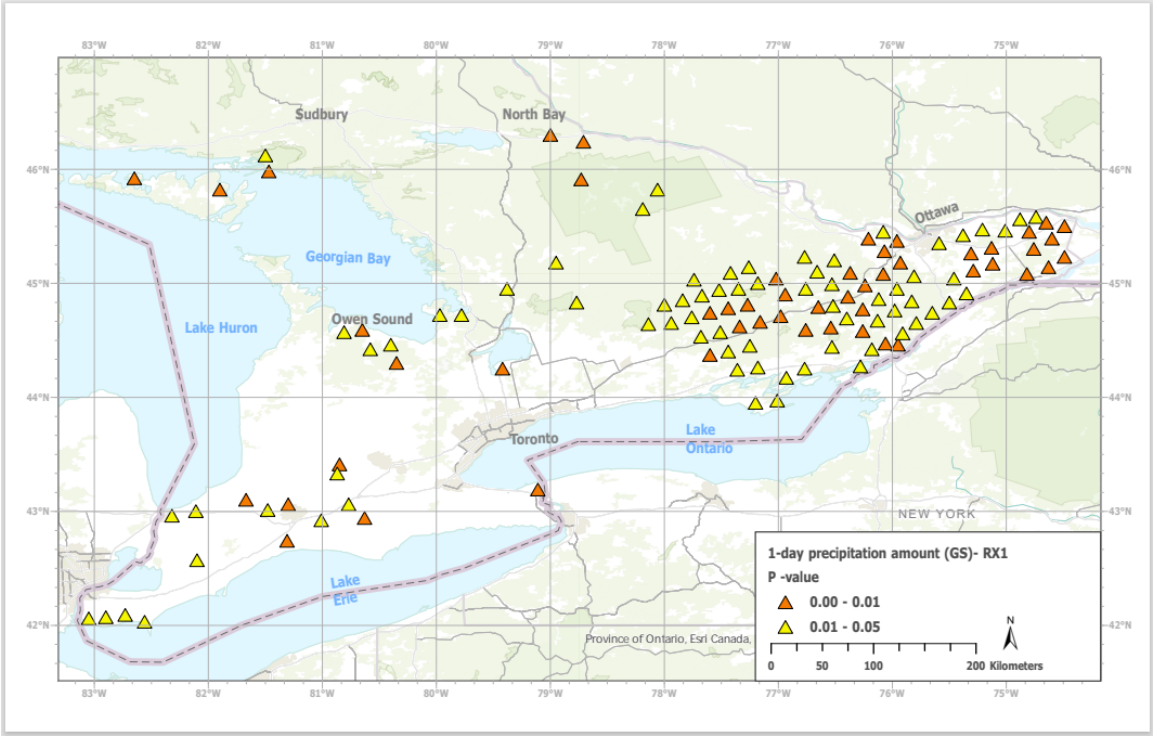

Figure 16: Map of trend significance for 1- day precipitation amount (RX1) in the GS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend

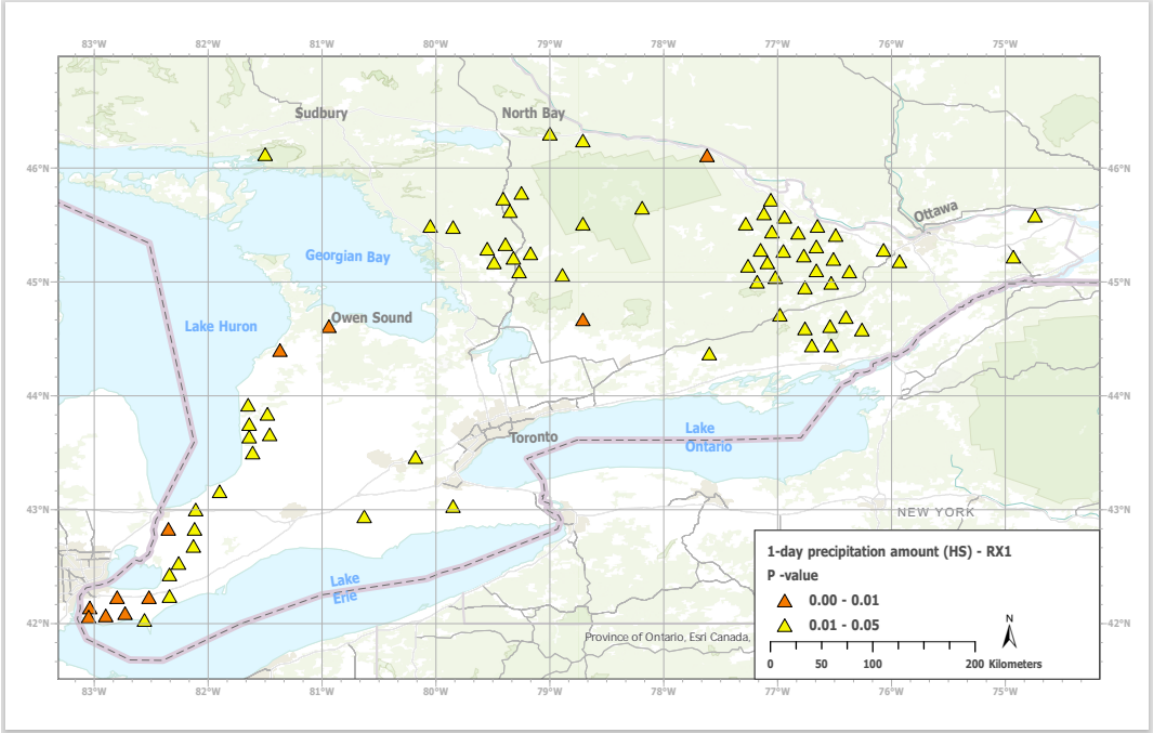

Figure 17: Map of trend significance for 1- day precipitation amount (RX1) in the HS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend

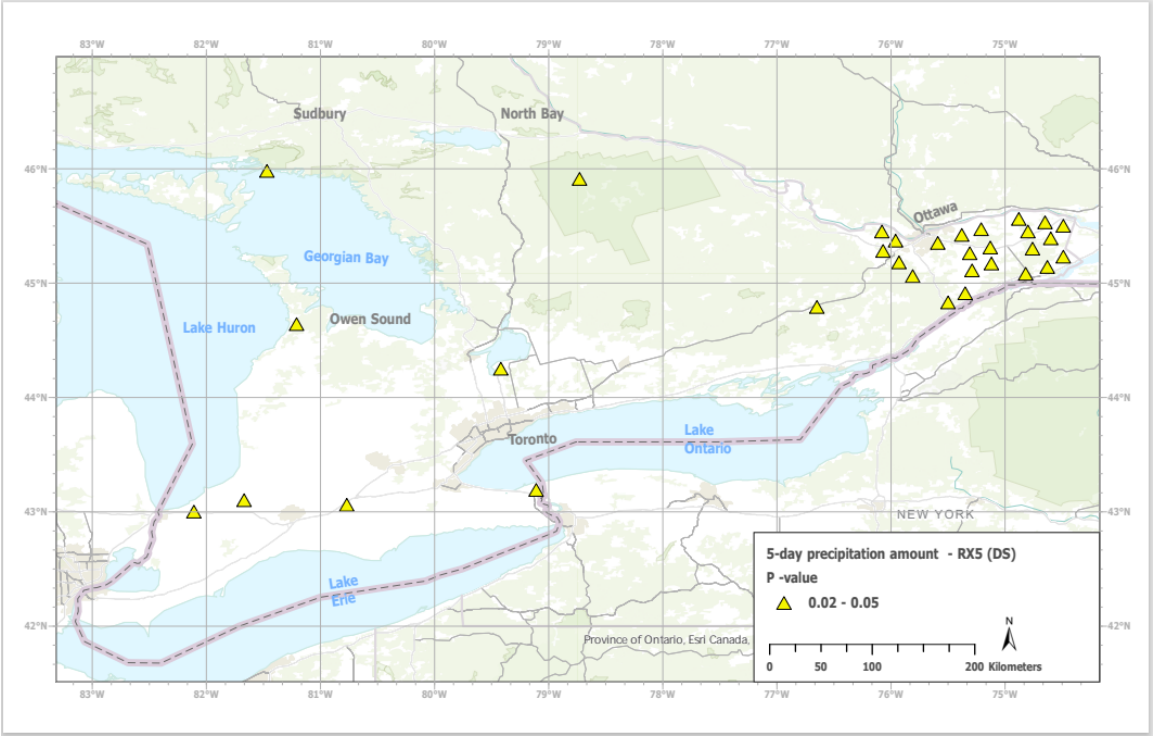

Figure 18: Map of trend significance for 5- day precipitation amount (RX5) in the DS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05). The empty space represents townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend

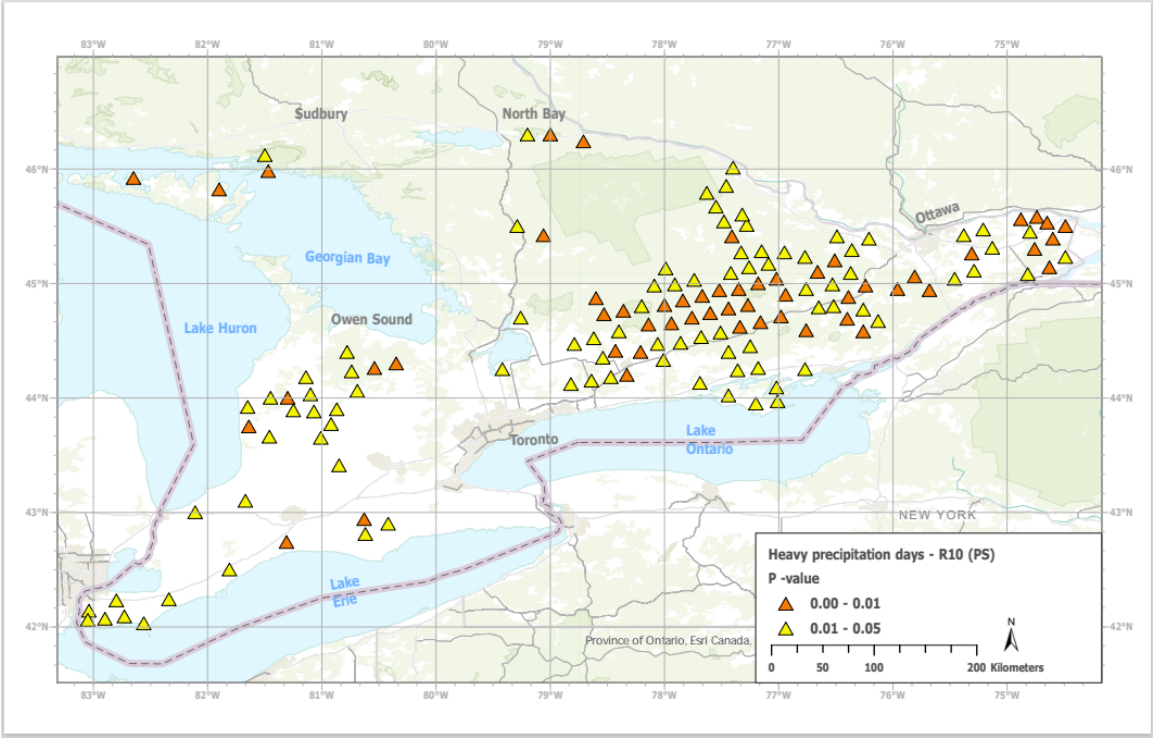

Figure 19: Map of trend significance for heavy precipitation days (R10) in the PS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend

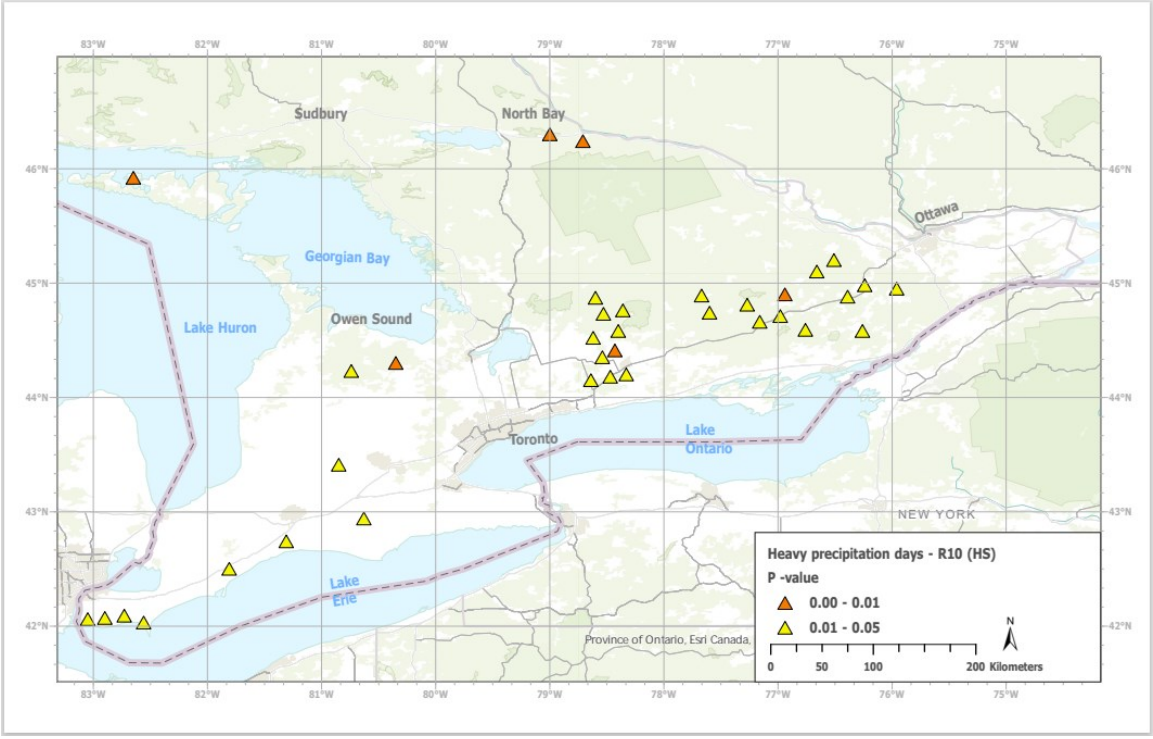

Figure 20: Map of trend significance for heavy precipitation days (R10) in the HS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend

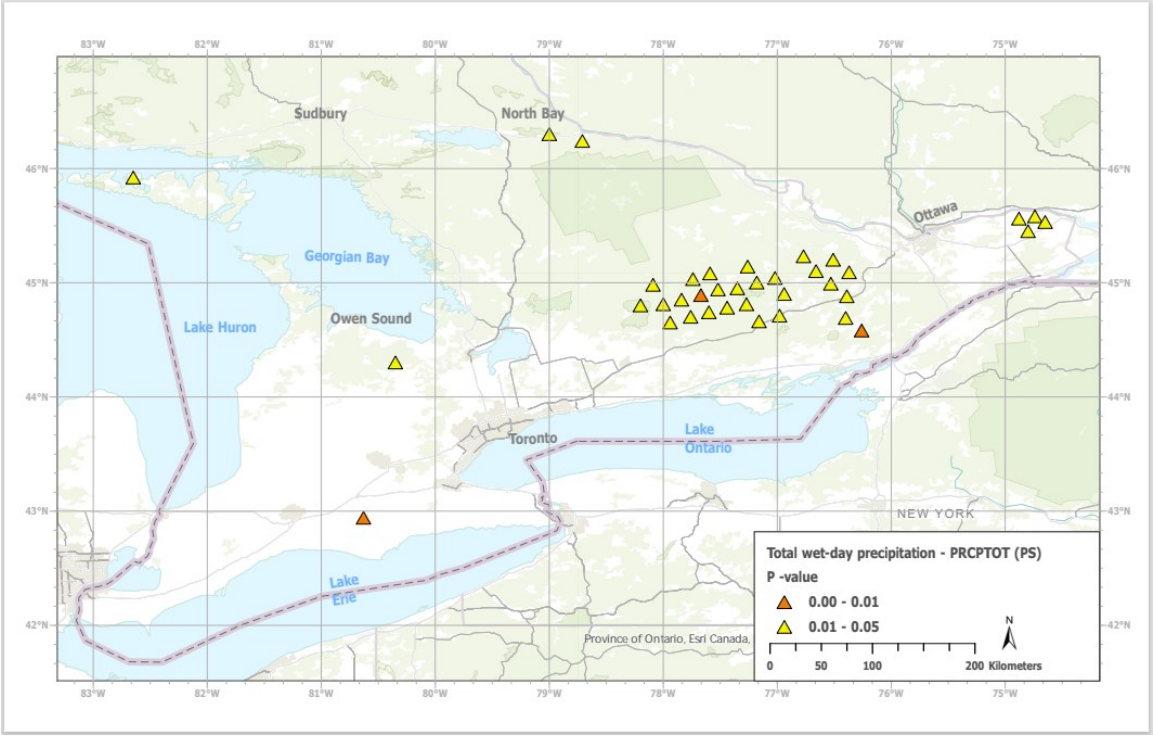

Figure 21: Map of trend significance for total wet-day precipitation (PRCPTOT) in the PS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend

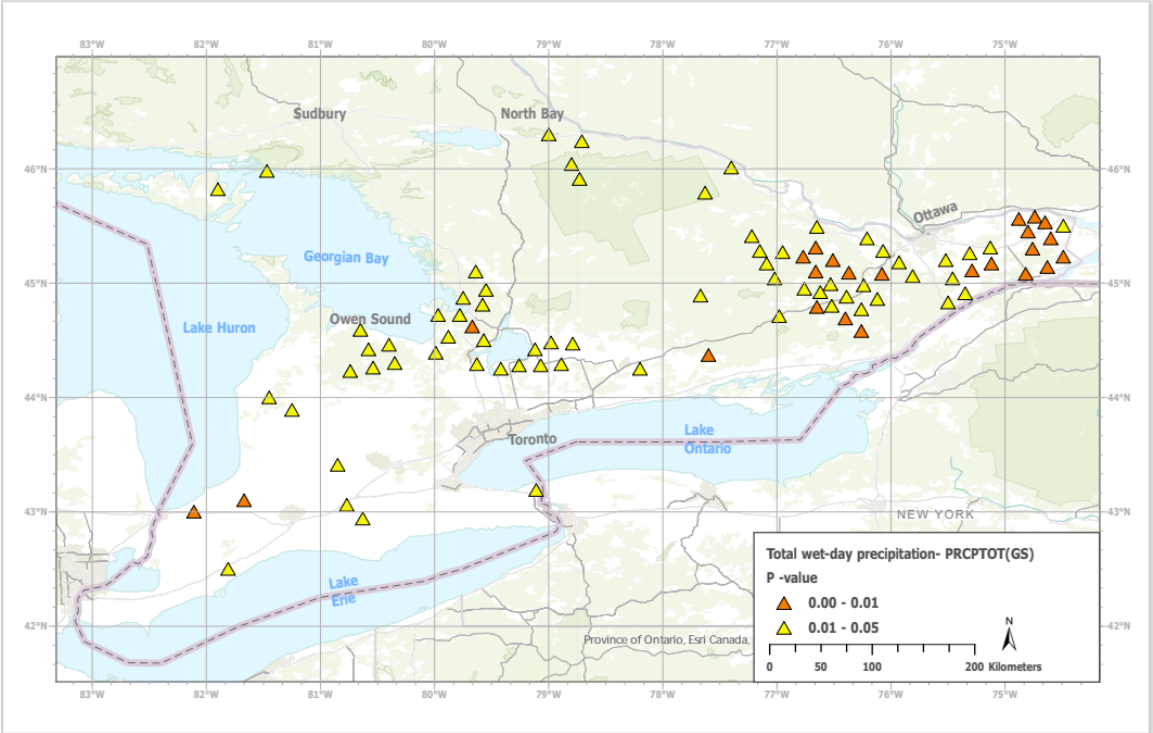

Figure 22: Map of trend significance for total wet -day precipitation (PRCPTOT) in the GS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend

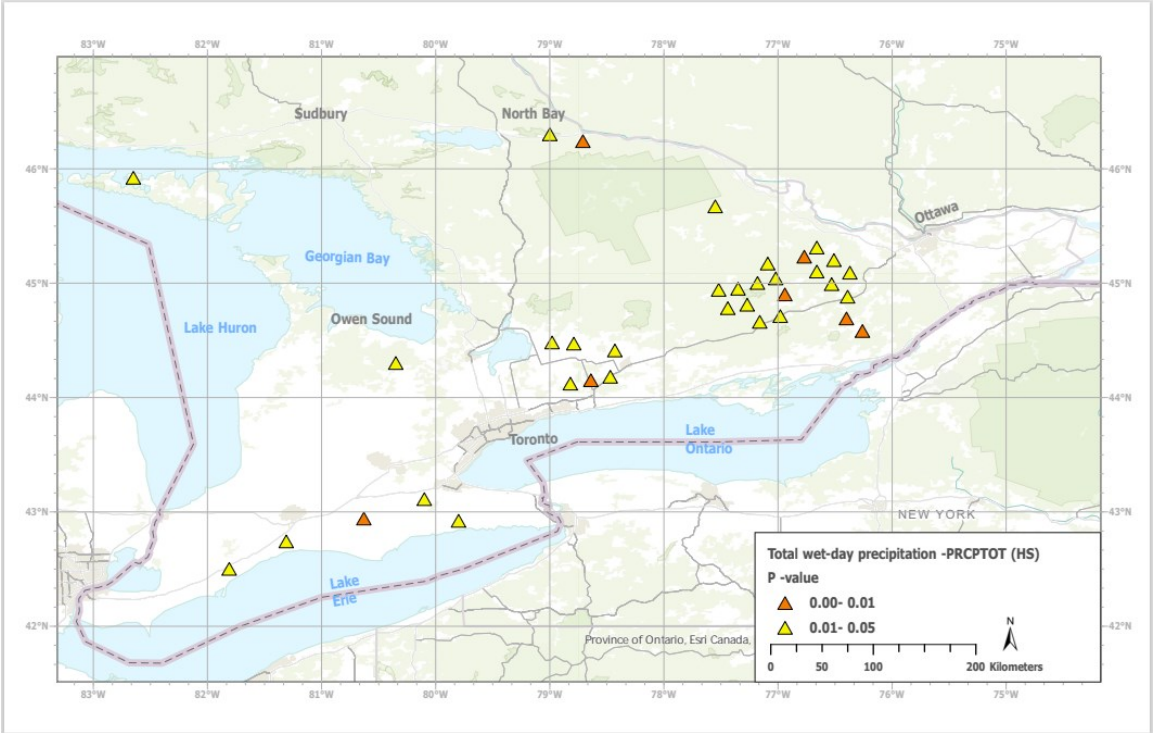

Figure 23: Map of trend significance for total wet-day precipitation (PRCPTOT) in the HS. Yellow triangles represent significant trends (P-value from 0.01 to 0.05), and red triangles represent high-ranking significant trends (P-value less than 0.01). The empty space represents townships where the trends were not statistically significant. Upright triangles indicate an upward trend, while downward triangles indicate a downward trend