Spatio-temporal patterns of extreme weather events and their impacts on corn (*Zea mays*) and soybeans (*Glycine max*) in eastern Ontario

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Abstract

Extreme weather events have adverse environmental and economic effects, with sectors such as agriculture being particularly vulnerable to their impacts. Changes in extreme weather events in eastern Ontario from 1961 to 2010 were investigated by calculating and analyzing spatial and temporal trends in extreme event indicators. In addition to widely used generic and agroclimatic indicators, a set of corn- and soybean-specific indices was developed taking into account individual crop tolerances to extreme weather at different crop growth stages. A shift to a warmer and wetter climate and increases in accumulated crop heat units and growing season length were prominent trends in the region. Flooding conditions during soybean planting season and early vegetative stages of corn development became more prevalent over time. Additionally, increases in drought events during critical reproductive stages were recorded for both crops. The most significant changes in extreme events were observed in the eastern part of the region and along the St. Lawrence River, where most agricultural lands are located. The results of this research will allow farmers and policy makers to better understand extreme weather events, identify opportunities and threats to crop production, and make informed decisions on modifying agricultural practices and developing tools to support strategic planning and adaptive policy development.

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Chapter 1. Introduction and Literature Review

1.1 Research context

Climate change is having an impact on the frequency and severity of extreme weather events such as heat waves, droughts, high intensity storms, and flash floods. As their frequency increases, extreme events are expected to adversely affect the environment and a variety of economic sectors such as agriculture. According to Ontario Ministry of Agriculture, Food and Rural Affairs (OMAFRA), the agri-food sector in Ontario accounts for 5.8% of provincial gross domestic product, with primary agriculture constituting 12% of the agri-food sector in the province (Staciwa 2016), making it an important industry in the region.

A significant increasing trend in annual and seasonal temperature extremes was recorded in both the lower and higher percentiles of daily minimum and maximum temperature distributions in Canada in the 20th century (Bonsal et al. 2001). Fewer days with extreme low temperatures and more days with extreme high temperatures were observed in most seasons (Vincent and Mekis 2006). Analyses of precipitation indices show an increase in total precipitation and the number of heavy precipitation events as well as a decrease in the maximum number of consecutive dry days (Zhang et al. 2001, Vincent and Mekis 2006). Overall, the frequency of extreme events in Canada, including high intensity storms, freezing rain and heat waves, increased significantly in the past decades (Chiotti and Lavender 2008), leading to issues such as soil erosion, crop damage, and an increase in livestock fatalities.

Research conducted on extreme weather events and their impacts on Canadian agriculture (Motha and Baier 2005; Reid et al. 2007) shows and increase in extreme

weather events are already occurring in all regions of the country and this trend is expected to persist into the future. Increasing rates of change may pose difficulties for adaptation, making farmers more susceptible to extremes (Wall et al. 2007; Kulshreshtha et al. 2010). Potential negative impacts of extreme weather events include crop damage from excess heat, increased moisture stress and droughts, increased soil erosion, excessive soil moisture, and more frequent plant diseases and pest outbreaks (Motha and Baier 2005). In a survey by Wreford et al. (2010) in Ontario, 80% of respondent farmers judged extreme events to be the most significant impact to which adaptation was required. The timing of extreme events in relation to stages of plant development has been identified as an important factor by a number of researchers, including Motha and Baier (2005) and Lemmen and Warren (2008). Extreme weather events may affect long-term yields if they occur at crucial plant developmental stages, such as germination and flowering. Extreme events may also make the timing of field applications more difficult, thus reducing the efficiency of farm inputs (Motha and Baier 2005).

Eastern Ontario experienced a number of extreme weather events in past decades, the most recent being the drought of 2012 that produced a devastating effect on the region's major crops, such as corn (Agricorp 2012). With recent increases in the total area of land under corn (31% increase between 2006 and 2011) and soybeans (57% increase between 2006 and 2011) reported by Statistics Canada (2011a), the need to adequately assess risks to these crops is growing.

Most earlier studies focused on changes in general temperature and precipitation regimes and the effects of these changes on crops (Bootsma et al. 2005; Lemmen and Warren 2008); however, little has been done to assess the sensitivity of crops to extreme

weather events. Changes and trends in extreme weather events are related to local climate variability and, therefore, not uniform across the globe (Jamieson 2011), so regional and/or single-site analyses are recommended in order to better understand spatial patterns and temporal variability of climate extremes (Bartholy and Pongracz 2007; Brown et al. 2010; Zhang et al. 2014). The necessity to conduct regional studies that assess levels of exposure and vulnerability of crops to climate extremes has also been identified by the Intergovernmental Panel on Climate Change (IPCC 2014). Significant improvements in data collection, dissemination, and analysis are required to support adaptation activities in the agricultural sector (Nelson et al. 2009).

Climate indices have been widely used to monitor climate change and develop characterizations of risk that can be used in planning (Frich et al. 2002; Moberg and Jones 2005; Alexander et al. 2006; Brown et al. 2010; Caesar et al. 2011). In addition to core climate indices developed by the World Meteorological Organization (WMO), specific indicators addressing the needs of the agricultural sector are required to better assess and respond to changes in weather extremes at critical phenological periods.

Examining past occurrences of extreme events can improve our understanding of the impacts of climate extremes on crop productivity and sensitivity of crops to extreme weather events. Information on the effects of extreme temperature and precipitation on corn and soybean production can be used to improve crop models and result in accurate quantification of the impacts of weather extremes on crop production at the regional level (Luo 2011). Assessing extreme weather related risks at critical phenophases will result in more focus-oriented impact assessments and help increase the resilience of the agricultural sector to climate change (Luo 2011). Providing user-oriented weather risk

information will help minimize crop losses and improve the yield and quality of agricultural products as well as reduce the impact of extreme events on infrastructure and natural ecosystems that are important for agricultural operations (Hay 2007).

1.2 Research goals and objectives

To provide end-users with information on spatial and temporal changes in weather extremes in eastern Ontario and increase their understanding of the nature of crop-specific extreme weather events, two main research goals were identified.

First, the investigation explored changes in temperature and precipitation extremes in eastern Ontario from 1961 to 2010, and identified core extreme event indices that showed the most spatial coherence and exhibited statistically significant trends at different temporal scales (annual, planting season, growing season, and harvesting season).

Second, the research focused on identifying critical temperature and precipitation thresholds for corn and soybeans at different phenological stages and using these to detect spatial and temporal changes in crop-specific extreme events in eastern Ontario from 1961 to 2010.

Research objectives met during the course of the study include: (i) selecting eleven weather stations to represent distinct ecodistricts in the eastern Ontario; (ii) analyzing historical observation records for these weather stations in order to characterize past trends in weather data, including extreme events; (iii) bringing together physical aspects of climate extremes and crop production to define and calculate a list of crop-specific extreme event indices relevant for eastern Ontario; and (iv) assessing trends in core and crop-specific extreme event indices for magnitude and statistical significance.

Meeting these objectives resulted in a detailed characterization of the region's climate, including past trends in mean temperature and precipitation values as well as extreme events, and the production of regionally explicit data on the impacts of extreme events on corn and soybeans.

1.3 Thesis structure

The thesis is organized into five chapters following Carleton University's 'integrated article thesis format'. Chapter 1 sets the context for the study, identifies research objectives and provides a detailed review of climatic and agronomic literature pertinent to the research. Chapter 2 offers an overview of the methodological approach used in the research and provides detailed descriptions of methods used for data selection, transformation and statistical analysis, subsequently discussed in the 'research paper' chapters. Chapters 3 and 4 are those research papers, showcasing results of spatio-temporal characterization of weather extremes in eastern Ontario (Chapter 3), and observed regional trends in key agroclimatic and phenological indices (Chapter 4); they are structured as manuscripts intended for submission to peer-reviewed journals. Chapter 5 summarizes thesis findings, offers a discussion of broader implications of the study along with its limitations, and identifies further research opportunities. A complete bibliography is provided at the end of the document. R-language scripts written to calculate and statistically analyse core extreme weather and phenological extreme event indicators are presented in appendices.

1.4 Global climate change and extreme weather events

Observed changes in the climate system in the past decades include ocean and atmospheric warming, precipitation increases in mid-latitudes, precipitation decreases in tropics and sub-tropics, rising sea levels, and diminishing snow and ice amounts (IPCC 2014). In addition to changes in mean temperature and precipitation values, changes in extreme weather events have been observed across the globe, and the magnitude of these changes has been unprecedented at a number of temporal scales (IPCC 2014).

Weather and climate extremes are meteorological phenomena that are rare within the statistical distribution of specific weather elements at a particular place and can be characterized in terms of their intensity, duration, or frequency (Kharin et al. 2007; Klein Tank et al. 2009). The characterization of climate extremes at the regional scale can provide important information for impact assessment studies (El Kenawy et al. 2011). Improving our understanding of climate extremes can be achieved by calculating indices, derived from available temperature and precipitation data, and analyzing spatial and temporal trends in extreme events.

Multiple studies of trends in extreme weather indices have been carried out globally (Frich et al. 2002; Alexander et al. 2006; Klein Tank et al. 2009) and regionally (Moberg and Jones 2005; Zhang et al. 2005a; Brown et al. 2010; Caesar et al. 2011) in recent years. The majority of the findings show significant upward trends in hot weather extremes and downward trends in cold weather extremes. Precipitation extremes show a smaller degree of spatial coherence globally; however, at more local scales, an increase in wet extremes has been observed in a number of regions, including eastern North America (Vincent and Mekis 2006; Griffiths and Bradley 2007; Brown et al. 2010; Insaf et al.

2013). Further details on past trends in extreme temperature and precipitation events are provided below.

1.4.1 Observed past trends in temperature extremes

Global scale studies of past temperature extremes have been conducted using both weather station and interpolated data and span multi-decadal time periods from as early as 1850 up to 2012 (Frich et al. 2002; Alexander et al. 2006; Klein Tank et al. 2009; IPCC 2014), and they consistently show decreases in the numbers of cold days and cold nights (with respective maximum and minimum temperature below the 10th percentile), and increases in the numbers of warm days and warm nights (with respective maximum and minimum temperature above the 90th percentile) (Figure 1.1).

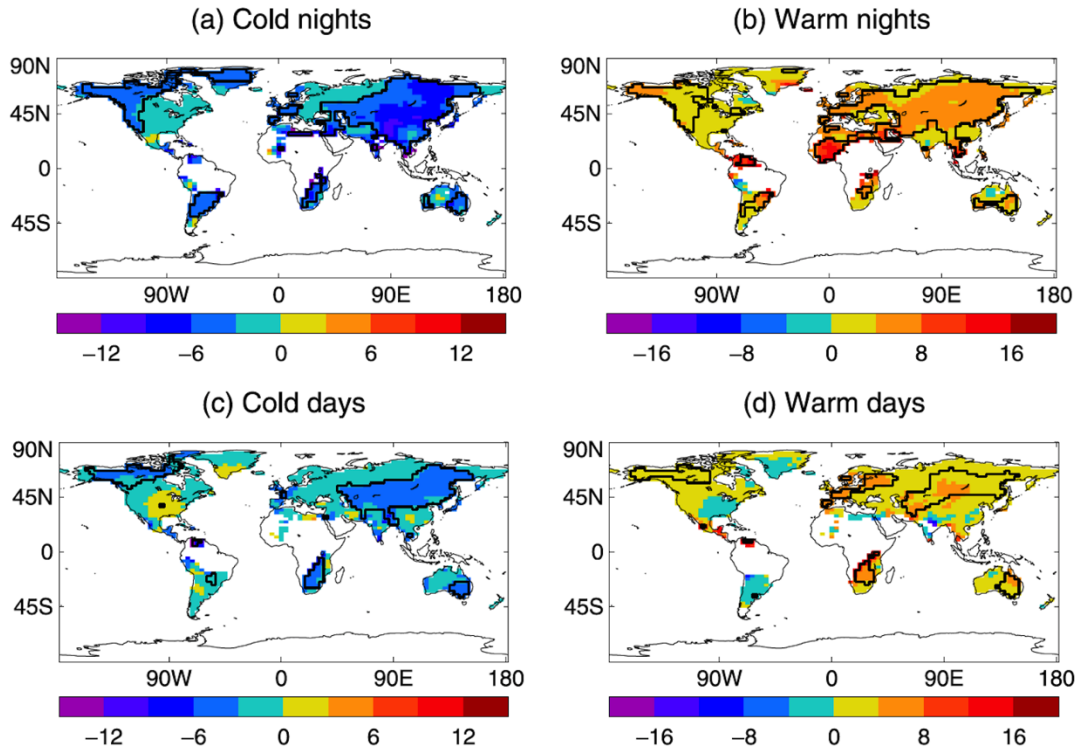


Figure 1.1: Trends (in days per decade) for annual series of temperature indices for 1951-2003 for (a) cold nights, (b) warm nights, (c) cold days, and (d) warm days. Source: Alexander et al. (2006).

A number of regions of the world such as Europe, Asia, and Australia have seen

increases in the frequency of heat waves, with the probability of heat wave occurrence doubling in certain locations (IPCC 2014). A finding that has emerged from multiple studies, including Frich et al. (2002) and Alexander et al. (2006), is that minimum temperatures have been increasing at a greater rate than maximum temperatures, resulting in a decreased daily temperature range, observed over a large percentage of land area. Changes in temperature extremes have been accompanied by considerable decadal and interannual variability (Figure 1.2).

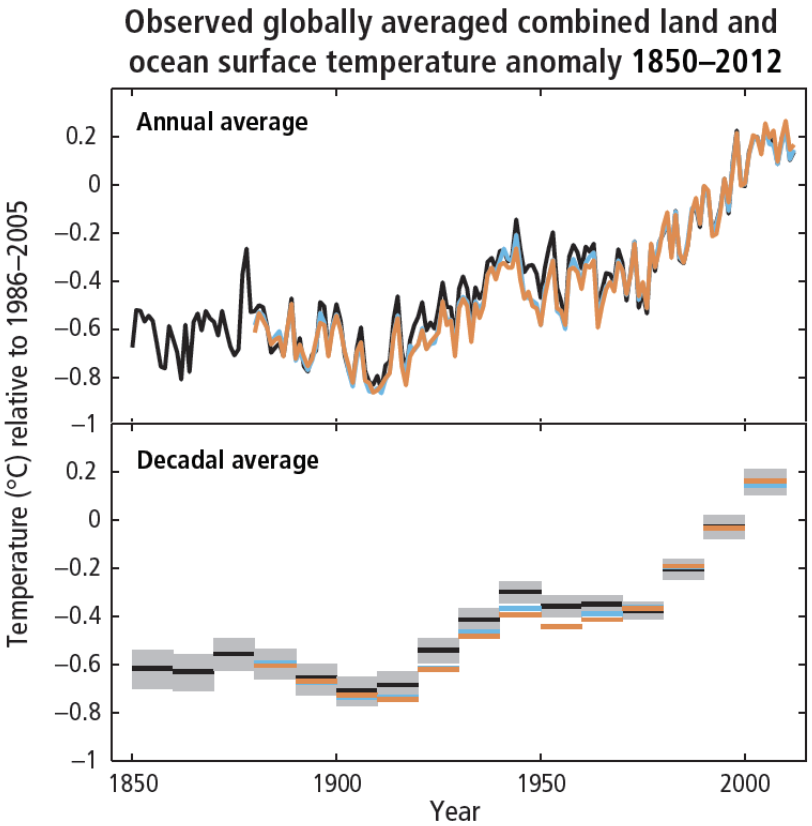


Figure 1.2: Observed global averages of combined land and ocean surface temperature anomalies for 1850-2012, relative to a 1986-2005 climatology, based on datasets produced by Met Office Hadley Centre (black line), NASA Goddard Institute for Space Studies (blue line), and NOAA National Climatic Data Centre (orange line). An estimate of decadal mean uncertainty (90% confidence interval) for the Met Office Hadley Centre dataset is presented in grey shading. Source: IPCC (2014).

Regionally, studies of temperature extremes in the past several decades

demonstrate decreases in cold extremes and increases in warm extremes in Europe (Klein Tank and Können 2003), Africa (Easterling et al. 2003), North America (Peterson et al. 2008), the Middle East (Zhang et al. 2005a), and the Indo-Pacific region (Caesar et al. 2011) among others.

In the North American context, there has been a decrease in cold spells and an increase in warm spells since 1950 and 1970, respectively (Peterson et al. 2008), showing that changes in hot and cold extremes span longer periods of time and are not limited to weather on single days. Increases in the lowest minimum and maximum temperatures have been greater than increases in the highest minimum and maximum temperatures, at approximately 3.5°C and 1°C since the 1960s (Peterson et al. 2008).

Temperature observations in Canada show an increase of 1.6°C in average annual temperature between 1948 and 2015, with regional values ranging from less than 0.6°C in Atlantic Canada to 2.6°C in the Mackenzie District (Environment and Climate Change Canada 2016). Bonsal et al. (2001) and Vincent and Mekis (2006) have noted significant increasing trends in temperature extremes in the higher percentiles of daily minimum and maximum temperature distributions and decreasing trends in extremes in the lower percentiles of daily temperature distributions in Canada in the 20th century. This has been manifested in decreases in cold nights and cold days and increases in warm nights and warm days across the country (Figure 1.3). Fewer days with extremely low temperatures and more days with extremely high temperatures have been observed in most seasons, most prominently in winter and spring (Bonsal et al. 2001; Vincent and Mekis 2006); however, there has only been a marginal change in the number of hot extremes during the summer (Bonsal et al. 2001). In contrast to other seasons, autumn has seen decreases in

both the higher and lower percentiles of daily maximum temperature distributions, specifically in southern Ontario and Quebec, while daily minimum temperature percentiles have increased over most of southern Canada (Bonsal et al. 2001). These observations show that Canada is warming largely because warmer temperatures are occurring in cooler seasons, while extreme cold temperatures are occurring less frequently (Vincent and Mekis 2006). Similar to global studies, the observed warming is associated with a stronger increase in minimum temperatures as opposed to maximum temperatures, resulting in a significant decrease in diurnal temperature range.

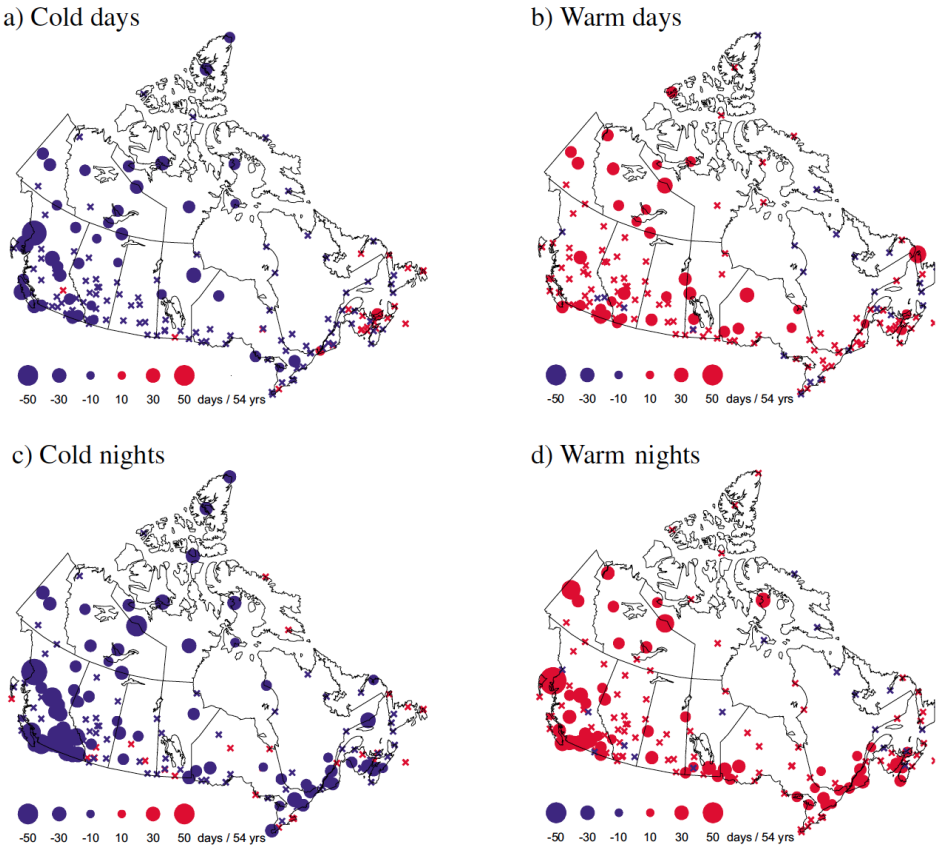


Figure 1.3: Trends for annual series of temperature indices for 1950-2003 for (a) cold days, (b) warm days, (c) cold nights, and (d) warm nights. Blue and red dots indicate trends significant at the 5% level. Crosses denote non-significant trends. Source: Vincent and Mekis (2006).

1.4.2 Observed past trends in precipitation extremes

In past decades heavy precipitation events have increased over most areas, and increases in rare precipitation events have been recorded in Europe and North America (IPCC 2014). Klein Tank et al. (2009) shows that mid-latitudes' storm tracks have shifted northward in the northern hemisphere, and that there has been a net increase in storm frequency/intensity resulting in a larger proportion of annual total rainfall being attributed to heavy rainfall events. Easterling et al. (1999) report that in most areas overall increases and decreases in total precipitation have been accompanied by corresponding increases and decreases in extreme precipitation events. According to Alexander et al. (2006), significant increases in heavy precipitation days (daily precipitation >10 mm) and daily precipitation intensity have been observed in North and South America as well as Europe and western Russia (Figure 1.4a and d). The percentage of annual precipitation on days exceeding the 95th percentile (very wet days) has increased by 1-2% in parts of North America, Europe, and western Russia (Figure 1.4b). The area affected by droughts has increased in many regions since 1970 (Klein Tank et al. 2009); however, the overall maximum number of consecutive dry days has decreased (Frich et al. 2002) (Figure 1.4c).

Importantly, it has been noted that there has been less spatial coherence and statistical significance in trends in precipitation extremes compared to temperature extremes. This is consistent with greater spatial and temporal variability of precipitation events (Alexander et al. 2006; Vincent et al. 2011) compared to temperature.

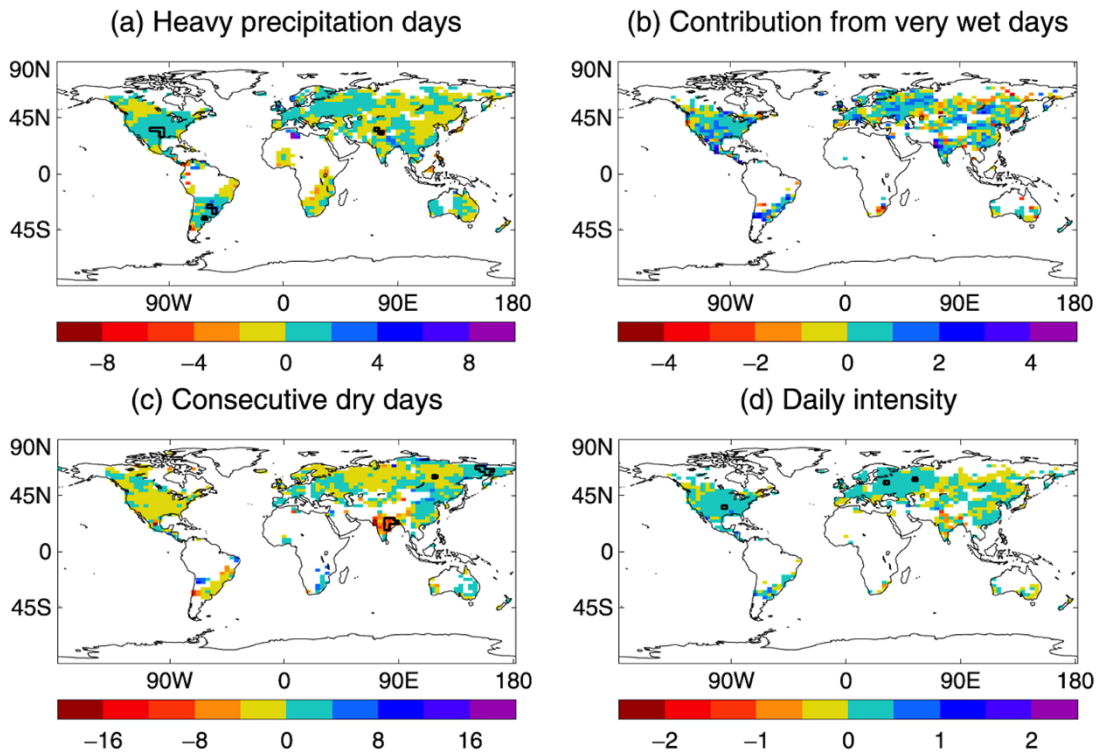


Figure 1.4: Trends for annual series of precipitation indices for 1951-2003 for (a) heavy precipitation days, (b) very wet days (in %), (c) consecutive dry days, and (d) daily precipitation intensity (in mm/day). Source: Alexander et al. (2006).

Analyses of precipitation extremes in Canada show an increase in total precipitation and the number of heavy precipitation events as well as a decrease in annual total snowfall and the maximum number of consecutive dry days (Zhang et al. 2001, Vincent and Mekis 2006) (Figure 1.5a and d). This is in agreement with research done in the Northeastern United States (Griffiths and Bradley 2007, Brown et al. 2010, Insaf et al. 2013), showing increases in precipitation extremes. Observed increases in total precipitation, averaging just under 20% between 1948 and 2015 (Environment and Climate Change Canada 2016), have been attributed to a greater number of small and moderate events, resulting in a decreased daily intensity (Zhang et al. 2001, Vincent and Mekis 2006) (Figure 1.5b). In the second half of the 20th century the number of very wet days and heavy precipitation days have increased by 0.4 days and 1.8 days, respectively

(Figure 1.5c and d). The number and intensity of precipitation events have not been uniform across the country, with no consistent trends found in the 20th century (Zhang et al. 2001). In Ontario, the maximum intensity for one-day, 60-minute and 30-minute rainfall events increased on average by 3-5% per decade from 1970 to 1998 (Adamowski et al. 2003). Overall, the frequency of extreme precipitation events, including high intensity storms and freezing rain, has increased significantly in the past decades (Chiotti and Lavender 2008), leading to issues such as soil erosion and crop damage.

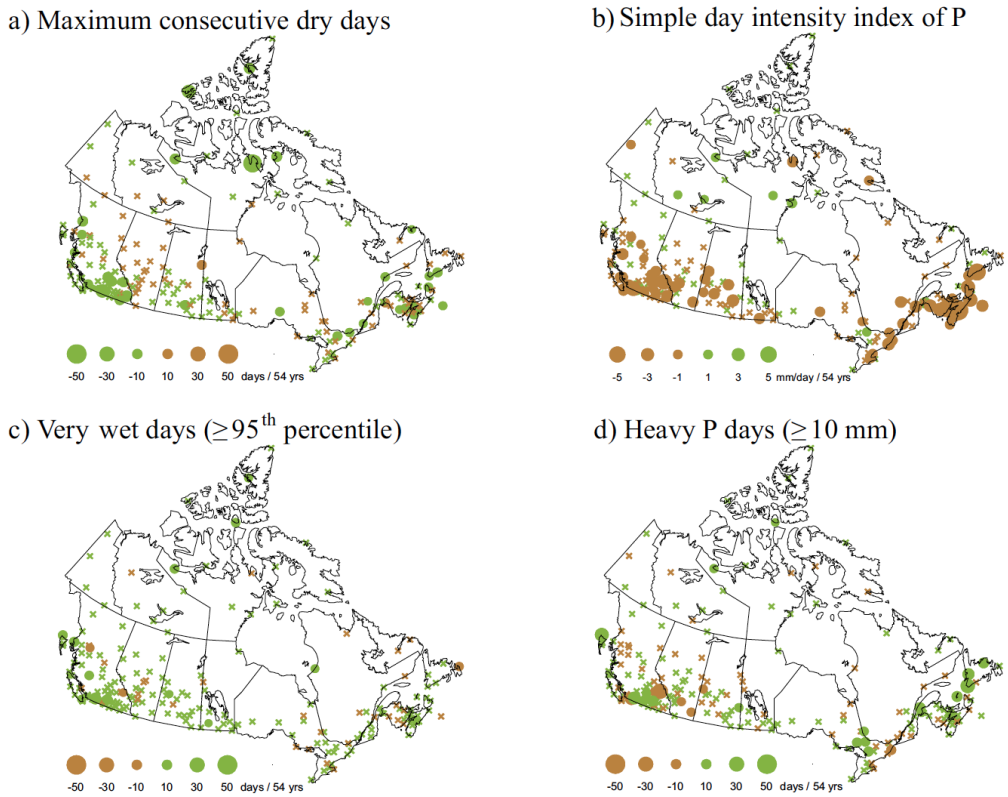


Figure 1.5: Trends for annual series of precipitation indices for 1951-2003 for (a) consecutive dry days, (b) daily precipitation intensity, (c) very wet days, and (d) heavy precipitation days. Brown and green dots indicate trends significant at the 5% level. Crosses denote non-significant trends. Source: Vincent and Mekis (2006).

1.5 Extreme weather events and agricultural crop production

Development and yield of warm-season crops such as corn and soybeans depend on a number of climatic and environmental factors, including temperature, precipitation,

soil fertility, soil moisture, and photoperiod (Brown and Bootsma 1993). Increased frequency and intensity of extreme weather events such as droughts, heat waves, and floods, coupled with lack of preparedness to increasing climate variability, has the potential to damage infrastructure and impact agricultural crop production and water supply (IPCC 2014).

Temperature stress occurs when crop-specific optimum temperature thresholds are exceeded, while severe plant damage and death are the results of the exceedance of critical temperature levels (Luo 2011). Stress and damage are especially great during early reproductive stages such as flowering and pollination as well as grain and fruit formation (Hatfield et al. 2011). Ultimately, temperature stresses during reproductive growth stages shorten the duration of these stages and result in yield reductions (Hatfield et al. 2011).

Excessive precipitation and drought can be major determinants of crop yield and affect field operations (Rosenzweig et al. 2002). Heavy rains in spring cause planting delays and often result in elevated disease risks, while excessive fall precipitation delays harvesting and has a detrimental effect on crop quality (Weber and Hauer 2003; Hatfield et al. 2011). Shifts in precipitation distribution and greater amounts of rain falling during high precipitation events result in insufficient water availability and drought conditions at critical crop growth stages (Hatfield and Prueger 2004). Lack of available soil moisture becomes a particularly important issue when air temperature is elevated because this increases moisture retention capacity of air and consequently evaporation, imposing further stress on crops.

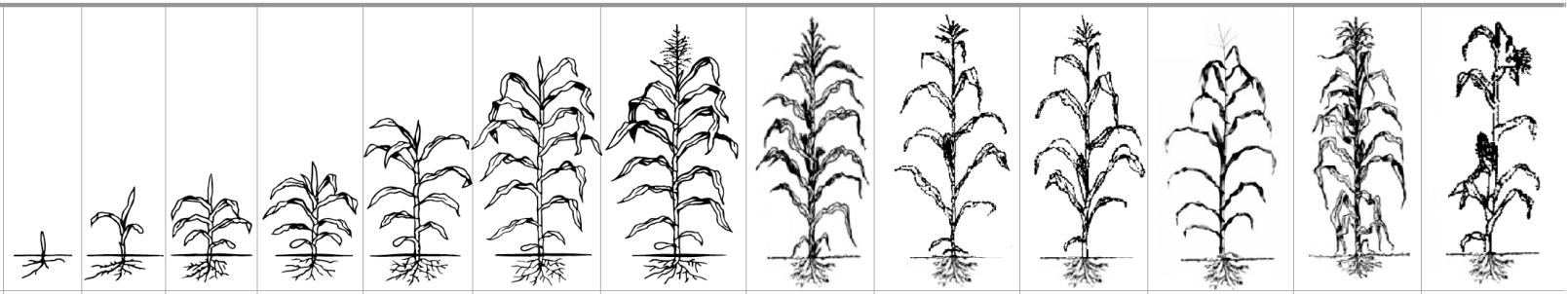
Sensitivity of specific crops to adverse climatic conditions varies from species to species and has to be taken into consideration when developing adaptation strategies and making farm management decisions.

1.5.1 Corn (Zea mays) phenology and sensitivity to extreme weather

Learning about corn phenology is important in order to better understand how the plant is affected by severe weather conditions at different growth stages. This would allow growers to maximize the use of available heat units and minimize the risks of exposure to flooding, drought, frost, and temperature stresses (Kumudini and Tollenaar 1998).

Corn growth and development can be divided into distinct vegetative and reproductive stages (Figure 1.6). Plant development, particularly during vegetative growth stages, is driven mostly by temperature (OMAFRA 2009a). Rates at which various development stages are reached can be quantified by the availability of temperature based crop heat units (CHUs) (Bootsma and Brown 1993), as shown in Figure 1.6.

The vegetative phase begins at planting, which typically occurs in eastern Ontario in the first half of May (OMAFRA 2009a). In favourable conditions, with sufficient moisture and soil temperature of over 10°C at 5 cm depth, emergence occurs within approximately two weeks (OMAFRA 2009a). It is achieved by the mesocotyl pushing the coleoptile containing embryonic leaves above the soil surface (Figure 1.7). Corn germination and emergence can be delayed under sub-optimal conditions, resulting in uneven seedling emergence. When 25% of the crop stand emerges a week late, yield losses can reach 7%, while a three-week delay in emergence of 50% of the crop stand



Stage	VE	V1	V4	V6	V8	V12	VT	R1	R2	R3	R4	R5	R6
Stage title	Emergence	One visible leaf collar	Four visible leaf collars	Six visible leaf collars	Eight visible leaf collars	Twelve visible leaf collars	Tasseling	Silking	Blister	Milk	Dough	Dent	Maturity
CHUs required	180	330	630	680	930	1,270	1,310	1,480	1,825	2,000	2,165	2,475	2,800

Figure 1.6: Vegetative and reproductive growth stages in corn. Not all vegetative stages are shown. Required CHUs represent approximate heat units required for reaching various stages of corn development.
Sources: University of Nebraska-Lincoln; Spaar et al. 2006; OMAFRA 2009; Purdue University 2009.

might cause a 20% yield loss (Nielsen 2000). The growing point of a corn plant remains below the ground until approximately V6 stage, when six leaves are visible above the soil surface (Kumudini and Tollenaar 1998). Rapid stalk elongation and root development are key processes during early vegetative stages of corn growth cycle, contributing to successful crop establishment (Abendroth et al. 2011).

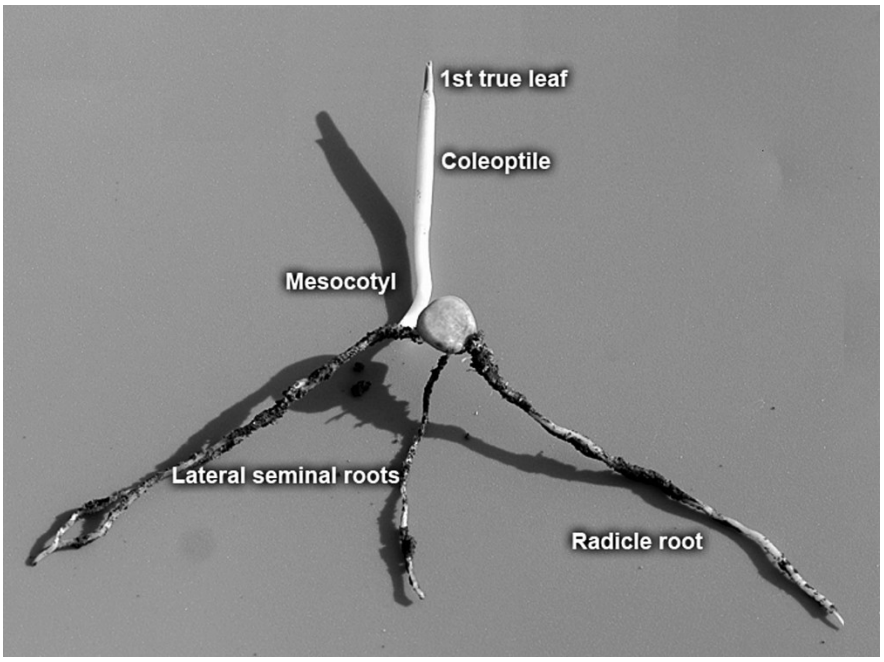


Figure 1.7: Corn seedling morphology at emergence. Source: Nielsen (2014).

During early vegetative stages most weather related problems in corn result in growth delays and poor stand establishment (Ritchie et al. 1993). Frost, hail, and extreme wind events do not pose significant risks to the corn plant when its growing point is below ground, while soil conditions are critical (Kumudini and Tollenaar 1998). Wetter than normal conditions shortly after planting increase disease rates and slow soil warming, making it too cool to sustain proper root growth, while overly dry conditions reduce the rate of nutrient uptake of corn plants, impacting the nutrient content of crops (Nielsen 2000). Early season flooding limits corn survival to five days in cool conditions

and in some cases to as little as 24 hours in temperatures of more than 25°C, by limiting oxygen supply in the soil (OMAFRA 2009a; Nielsen 2000).

After the V6 stage, the growing point moves above the ground and the plants become more tolerant to flooding, yet more susceptible to frost injury (OMAFRA 2009a). Temperatures below 0°C are lethal to corn during vegetative stages of development and can result in yield losses of 40-50% if >70% of the leaves are damaged, and a 15-30% decrease in yield if 30-50% of the leaves are damaged at or after the V8 stage (Carter 1995; Coulter 2010). Frost can also arrest the development of the reproductive organs, causing significant yield losses and in some cases complete crop failure (Nielsen 2000). During the later (post V8) vegetative stages, marked by early ear and tassel development and continuing leaf emergence, dry conditions can be beneficial to corn growth by encouraging the more rapid downward growth of the roots (OMAFRA 2009a).

VT (tasseling) and R1 (silking) stages represent the emergence of male (tassel) and female (silks) flowers of a corn plant, respectively (Figure 1.8). The combined length of both stages ranges from several days to a week, during which both pollination (the transfer of pollen from the tassel to the silks) and fertilization (the union of male and female gametes in the ovule) take place (Nielsen 2000). Corn sensitivity to environmental stressors is highest during the two stages, when hail, heat, and drought conditions can result in tassel and leaf damage, decreased pollen viability, poor silk development, insufficient ear size, and ultimately in yield reduction (Kumudini and Tollenaar 1998; Nielsen 2000). Specifically, a 100% leaf loss due to hail during the tasseling stage is likely to result in complete yield loss (Nielsen 2000). Temperatures above 32°C cause a

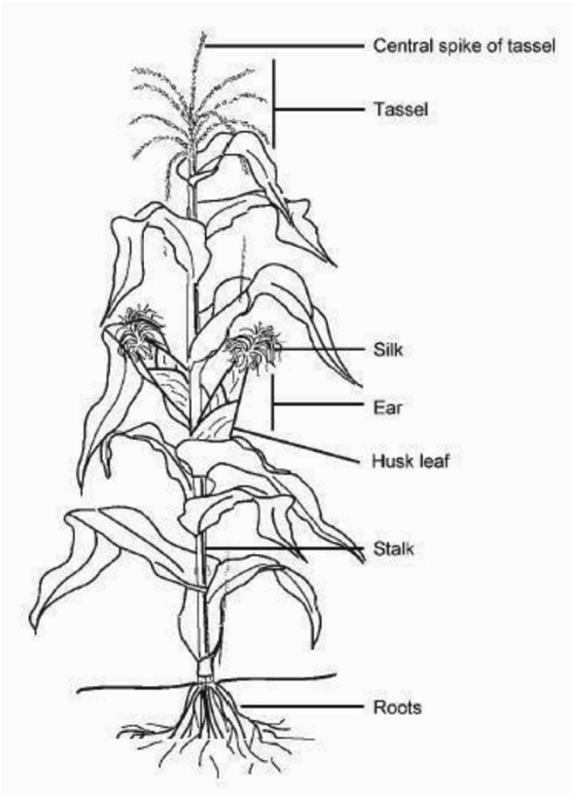


Figure 1.8: A grown corn plant. Source: Pacific Field Corn Association (2012).

decrease in pollen viability, increasing the percentage of non-germinated pollen up to 51% (Schoper et al. 1987). More importantly, high temperatures also affect the receptiveness of silks to pollen, causing low numbers of kernel numbers per ear (Nielsen 2000). Corn is fairly drought resistant, with drought tolerance rated as medium-high compared to other common crops (Brouwer and Heibloem 1986); however, the plant is still susceptible to dry conditions, particularly during the VT and R1 stages (OMAFRA 2009a). Corn evapotranspiration requirements during pollination are approximately 8 mm per day, with average yield loss due to insufficient moisture being close to 7% per day (Shaw 1988; Rhoads and Bennett 1990). Additionally, Runge (1968) found that low rainfall during VT and R1 stages reduces yield by 1.2 to 3.2% per 1°C rise. Corn plants that are weakened by heat and drought stress are more susceptible to damage from insects

and diseases and have poor nutrient uptake (Lauer 2006).

Corn reproductive stages from R2 (blister) to R6 (maturity) represent the grain fill period, when crop yield potential is realized (OMAFRA 2009a). After the kernels have been initiated, they progress from blisters containing clear fluid (R2) to starch accumulating yellow coloured kernels filled with milky fluid (R3) to kernels with thicker doughy filling (R4) to dented, mostly solid kernels that have reached about 95% of their potential dry weight (R5) (Abendroth et al. 2011). The grain filling process is typically complete within 60 days of fertilization when a black layer has formed at the base of the kernel and maximum dry weight has been reached (Ritchie et al. 1993). Kernel moisture content decreases as the plant matures, going down from 85 and 80% during the blister and milk stages to 70% at the dough stage, 55% at the dent stage, and 30% at maturity (Nielsen 2000).

The absence of stress during the grain fill period results in high yields, while extreme weather conditions during early and late reproductive stages can result in kernel abortion and lightweight grain, respectively (Abendroth et al. 2011). Some of the common reasons for low corn yield due to stresses during the reproductive phase include incomplete kernel set, low kernel weight, and premature plant death resulting in stand loss (Nielsen 2000). Reduced photosynthesis due to severe drought and heat stress can result in the abortion of large numbers of developing kernels during R2 and R3 stages and negatively affect kernel size during R4 and R5 stages, often leading to premature black layer formation and lower grain yield (Lauer 2006). Corn daily water needs during milk, dough, and dent stages average 6.5 mm, with drought stress resulting in daily yield reduction of 2.5 to 6%, depending on drought severity (Shaw 1988; Rhoads and Bennett

1990). High temperatures (over 34°C during the day and 20°C at night) increase drought related yield losses by 1, 2, and 4% after 4, 5, and 6 days of heat stress, respectively (Ohio State University 2012). Frost damage to corn occurs when temperatures fall below 0°C for over 4 hours or below -2°C for several minutes (Nielsen 2000), being the greatest in low-lying areas and in dry soils (OMAFRA 2009a). The impact of frost damage is proportional to the stage of corn development as well as the amount of vegetation tissue killed (Lauer 2004), with estimated grain yield loss of 58, 45, and 12% after complete plant damage occurring at dough, early dent, and late dent stages, respectively (Staggenborg et al. 1996). Premature leaf loss due to frost can result in losses of 35, 26, and 6% at dough, early dent and late dent stages, respectively (Staggenborg et al. 1996). After the plant has reached physiological maturity (R6), stress has little effect on grain yield (Nielsen 2000), although crop harvesting can be affected by excessive precipitation.

1.5.2 Soybean (Glycine max) phenology and sensitivity to extreme weather

Soybean is a photoperiod sensitive plant; therefore, in addition to heat unit accumulation, its development is affected to a large degree by day length and the amount of sunlight it receives (OMAFRA 2009a). Rates of plant development are generally faster under warm temperatures and slower under cool temperatures (Kumudini and Tollenaar 2000). Known as short-day plants, soybeans develop vegetatively until day length becomes short enough to trigger flowering (OMAFRA 2012). Following the onset of flowering, vegetative development of a soybean plant either stops or continues, putting the variety into a determinate or an indeterminate class, respectively (Kumudini and Tollenaar 2000). Determinate soybean varieties are commonly grown in southern latitudes, whereas indeterminate types are prevalent in northern latitudes, where

continuous node production and flowering allows them to adjust to possible short-term stresses and unfavourable environmental conditions and to better exploit the shorter growing season (Kumudini and Tollenaar 2000; University of Wisconsin 2012). The majority of soybean varieties grown in eastern Ontario are of the indeterminate type (OMAFRA 2009a) and fall in 00, 0, I, and II maturity groups according to their response to the photoperiod (Figure 1.9).

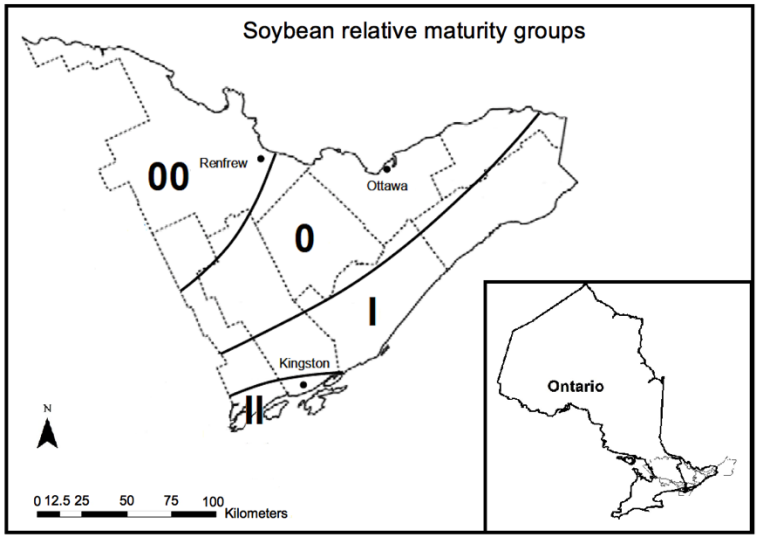
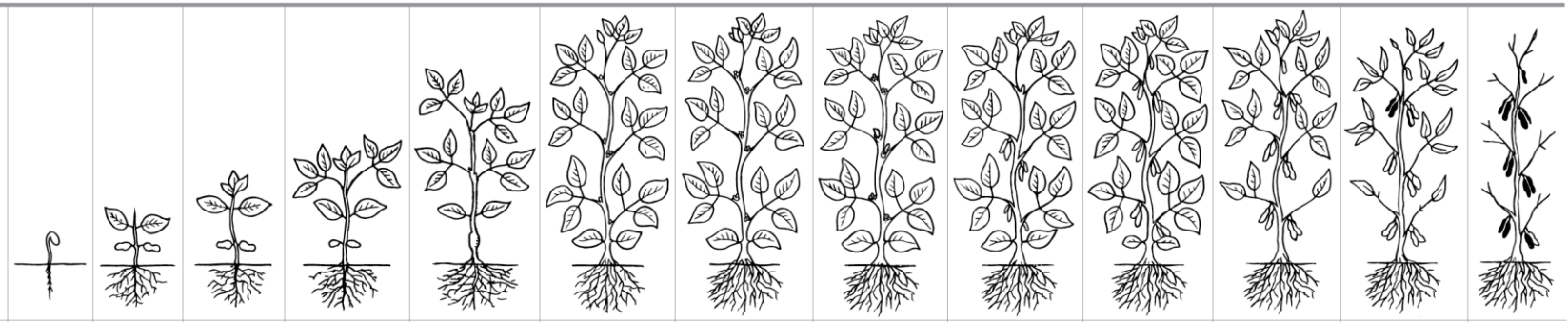


Figure 1.9: Distribution of soybean relative maturity groups in eastern Ontario. Source: OMAFRA (2012).

Soybean development stages are shown in Figure 1.10 and are characterized by criteria established by Fehr and Caviness (1977), falling into vegetative (V) and reproductive (R) phases.

Soybean planting in eastern Ontario typically occurs in May, with the highest yields obtained from plantings in the first half of the month (OMAFRA 2009a). Delayed planting causes a corresponding delay in maturity, with each three days of planting delay resulting in a 1-day delay in maturity (OMAFRA 2009a). In addition to delays in maturity, late planting can lead to yield reductions of about 4% for each week of planting



Stage	VE	VC	V1	V3	V5	R1	R2	R3	R4	R5	R6	R7	R8
Stage title	Emergence	Unifoliate	First trifoliate	Third trifoliate	Fifth trifoliate	Beginning bloom	Full bloom	Beginning pod	Full pod	Beginning seed	Full seed	Beginning maturity	Full maturity
Days after seeding	12	17	22	32	42	55	65	75	85	95	115	120	130+

Figure 1.10: Vegetative and reproductive growth stages in soybean. Not all vegetative stages are shown. Days to reach growth stages have been estimated using the optimum seeding date of May 10.
Sources: OMAFRA 2009; Casteel 2010.

delay due to the reduction in the vegetative size of the plants, fewer nodes, and a reduced number of pods per plant (Ball et al. 2001; OMAFRA 2009a; Robinson et al. 2009; University of Wisconsin 2012). Late planting can also lead to soybeans' exposure to freezing temperatures during the fall, before they have reached maturity (Staggenborg et al. 1996). Cold spells and rain during the planting season are likely to impact seedbed conditions, create a poor operating environment for farm machinery, and prevent timely seeding (Vonk 2013).

Emergence typically occurs within 1 to 3 weeks after planting, provided soil moisture and temperature conditions are optimal (OMAFRA 2009a; University of Wisconsin 2012). Given that a soybean seed needs to absorb 50% of its weight in water in order to germinate (Ritchie et al. 1994), moisture availability after planting is critical. According to Board and Kahlon (2011), drought stress during seedling emergence can lead to low plant populations and, ultimately, lower yields.

The appearance of fully developed unifoliate (cotyledonary) leaves marks the VC stage of soybean development (Kumudini and Tollenaar 2000). Following that, a new V stage is reached approximately every 5 days when trifoliate leaves are fully open at plant nodes on the main stem (University of Wisconsin 2012). After the plant has reached the V5 stage, new trifoliate leaves appear every 3 days (University of Wisconsin 2012). Given that the growing point of a soybean plant is above the ground starting at the VC stage, it can be killed by spring frost if air temperature falls below -2.8°C; however, if frost or hail damage the growing point, but not the entire stem below the unifoliate leaves, the plant can recover by sending new shoots from the base of the cotyledons (OMAFRA 2009a). Severe damage to the plant stem that can be caused by frost or hail

makes the plant more susceptible to disease; recovery is often difficult, resulting in yield losses of up to 10% if stem loss approaches 50% (OMAFRA 2009a). Leaf loss is less critical, with the loss of 50% of foliage at the V6 stage resulting in just 3% yield loss (University of Wisconsin 2012). During vegetative growth stages soybean plants are sensitive to extreme water regimes (Sullivan et al. 2001; VanToai et al. 2010; Board and Kahlon 2011). Drought conditions can reduce a plant's leaf area and affect future crop growth rate by impairing its future potential for obtaining water (Board and Kahlon 2011), and cause a premature switch to reproductive development, resulting in a smaller amount of nodes produced, and hastened flower and pod appearance (Frederick et al. 1989; Desclaux and Roumet 1996). Three days of flooding at V2 and V3 stages can result in up to 20% yield reduction, while six days of flooding at the same stages could decrease the yield by over 90% (Sullivan et al. 2001). Waterlogging, or root flooding, for as little as two days at the V4 stage can result in an 18% reduction in soybean grain yield (Fehr and Caviness 1977).

The reproductive phase of soybean development is marked by the onset of flowering, which, for the indeterminate varieties grown in eastern Ontario, typically begins around the V5 vegetative stage (OMAFRA 2009a). The plant continues to grow and produce new nodes till the R5 stage, so vegetative and reproductive stages occur concurrently (Egli and Leggett 1973; OMAFRA 2009a).

The two flower stages (R1 and R2) are marked by the appearance of open flowers, initially at the fifth node, and then moving to upper and lower nodes along the stem (OMAFRA 2009a). Exposure to extreme temperatures during these stages has dramatic effects on pollen growth and survival and, consequently, results in poorly

developed pods and reduced yields (OMAFRA 2009a; Hatfield et al. 2011). According to Salem et al. (2007), soybean pollen viability is reduced at temperatures above 30°C, reaching complete failure at 47°C. Exposure to high temperatures of 38°C during the day and 30°C at night can reduce pollen production and germination by 34 and 56%, respectively, compared to a more favourable regime of 30°C during the day and 22°C at night (Salem et al. 2007). Severe frost (-2 to -1°C) can reduce yield by up to 80% and impact yield quality (Snyder and de Melo-Abreu 2005; OMAFRA 2009a; Berglund 2011). Water stress as well as excessive moisture during R1 and R2 stages result in increased flower and pod abortion and lower yields (Westgate and Peterson 1993; VanToai et al. 2010). Specifically, four weeks of waterlogging at R1 and R2 stages can reduce soybean yield by 25% (VanToai et al. 1994). In field experiments conducted by VanToai et al. (2010), two weeks of above the surface flooding at the R2 stage resulted in average yield losses of 48.5% and a median yield loss of 54.4%. Since flowering lasts between three and five weeks, the plants are able to adjust to the effects of possible short-term stresses during that period (University of Wisconsin 2012).

Short pods, 0.5 and 2 cm in size, are visible at the top four nodes of a soybean plant at the R3 and R4 stages, respectively (Kumudini and Tollenaar 2000; OMAFRA 2009a). Formation of a full-length pod usually occurs two weeks after flowering (University of Wisconsin 2012). Seed development begins at the R5 stage, by which flowering has completed at all nodes of the plant and maximum plant height has been reached (OMAFRA 2009a). As the seed weight increases, the percentage of yield produced during seed development grows from 25% at the R5 stage to 47% at the R6 stage, when all pods have reached the mature length (Berglund 2011; University of

Wisconsin 2012). Starting at the R4 stage, soybean's ability to compensate for the effects of environmental stresses once favourable conditions return decreases significantly (Ritchie et al. 1994; Egli 2010); therefore, stresses at later reproductive stages, most notably R5, have the greatest impacts on crop yield.

Optimum mean daily temperature during post-flowering stages of soybean development is 23°C, with seed growth rate decreasing and reaching zero when mean temperature reaches 39°C (Baker et al. 1989; Pan 1996; Thomas 2001; Boote et al. 2005). A 1.3% decrease in soybean yield has been observed per 1°C increase in mean temperature (Lobell and Field 2007). Pod formation and seed development are affected by temperatures exceeding 29°C and severely limited by temperatures above 35°C, with 22 and 38% yield loss resulting from air temperatures of 33 and 35°C, respectively (Dornbos and Mullen 1991). High nighttime temperatures of over 24°C reduce yields by about 10% compared to the optimum temperature regime of 16-18°C, while low night temperatures between 1 and 10°C disrupt cell metabolism and result in yield reduction of up to 24% (Seddigh and Joliff 1984). In addition to reducing yield by affecting seed size, cool temperatures delay crop maturity, potentially subjecting plants to a risk of damage by fall frost (Egli 2010). Killing frost during soybean reproductive stages can cause a yield reduction of up to 75% if a large percentage of leaves is destroyed (OMAFRA 2009a). Freezing temperatures of -1°C during seed development result in yield losses of 24 to 65% (Saliba et al. 1982; Staggenborg et al. 1996; Berglund 2011).

The effects of temperature stresses on soybean development are especially severe when soil moisture is limited, the most sensitive periods being the end of pod development and seed filling (Korte et al. 1983; Kadhem et al. 1985; Morrison et al.

2006). As a crop with low-medium sensitivity to drought (Brouwer and Heibloem 1986), soybeans require 450-600 mm of water during the growing season, which translates to approximately 50 mm of water per week during critical water use periods (Boersma and Specht 2004). Plants that are subjected to drought stress during pod formation have a lower seed number and a shorter pod appearance period, with stressed pods ripening one week earlier compared to non-stress conditions (Meckel et al. 1984; Desclaux and Roumet 1996; Egli and Bruening 2004). Drought conditions during R5 and R6 stages reduce the duration of seed maturation, accelerate senescence, and result in lower seed weight and germination rates (Meckel et al. 1984; Dornbos and Mullen 1991; Desclaux and Roumet 1996; Souza et al. 1997; Brevedan and Egli 2003). A week of water stress during seed filling can reduce soybean yield by up to 23% (Brevedan and Egli 2003), whereas continuous stress can result in yield losses of 38-47% and 42-64% at optimal (27-29°C) and elevated (33-35°C) air temperatures, respectively (Dornbos and Mullen 1991).

The growth cycle ends with two maturity stages (R7 and R8), when pods turn brown and maximum dry weight is achieved (OMAFRA 2009a), with 95 and 100% of total yield produced by R7 and R8 stages, respectively (Berglund 2011). Stresses that occur after the soybean plant has reached physiological maturity at the R7 stage have little to no effect on the final yield (Ritchie et al. 1994).

Chapter 2. Methodology

This study has taken an exploratory approach to investigate historic changes in weather extremes in eastern Ontario, identify extreme event indices that exhibit statistically significant trends and a have high degree of spatial coherence, and define indices to detect spatial and temporal changes in crop-specific extreme weather events in the region. Research objectives were met using a combination of quantitative and qualitative methods and involved the use of statistical analysis, scripting, and GIS tools, as well as a comprehensive literature review and consultations with crop specialists.

This chapter introduces the concept of extreme event indicators, provides details on data quality requirements for their calculation, and outlines procedures that were taken to process weather data, calculate and analyze selected indices. Methods pertaining to data selection, transformation and quality control (including gap filling), and statistical data analysis (including trend analysis and probability density functions) are relevant to both the generic and crop-specific indices that are discussed in Chapters 3 and 4, respectively. Therefore, in the interests of overall cohesiveness, they are discussed in detail in the sections below and only briefly referred to in later chapters. Conversely, details of methods for developing phenological indices used solely for crop-specific analysis are provided within Chapter 4.

2.1 Extreme event indices

2.1.1 Core indices for climate extremes

The World Meteorological Organization (WMO) and the World Climate Research Program (WCRP) have coordinated their efforts to develop a suite of climate indices with a focus on climate extremes (Alexander et al. 2006). They are known as ETCCDI indices,

after the Expert Team on Climate Change Detection and Indices that developed them (Alexander et al. 2006). The indices can be obtained from simple climate statistics, are statistically robust, and can be used in a wide range of climates around the globe (Vincent and Mekis 2006; Zhang et al. 2011). Development and coordination of these indices resulted in improved monitoring of climate extremes worldwide (Zhang et al. 2005a), with consistent and widely tested methodology allowing the results of studies from different regions to fit together in a straightforward manner (Zhang et al. 2005a; 2011). In addition to being valuable for monitoring changes in climate, these indices can be also used for evaluating climate change scenarios (Gachon et al. 2005). A complete list of 27 indices (16 temperature related and 11 precipitation related) is available in Appendix 1.

ETCCDI indices cover multiple aspects of the changing climate and fall into five categories. (1) *Percentile-based indices* include cold nights (TN10p), cold days (TX10p), warm nights (TN90p), and warm days (TX90p), corresponding to the highest and lowest deciles for maximum and minimum temperatures, plus wet days (R95p) and extremely wet days (R99p), representing the amount of rainfall in the most extreme precipitation events in a year or season. (2) *Absolute indices* such as maximum daily maximum temperature (TXx), maximum daily minimum temperature (TNx), minimum daily maximum temperature (TXn), and minimum daily minimum temperature (TNn) represent maximum or minimum temperature values, while RX1day and RX5day represent maximum precipitation values within a year or season. (3) *Threshold indices* represent the number of days on which a temperature or precipitation value falls above or below a pre-defined threshold and include the annual occurrence of frost days (FD), ice days (ID), summer days (SU), tropical nights (TR), number of heavy precipitation days (R10), and

number of very heavy precipitation days (R20). Changes in these indices often have significant impacts on various economic sectors, even though the indices are not always comparable for different climates and therefore are not universally applicable across the globe (Alexander et al. 2006). (4) *Duration indices* represent periods of excessively dry (CDD), wet (CWD), cold (CSDI), warm (WSDI) or mild (GSL) conditions and are particularly relevant in the mid-latitude agricultural context. (5) *Other indices* do not fall into any of the above categories and include annual precipitation total (PRCPTOT), diurnal temperature range (DTR), simple daily intensity index (SDII), and annual contribution from very wet days (R95pT).

These indices represent the so-called 'moderate extremes' that occur several times per year or season and allow for a more comprehensive statistical analysis than 'severe extremes' that are only observed once every few years and cause significant difficulties in trend detection (Klein Tank and Können 2003; Moberg and Jones 2005; Alexander et al. 2006).

In addition to core indices, others can be developed to provide results that are specific for adaptation needs in certain regions and highlight particular characteristics of climate change in those regions (Zhang et al. 2011). An example of such regionally specific indices is a set developed at Environment and Climate Change Canada for eastern Canada, the climate zone that includes southern Quebec and southern and eastern Ontario (Gachon 2005). It consists of 12 temperature and 6 precipitation indices (see Appendix 1) that were adapted to the main characteristics of climate conditions at the regional scale and recognize seasonal variability and other specifics of eastern Canada (Gachon 2005).

Based on the literature cited above, 15 moderate extreme event indices were selected for calculation and analysis of extreme weather events in eastern Ontario. Their abbreviations, definitions and units are presented in Table 2.1. Each of the indices, when calculated, provides an account of the intensity, length or frequency of a particular extreme, such as maximum single day precipitation event (RX1day), a dry spell (CDD), or a heavy precipitation event (R10). In addition to core ETCCDI indices, two others were selected to provide results that are specific for adaptation needs in the study region. They are HWE, which uses a 30°C 'heat alert' threshold defined by Environment and Climate Change Canada (2015) and CWE, which uses a -20°C threshold to describe severe winter conditions (Gachon 2005). All of the selected indices are relevant in the eastern Ontario context and have implications for agriculture and other activities in the region.

Table 2.1: Definitions of climate indices used in the study. HWE and CWE use thresholds defined by Environment and Climate Change Canada (2015) and Gachon (2005) respectively. The remaining 13 indices come from the list developed by ETCCDI (ETCCDI/CRD Climate Change Indices 2009)

Index ID	Index name	Definition	Units
Temperature:			
HWE	Extreme heat days	TMax >=30°C	days
CWE	Extreme cold days	TMin<=-20°C	days
DTR	Diurnal temperature range	Annual mean difference between TMax and TMin	°C
GSL	Growing season length	Annual (1st Jan to 31st Dec) count between first span of at least 6 days with TMean > 5°C and first span after 1st July of 6 days with TMean < 5°C	days
TN10p	Cool nights	Percentage of days when TMin < 10th percentile	% days
TX10p	Cool days	Percentage of days when TMax < 10th percentile	% days
TN90p	Warm nights	Percentage of days when TMin > 90th percentile	% days
TX90p	Warm days	Percentage of days when TMax > 90th percentile	% days
Precipitation:			
RX1day	Max 1-day precipitation amount	Annual maximum 1-day precipitation	mm
RX5day	Max 5-day precipitation amount	Annual maximum 5-day precipitation	mm
SDII	Simple daily intensity index	Annual total precipitation divided by the number of wet days (PRCP >=1.0mm) in the year	mm/day
R10	Number of heavy precipitation days	Annual count of days when PRCP >=10mm	days
CDD	Consecutive dry days	Maximum number of consecutive days with PRCP<1mm	days
R95p	Very wet days	Annual total PRCP when daily PRCP > 95th percentile	mm
PRCPTOT	Annual total wet day precipitation	Annual total PRCP in wet days (daily PRCP >=1mm)	mm

2.1.2 Agroclimatic and phenological extreme event indices

The majority of climate indices used to characterize extreme weather events and assess their frequency and intensity are designed to be applicable in a variety of spatial contexts (Frich et al. 2002; Alexander et al. 2006), but are less relevant when there is a need to address specific needs of a particular economic sector such as agriculture (Qian et al. 2010). In order to capture impacts of the changing climate on agricultural crops and operations, a suite of agroclimatic and phenological (crop-specific) extreme indices were selected and calculated as part of this research.

Agroclimatic indices, including growing season length (GSL), growing season start (GSS), growing season end (GSE), and crop heat units (CHU), provide information important for crop growth (Qian et al. 2010) and were calculated using formulas given in Table 2.2. Please note, that the formula for the agroclimatic GSL indicator differs slightly from the GSL indicator defined by ETCCDI.

Table 2.2: Definitions of agroclimatic indices used in this research. Sources: ETCCDI/CRD Climate Change Indices 2009; OMAFRA 2009b

Index ID	Index name	Definition	Units
GSL	Growing season length	Annual (1st Jan to 31st Dec) count between first span after April 1 of at least 6 days with Tmean > 5°C and first span after July 1 of 6 days with Tmean < 5°C	days/year
GSS	Growing season start	First day following a period of 6 days with Tmean >5°C	day of year
GSE	Growing season end	First day (after July 1) following a period of 6 days with Tmean <5°C	day of year
CHU	Crop heat units	Daily CHU = (Ymax + Ymin) ÷ 2, where Y max = (3.33 x (T max-10)) - (0.084 x (T max-10.0)2) and Y min = (1.8 x (T min - 4.4)) (If values are negative, set to 0). Accumulation begins on May 1st and ends with the first occurrence of -2°C in the fall.	crop heat units (CHUs)

Phenological indices were designed to incorporate sensitivities of locally grown corn and soybeans by identifying specific thresholds of frost, heat, moisture and drought tolerance for these crops. Initial analysis of agronomic literature showed that early vegetative and early and mid-reproductive stages are the most sensitive periods in crop

growth cycles (Nielsen 2000; Brevedan and Egli 2003), while farming operations are most affected by extreme weather conditions during planting and harvesting seasons (Reid et al. 2007). Subsequent work, therefore, focused on weather conditions and their impacts on crop yields during these periods.

A detailed account of the development of corn and soybean-specific indices, reflecting their tolerance to extreme weather events, along with data analysis and graphic representation of results is provided in Chapter 4.

2.2 Weather data: station selection and gap filling

2.2.1 Spatial data representativeness and station selection

To characterize climate extremes in eastern Ontario eleven weather stations were selected to represent distinct ecodistricts located in the study area. Ecodistricts form one of the hierarchical levels of the national ecological framework of Canada, with each ecodistrict being an ecologically distinct area of the earth's surface, characterized by uniform climatic and biophysical conditions (Ecological stratification working group 1995). The western portion of this region is dominated by boreal shield and has minimal agriculture, whereas the Ottawa and St. Lawrence valleys are well suited for agriculture.

It is evident by studying Figure 2.1 that there are two clusters of weather stations in the study area portion of the Algonquin ecodistrict, and analysis of temperature and precipitation conditions of the two clusters showed that there are substantial differences between the northern and southern parts of the ecodistrict (Table 2.3). For further work, it was therefore split into two parts, Algonquin North and Algonquin South (separated by a dashed line in Figure 2.1), to better capture the observed differences.

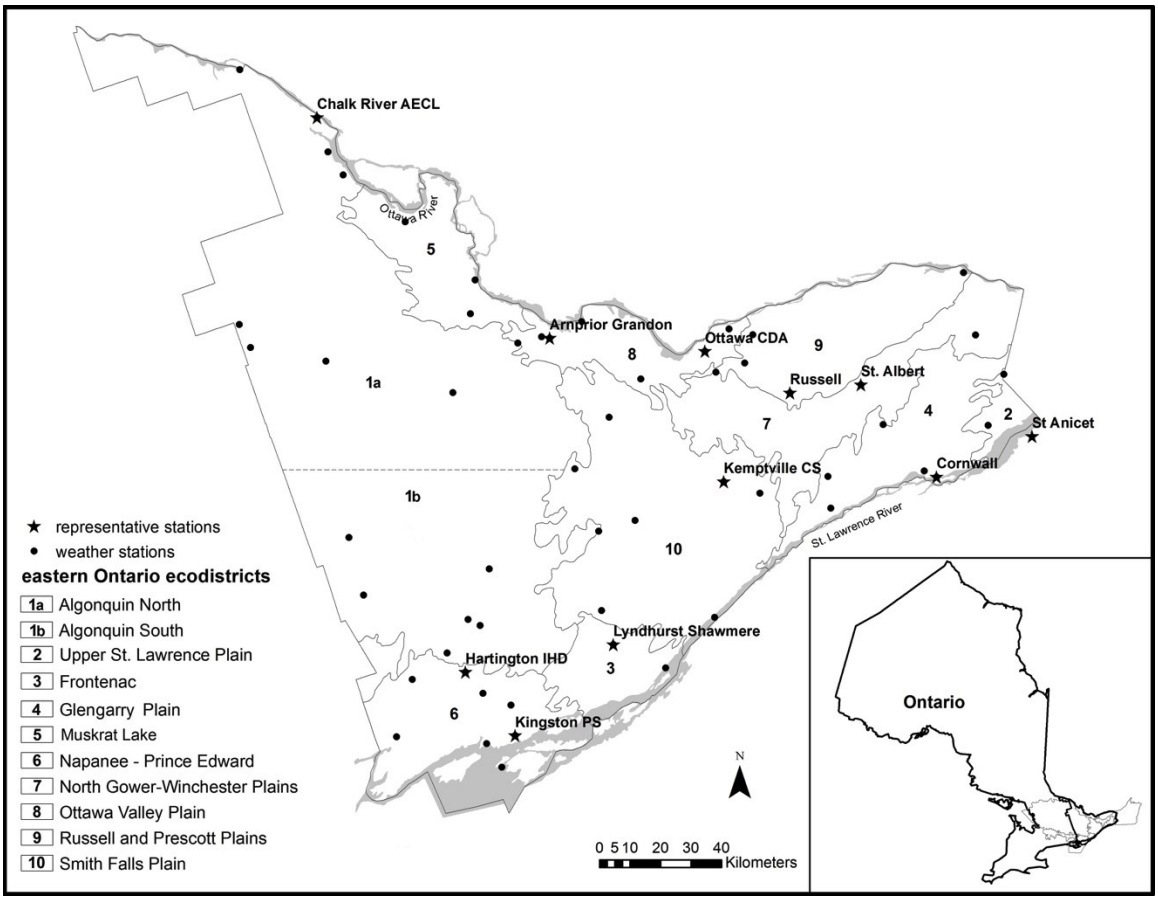


Figure 2.1: Location of all studied and selected representative weather stations by ecodistrict in eastern Ontario.

Table 2.3: Annual totals and means of basic climatological variables for weather stations in Algonquin ecodistrict, 1960-2000. Weather stations in the northern and southern parts of the ecodistrict are shown in black and grey, respectively. Averages across weather stations in both parts of the ecodistrict are shown in bold.

Name	TotPrecip (mm)	TotSnow (cm)	TotRain (mm)	Tmean (°C)	Tmin (°C)	Tmax (°C)
Barrett Chute	**789**	**185**	**604.1**	**5.2**	**-0.4**	**10.9**
Barrys Bay	**833.3**	**199.5**	**633.8**	**4.7**	**-0.7**	**10.2**
Chalk River AECL	**828.5**	**195.6**	**632.8**	**5**	**-0.4**	**10.4**
Combermere	**818.7**	**190.5**	**628.1**	**4.3**	**-1.7**	**10.3**
Des Joachims	**872**	**198**	**674**	**4.4**	**-1.5**	**10.4**
Foymount	**780.5**	**180.5**	**600**	**4.6**	**-1.2**	**10.5**
Petawawa A	**803.8**	**213.7**	**590.1**	**4.3**	**-2.1**	**10.6**
Petawawa Hoffman	**773**	**166**	**607**	**5.5**	**0.3**	**10.8**
Bellrock	909.5	154.2	755.3	5.8	0.3	11.4
Cloyne ONT Hydro	900.5	183.4	717	5	-0.5	10.5
Crow Lake	943.4	159.4	784	6.2	0.9	11.6
Godfrey	883	177.6	705.4	6.2	0.9	11.5
Hinchinbrooke	865.9	144	721.9	6.3	1	11.6
Kaladar	887	219.2	667.8	6.1	0.8	11.4
Rideau Ferry	785.3	117.8	667.5	6.4	1.1	11.6
Algonquin North	**812.4**	**191.1**	**621.2**	**4.8**	**-1**	**10.5**
Algonquin South	882.1	165.1	717	6	0.7	11.4

A daily temporal scale was determined to be suitable for the purposes of this research, to enable the analysis of changes in extremes (c.f. Alexander et al. 2006). The decision to use weather station data as opposed to interpolated grids in the analysis was based on the fact that averaging and interpolating daily weather observations is known to reduce the signal of extreme events (Zhang et al. 2011), while weather station data for temperature and, to a lesser extent, precipitation are representative of much larger regions (Yan et al. 2002; Pfahl and Wernli 2011; Orlowsky and Seneviratne 2014).

Assessing spatial representativeness of weather station observations in a region has long been of interest to climatologists (Milewska and Hogg 2001) and is important for climate model validation, producing gridded data, and climate network improvement (Orlowsky and Seneviratne 2014). Studies in Europe (Pfahl and Wernli 2011; Orlowsky and Seneviratne 2014), China (Yan et al. 2002), and Canada (Milewska and Hogg 2001)

have used a variety of methods and techniques to determine whether a network of stations can provide accurate climatological information for large areas. Findings reveal that there is fairly good spatial correlation between stations in southern Canada (Milewska and Hogg 2001), central and eastern Europe (Orlowsky and Seneviratne 2014), central England and northern China (Yan et al. 2002), showing that single sites can be considered representative for larger regions (Yan et al. 2002). Overall, stronger representativeness has been observed for temperature than precipitation, while seasonally, both temperature and precipitation show higher representativeness in winter compared to summer, presumably due to the winter dominance of synoptic weather systems (Pfahl and Wernli 2011; Orlowsky and Seneviratne 2014).

A quality controlled, infilled dataset was produced by Schroeter and Associates for the Ontario Ministry of Natural Resources (OMNR) in 2006 (Schroeter et al. 2008) for the period from 1960 to 2000 for all weather stations that operated in Ontario during that period. Of these stations, 56 are located in eastern Ontario (see Appendix 2) and were examined in detail. In order to extend the time series until 2010, records in Environment and Climate Change Canada's weather archive were studied. It was found that 15 of the original 56 stations were in operation in 2010 (Appendix 2); these stations were considered as potential representative stations for eastern Ontario ecodistricts, provided they had been in operation for at least 25 years prior to 2010. Despite being decommissioned prior to 2010, Arnprior Grandon, Kingston A, and Kingston PS weather stations were also considered due to the length of available data series prior to that year.

To determine whether selected stations are representative of the entire area of the ecodistricts in which they are located, changes in mean and extreme temperature and total

and extreme precipitation cycles between a station and a number of surrounding stations were compared for the period from 1960 to 2000. First, smoothed daily climatological annual cycles were obtained for each of the weather stations by calculating mean daily temperature for each day using daily minimum and maximum values for the central day as well as a day on either side (Yan et al. 2002; Orlowsky and Seneviratne 2014). A percentile-based definition of extremes was used to create time series of temperature anomalies, defined as values corresponding to the 5th and 95th percentiles of daily mean values for each calendar day in the annual cycle (Yan et al. 2002; Pfahl and Wernli 2011). In this way, anomalous conditions related to a common reference daily series from different weather stations could be directly compared (Yan et al. 2002). Time series of potential representative stations were compared to time series of spatially averaged data of all other stations in each ecodistrict, as suggested by Yan et al. (2002). The comparison was done by estimating correlations between time series by Spearman's rank based correlation coefficient, which is known to be robust against outliers (Orlowsky and Seneviratne 2014), as well as by visual assessment of the plotted time series. Total monthly precipitation and the 95th percentile of single day precipitation for each month in the baseline period were calculated for all weather stations, after which the values of potential representative stations were compared to averaged time series of all other weather stations in each ecodistrict. Similar to temperature time series, the comparison was done by calculating the Spearman's rank based correlation coefficient and by visual assessment of the plotted time series. For mean and extreme temperature series, correlation was consistently strong at 0.99 (Table 2.4). For precipitation series, correlation coefficients ranged from 0.83 to 0.95 and from 0.74 to 0.95 for total

precipitation and the 95th percentile of monthly precipitation, respectively (Table 2.4).

Table 2.4: Weather stations in eastern Ontario by ecodistrict and correlation coefficients calculated for time series of selected meteorological variables for potential representative stations (in bold) and means of all stations in each ecodistrict. Notes: Arnprior Grandon station is located in Ottawa Valley Plain ecodistrict and Hartington IHD station is located in Napanee - Prince Edward ecodistrict.

Ecodistrict name	Station name	Correlation coefficients of:				
		Total monthly precipitation	95th percentile of daily precipitation	Mean daily temperature	5th percentale of mean daily temperature	95th percentale of mean daily temperature
Muskrat Lake	Chenaux					
Muskrat Lake	Pembroke SE					
Muskrat Lake	Renfrew					
Muskrat Lake	**Arnprior Grandon**	0.87	0.8	0.99	0.99	0.99
Russell and Prescott Plains	Gloucester Kettles					
Russell and Prescott Plains	Hawkesbury					
Russell and Prescott Plains	Navan					
Russell and Prescott Plains	**Russell**	0.89	0.81	0.99	0.99	0.99
North Gower-Winchester Plains	Dalkeith PYM					
North Gower-Winchester Plains	**Ottawa Macdonald-Cartier Intl**	0.82	0.74	0.99	0.99	0.99
North Gower-Winchester Plains	**St. Albert**	0.89	0.8	0.99	0.99	0.99
Ottawa Valley Plain	Arnprior Grandon					
Ottawa Valley Plain	Carp					
Ottawa Valley Plain	Chats Falls					
Ottawa Valley Plain	Claybank					
Ottawa Valley Plain	**Ottawa CDA**	0.91	0.85	0.99	0.99	0.99
Ottawa Valley Plain	Ottawa NRC					
Ottawa Valley Plain	Stewartville					
Glengarry Plain	Avonmore					
Glengarry Plain	Chesterville 2					
Glengarry Plain	Cornwall ONT Hydro					
Glengarry Plain	**Cornwall**	0.93	0.88	0.99	0.99	0.99
Glengarry Plain	Morrisburg					
Smith Falls Plain	Appleton					
Smith Falls Plain	**Brockville PCC**	0.83	0.74	0.99	0.99	0.99
Smith Falls Plain	Delta					
Smith Falls Plain	**Drummond Centre**	0.88	0.82	0.99	0.99	0.99
Smith Falls Plain	**Kemptville CS**	0.89	0.83	0.99	0.99	0.99
Smith Falls Plain	Smiths Falls					
Smith Falls Plain	South Mountain					
Frontenac	**Lyndhurst Shawmere**	0.9	0.95	0.99	0.99	0.99
Frontenac	Mallorytown Landing					
Napanee - Prince Edward	Cataraqui TS					
Napanee - Prince Edward	**Centreville**	0.9	0.85	0.99	0.99	0.99
Napanee - Prince Edward	Hartington IHD					
Napanee - Prince Edward	Glenburnie					
Napanee - Prince Edward	**Kingston A**	0.95	0.88	0.99	0.99	0.99
Napanee - Prince Edward	**Kingston PS**	0.95	0.9	0.99	0.99	0.99
Napanee - Prince Edward	Napanee					
Napanee - Prince Edward	Wolfe Island					
Upper St. Lawrence Plain	Dalhousie Mills					
Upper St. Lawrence Plain	Glen Gordon					
Upper St. Lawrence Plain	**St Anicet**	0.86	0.76	0.99	0.99	0.99
Algonquin North	Barrett Chute					
Algonquin North	Barrys Bay					
Algonquin North	**Chalk River AECL**	0.87	0.82	0.99	0.99	0.99
Algonquin North	Combermere					
Algonquin North	Des Joachims					
Algonquin North	Foymount					
Algonquin North	**Petawawa A**	0.83	0.77	0.99	0.99	0.99
Algonquin North	Petawawa Hoffman					
Algonquin South	Bellrock					
Algonquin South	Cloyne ONT Hydro					
Algonquin South	Crow Lake					
Algonquin South	Godfrey					
Algonquin South	Hinchinbrooke					
Algonquin South	Kaladar					
Algonquin South	Rideau Ferry					
Algonquin South	**Hartington IHD**	0.88	0.83	0.99	0.99	0.99

Stations with the highest correlation coefficients with averaged time series of all other stations in each ecodistrict were selected as representative stations. In cases when no stations with a consistent record of over 35 years in the study period or 25 or more consecutive years up to 2010 were located in an ecodistrict, a suitable station in close proximity to the boundary was selected in a neighbouring ecodistrict. In this way, Hartington IHD and Arnprior Grandon were selected to represent Algonquin South and Muskrat Lake ecodistrict, respectively. For the Upper St. Lawrence Plain ecodistrict, St Anicet weather station, located outside the study area boundary, was selected due to lack of a consistent data series within the study area portion of the ecodistrict. A summary of representative weather station information is provided in Table 2.5.

Table 2.5: List of Eastern Ontario representative weather stations, their coordinates, elevation and years of operation. Data for time periods outside of the ones indicated were infilled along with gaps in recorded data series. Kemptville CS is a successor station to Kemptville weather station that was in operation from 1928 to 1997.

Station name	Station ID	Province	Latitude	Longitude	Elevation (m)	Start year	End year	Ecodistrict
Arnprior Grandon	6100345	ON	45°25' N	76°22' W	107	1959	1999	Muskrat Lake
Chalk River AECL	6101335	ON	46°03' N	77°22' W	122	1960	2010	Algonquin North
Cornwall	6101874	ON	45°01' N	74°45' W	64	1950	2010	Glengarry Plain
Hartington IHD	6103367	ON	44°26' N	76°41' W	160	1967	2010	Algonquin South
Kemptville CS	6104027	ON	45°00' N	75°38' W	99	1997	2010	Smith Falls Plain
Kingston PS	6104175	ON	44°14' N	76°29' W	77	1960	2007	Napanee - Prince Edward
Lyndhurst Shawmere	6104725	ON	44°31' N	76°05' W	87	1976	2010	Frontenac
Ottawa CDA	6105976	ON	45°23' N	75°43' W	79	1889	2010	Ottawa Valley Plain
Russell	6107247	ON	45°16' N	75°22' W	76	1954	2010	Russell and Prescott Plains
St. Albert	6107276	ON	45°17' N	75°04' W	80	1986	2010	North Gower - Winchester Plains
St Anicet	7026836	QC	45°08' N	74°21' W	53	1960	2010	Upper St. Lawrence Plain

2.2.2 Missing data and gap filling procedures

The analysis of extremes is sensitive to the presence of missing values (El Kenawy et al. 2011); therefore, ways to infill minimum and maximum daily temperature and daily precipitation data series for selected weather stations were investigated. Commonly used methods can be classified as within-station, between-station, and regression-based (Allen and De Gaetano 2001). Within-station methods are applicable

when one or a small number of days in a row are missing, and include the use of moving averages (Kemp et al. 1983) or non-linear regression to fill in the gap, using data from several days before and after dates with missing data (Acock and Pachepsky 2000). Between-station methods are used when periods with missing data are longer, and include spatial interpolation such as inverse distance weighting (IDW) and kriging, as well as simple spatial averaging (Tardivo and Berti 2012). IDW methods estimate missing values at a station based on a weighted average from values at neighbouring stations, considering weights as a function of distances between stations (Teegavarapu and Chandramouli 2005). Kriging also uses distance-based weighting, but the weighting is determined by geostatistical analysis to break down the variance of a variable being studied in a particular study area into spatial and non-spatial components. One of the common issues with interpolation approaches is that faulty measurements at any of the stations used for filling in the missing data affect filled-in values; similarly, precipitation amounts are often overestimated if rain or snow has been recorded at any of the stations used for filling in the missing data (Teegavarapu 2009; Hasan and Croke 2013). Regression-based methods (e.g. parametric regression and ranked regression) take into account a variety of factors, such as elevation, topography, proximity to large water bodies etc., using them as explanatory variables to estimate missing values at a station (Presti et al. 2010).

For this project missing data in representative weather stations time series were infilled by Dr. Harold Schroeter of Schroeter and Associates, using methodology discussed in Schroeter et al. (2000; 2008). DTRANS (Data TRANSfer) and METCLN (METeorological data CLeaNsing) programs developed by Schroeter et al. (2000; 2008)

were used to convert weather station data to appropriate formats and process them, respectively.

The method for infilling gaps in daily temperature and precipitation data series combines within-station, between-station and regression-based techniques and involves the use of 'surrogate' weather stations to estimate missing records in a 'target' station. Surrogate stations selection is based on their proximity to the target station, record length, and record completeness (Schroeter et al. 2008). The summary of surrogate weather stations that were used for missing value fill-in work for selected representative stations in eastern Ontario is given in Table 2.6.

Table 2.6: Surrogate stations used to fill in missing data for representative stations in eastern Ontario. Due to the decommissioning of a large number of stations in the early 2000s, additional or new surrogate stations were often used to fill in missing data for representative stations post 2005. Recent surrogate stations are shown in italics, where applicable.

Station name	Station ID	Surrogate stations	Station ID
Arnprior Grandon	6100345	Arnprior	6100340
		Claybank	6101555
		Chats Falls	6101440
		Shawville	7038040
Chalk River AECL	6101335	Des Joachims	6102009
		Pembroke SE	6106369
		Petawawa Hoffman	610FC98
Cornwall	6101874	Cornwall ONT Hydro	6101901
		Avonmore	6100398
		Morrisburg	6105460
		Cornwall	6101875
		St. Albert	6107276
Hartington IHD	6103367	Kingston PS	6104175
Kemptville CS	6104027	Kemptville	6104025
		Morrisburg	6105460
		Ottawa Macdonald-Cartier Intl	6106000
Kingston PS	6104175	Kingston A	6104146
		Kingston ONT Hydro	6104165
		Kingston Beverly St	6104147
		Belleville	6150689
		Kingston Climate	6104142
Lyndhurst Shawmere	6104725	Brockville PCC	6100971
		Kemptville CS	6104027
Ottawa CDA	6105976	Ottawa Macdonald-Cartier Intl	6106000
Russell	6107247	Ottawa Macdonald-Cartier Intl	6106000
St. Albert	6107276	St. Elmo	6107310
		Russell	6107247
St Anicet	7026836	Dalhousie Mills	6101958
		Cornwall	6101874

In order to use values from surrogate stations to fill in the gaps in target stations data series, long-term climatic relationships between each pair of stations were determined. The relationships were based on the 1951-1980 climate normals that were available for the largest number of stations in the region, compared to 1961-1990 and 1971-2000 normals that had a more limited coverage due to the decommissioning of multiple weather stations in the 80s and 90s (Schroeter et al. 2008). In cases when mean values were not available in pre-existing tables of normals, they were estimated from available records (Schroeter et al. 2008). Long-term relationships resulted in defined differences (for temperature) and ratios (for precipitation) that were used to adjust data from surrogate stations and create infill data for target stations. In cases when the first surrogate station had a gap in data at the same time as the target station, data from the second (and so forth) surrogate station were used. In instances when observations of only one temperature value (e.g. daily minimum temperature) were missing in the station record, they were estimated using available daily maximum temperature observations and the average difference between maximum and minimum temperature values taken from the long-term normals for that station (Schroeter et al. 2000). If the missing air temperature value was isolated between two dates that had both values, the average difference between maximum and minimum values on adjacent dates was used to find the missing value (Schroeter et al. 2000). Overall, it has been demonstrated that this technique offers an appropriate reflection of spatial trends and relationships between nearby climate stations (Schroeter et al. 2000; 2008), and an iterative data quality check and exchange mechanism between this author and Schroeter and Associates ensured that the data used here were free from obvious technical errors.

2.3 Index calculation and statistical data analysis

2.3.1. Data requirements, quality control, and index calculation

Data availability and quality are some of the prerequisites for successful calculation and statistical analysis of extreme events (El Kenawy et al. 2011). Artificial step changes and outliers in climate data caused by site relocation, changes in observing procedures and instrumentation as well as measurement program deficiencies result in overall data series inhomogeneity that can significantly affect trend assessment (Aguilar et al. 2003; Moberg and Jones 2005; Vincent et al. 2011). Existing dataset with adjusted and homogenized temperature and precipitation data produced by Environment and Climate Change Canada (Environment and Climate Change Canada 2013) provides limited spatial coverage in eastern Ontario and was therefore not used in this study. Even though there have been improvements in tests for assessing data homogeneity (Reeves et al. 2007; Caesar et al. 2011) including the wider use of two-phase regression models to identify step changes at multiple change points (Wang 2003), there is still considerable uncertainty in methods for homogenizing and adjusting climate data for detected shifts (Casear et al. 2011; Vincent et al. 2011). Homogeneity adjustments were not part of quality control measures used in this research; in view of this, it is most appropriate to focus on the sign and relative size of trends rather than on their numeric values during interpretation of results. For a more accurate quantitative assessment of trends in climate extremes, an extensive homogeneity testing exercise is recommended.

Quality control is essential in analyses of climate and weather data and serves to identify errors in daily data sets that may interfere with the correct assessment of extremes (Vincent et al. 2011). A number of quality control measures were taken to

identify errors that might interfere with assessing extremes and affect the reliability of the finalized data series. This was done in RClimDex software (Zhang et al. 2015) and included checking for (a) non-numeric values, (b) negative precipitation values, (c) daily maximum temperature values less than daily minimum temperature values, (d) daily temperature values greater than 70°C or less than -70°C, (e) values corresponding to impossible dates such as the 32nd of March, (f) identifying outliers greater than 3 times standard deviation from the mean value for that calendar day, and (g) daily precipitation value greater than 200 millimeters.

Following quality control checks, all extreme event, agroclimatic, and crop-specific indices were calculated using scripts written in R (R Core Team 2015). Scripts for index calculation as well as additional R scripts for subsequent trend and distribution analyses, are provided in Appendix 3.

Some of the indices (TN10p, TX10p, TN90p, and TX90p) require the use of a base period to estimate their respective percentiles. In this research the percentiles were calculated relative to the 1961-1990 base period, most commonly used in climate literature (EBNFLO Environmental AquaResource Inc 2010). Thresholds for each calendar day were estimated by the empirical quantile method, using a moving window of five consecutive days (5CD) centered on each calendar day (Zhang et al. 2005b). In other words, to calculate a threshold value for a particular day, observations for that day and two days on either side for all years in the base period were used to determine the empirical quantile corresponding to the pth percentile of minimum or maximum temperature using a linear interpolation of two values in the sorted data closest to the pth percentile (Frich et al. 2002; Zhang et al. 2005b).

Percentile indices may have artificial discontinuities at the tails of the base period due to sampling error, and thus overestimate threshold exceedance rates outside the base period (Zhang et al. 2005b). To eliminate this possibility, a bootstrapping procedure was used, as suggested by Zhang et al. (2005b), to make the estimation of threshold exceedance rates for in-base and out-of-base periods comparable. This is achieved by not using data from a year within the base period to estimate the index threshold for that year (Zhang et al. 2005b), thus estimating in-base and out-of-base period exceedance rates in a similar manner. The bootstrap procedure, performed for the in-base period (1961-1990), consists of the following steps, listed below (adapted from Zhang et al. 2005b). First, (1), the 30-yr base period is divided into one 'out-of-base' year for which threshold exceedance will be estimated, and a 'base period' consisting the remaining of 29 years that will be used to estimate the thresholds. Then, (2), a 30-year block of data is constructed using 29 years from the 'base period' and one additional (repeated) year from the same period. This 30-yr block is then used to estimate percentile thresholds. Next, (3), the 'out-of-base' year is compared with the estimated thresholds, and the exceedance rate is obtained. After that, (4), steps 2 and 3 are repeated 28 times, by iterating through the remaining 'in-base' years to construct the 30-yr block. Lastly, (5), 29 estimates obtained from steps 2, 3, and 4, are averaged to acquire the threshold exceedance value for the 'out-of-base' year.

2.3.2 Trend analysis

Time series of 50 years were produced for extreme event and agroclimatic indices at annual and seasonal (planting, growing, and harvesting seasons) scales from 1961 to 2010. Using these time series, trends were calculated to obtain average rates of change

per year in each indicator over the study period. Following that, statistical significance of trends was assessed. Trend assessment was conducted for each individual weather station in eastern Ontario, after which trend magnitude numbers were multiplied by ten to obtain decadal trend values to ease understanding of the temporal dynamics and facilitate comparisons to other work (Caesar et al. 2011; Insaf et al. 2013). To obtain regional trend values, decadal trend magnitude values were averaged across all weather stations, with equal weight assigned to each station.

Trends were calculated using a non-parametric approach proposed by Sen (1968) and trend assessment was carried out by means of the rank-based non-parametric Mann-Kendall (MK) test (Mann 1945; Kendall 1975). This method is suitable for extremes analyses, as it does not assume that data are normally distributed and is robust to the effect of outliers that are fairly common in climate data series (Bonsal et al. 2001; Caesar et al. 2011; Vincent et al. 2011). Lack of assumptions about data distribution makes it more suitable for working with time series data than parametric methods (Yue et al. 2002). The method first divides the difference between two observations in a time series by the length of the time period to estimate a linear trend between the two observations. After that, trends computed from all possible data pairs are ranked and median values of the trends are used as the final result (Sen 1968; Zhang et al. 2000; Wang and Swail 2001). The magnitude and statistical significance of the trend are obtained based on Kendall's tau, one of the key outputs of the MK test – a coefficient that measures the association between two quantities; if they are independent, the value of the coefficient is approximately zero (Hipel and McLeod 2005). The null hypothesis of the MK test is that the data sample is independent and identically distributed, while the alternative

hypothesis suggests the presence of a monotonic trend in the data series (Yue et al. 2002). The null hypothesis is commonly rejected when the two-sided p-value is greater than a selected threshold, which, for the purposes of this project, was set at 0.05.

Results of the MK test are sensitive to serial autocorrelation; therefore, a significant trend may be falsely detected due to the presence of autocorrelation in the series (Caesar et al. 2011). According to Yue et al. (2002), the existence of serial correlation affects the variance of the MK statistic; consequently, if a positive correlation is present, the variance increases and with it the probability of detecting a statistically significant trend increases as well (Figure 2.2).

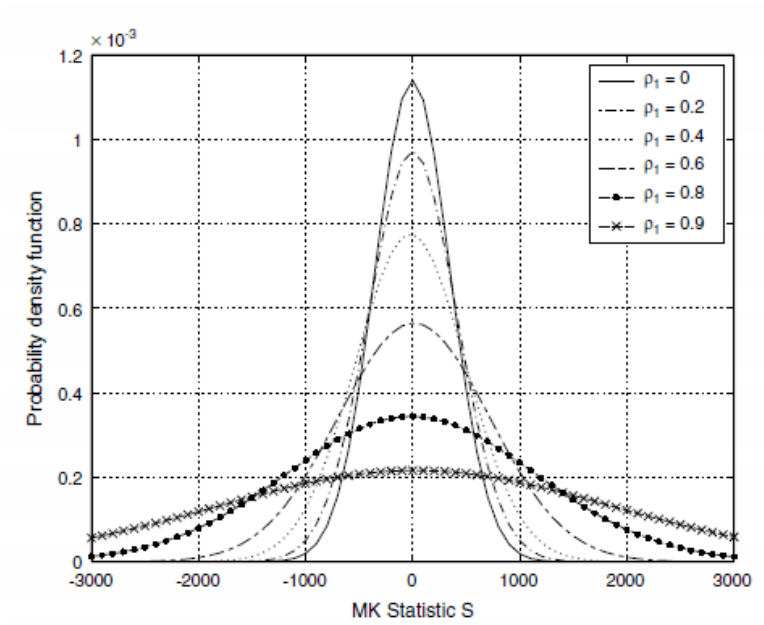


Figure 2.2: Effect of positive serial correlation on the MK statistic. Source: Yue et al. (2002).

The effect of autocorrelation can be eliminated using a method known as pre-whitening, which removes serial correlation using a lag-1 autoregressive model and applying the MK test to serially independent residuals (von Storch 1995; Yue et al. 2002). The pre-whitened trend computation technique was previously applied in multiple

studies of extreme weather events (Vincent et al. 2005; Zhang et al. 2005a, Aguilar et al. 2009).

In this research, an iterative de-trending and pre-whitening technique, suggested by Zhang et al. (2000) and later refined and described in Wang and Swail (2001), was used to account for lag-1 autocorrelation effect in the time series. In the context of this research the procedure can be described as follows below. First, the order of the autoregression (AR) is determined by computing the autocorrelation and partial autocorrelation functions of each climate indicator at individual weather stations. Partial correlations are calculated for lag-1, lag-2, …, lag-10 in each time series. According to Zhang et al. (2000), the partial autocorrelation for lags larger than one is typically close to zero; therefore, the AR(1) process is used to model the noise, using the following equation:

$Yt = \mu + \beta t + \varphi Yt{-}1 + \varepsilon t$ (Eq. 1),

where Yt is a climate variable at time t, μ is the constant term, βt is the trend with slope β, φ is the parameter of the autoregressive process, and εt is white noise (Zhang et al. 2000). Then, autocorrelation is removed from the time series using a value of φ, computed directly from the dataset. The slope β and its significance level are obtained from the de-autocorrelated time series, based on the value of Kendall's tau, and used to remove the trend from the original series. The resulting residuals are used to obtain a more accurate estimation of the lag-1 autocorrelation coefficient (φ), which is then used to pre-whiten the original series, at which time a second slope estimate is obtained. This iterative procedure continues until the differences in slope estimates and AR(1) in two consecutive iterations are smaller than 1 percent (Bronaugh and Werner 2015). The

resultant time series is used to run the MK test for trend, while the Sen approach (Sen 1968) is used to compute the slope of the trend.

The 'Zyp' package (Bronaugh and Werner 2015) was used to calculate pre-whitened non-linear trends and assess their significance in R. Graphic representation of results was done using ArcGIS Desktop version 10.3 (Esri, Redlands, CA, USA).

2.3.3 Probability density functions

To complete the analysis of temporal changes in climate extremes in eastern Ontario, the study period was split into two 25-year intervals, 1961-1985 and 1986-2010, roughly corresponding to the most commonly used (1961-1990) and the most recent (1981-2010) climate normals, after which regional averages were computed for every index as the mean of the indices at individual stations. Following that, probability density function (PDF) graphs were produced to compare temporal changes in extreme event and agroclimatic indices as well as basic climate variables (daily minimum temperature, daily maximum temperature, total precipitation) at annual and seasonal time periods.

A probability density function of a continuous random variable (e.g. mean daily temperature) describes the relative likelihood for this random variable to take on a given value (Harris and Jarvis 2011). It can be represented graphically as a normal curve, where the probability of occurrence of a given value under the curve can be given by the integral of the variable's density over a region (Harris and Jarvis 2011). Changes in data distribution over time can be visualized using PDF graphs, as shown in Figure 2.3 that demonstrates the effects of changes in temperature on the distribution of extremes.

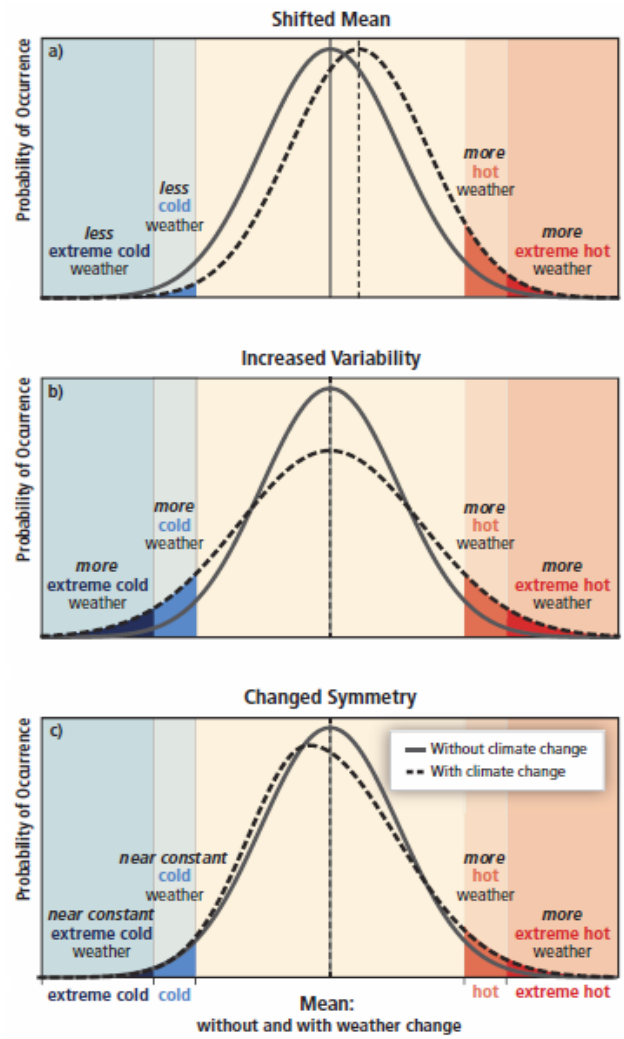


Figure 2.3: The effect of changes in temperature distribution on extremes:
(a) effects of a simple shift of the entire distribution toward a warmer climate; (b) effects of an increase in temperature variability with no shift in the mean; (c) effects of an altered shape of the distribution, in this example a change in asymmetry toward the hotter part of the distribution. Source: IPCC (2012).

Calculations of probability density functions were done using the *density* function in the R Stats Package (R Core Team 2015) and graphically represented using R. The *density* function uses a non-parametric method, called kernel density estimation, to estimate the probability density function of a random variable (Kabacoff 2011). Similar to the approach used by Frich et al. (2002) and Vincent and Mekis (2006), values for each time series were binned across their range for 1961-1985 and 1986-2010 periods to compute

their frequency, after which the results were normalized to the sum of one to give the estimated probability distribution. Twenty-five-year periods were chosen to assess changes in trends using similar time scales to those used by Alexander et al. (2006) in their long-term global climate indices study. PDF plots were examined to detect and describe changes in the distribution of indicator values between the earlier (1961-1985) and later (1986-2010) sub-periods.

Chapter 3. Research Paper: "Spatio-temporal characterization of temperature and precipitation extremes in eastern Ontario, 1961-2010"

3.1 Abstract

Climate change has been observed in different regions of the world over the past several decades. Extreme weather events such as heat waves, droughts, high intensity storms and flash floods present a particular concern and are expected to have adverse environmental and economic effects. Agriculture and food production are expected to be particularly vulnerable to such effects. This study characterizes climate extremes in eastern Ontario from 1961 to 2010, annually, and in relation to agriculturally sensitive time periods: the planting, growing and harvesting seasons. The main goal of the research is to detect and analyze trends in temperature and precipitation extremes in eastern Ontario and identify extreme event indices that show the most spatial coherence across the region. A set of 15 temperature and precipitation indices was calculated for eleven locations in eastern Ontario using daily temperature and precipitation data. These locations were selected to represent distinct ecological districts within the region. Trends in calculated indices were detected and calculated using non-parametric Mann-Kendall test. Probability distributions of each index were analyzed for 1961-1985 and 1986-2010 time periods. The results show an increase in warmer and wetter conditions in eastern Ontario. The greatest changes in both temperature and precipitation extremes were observed in the eastern part of the region and along the St. Lawrence River, where most agricultural lands are located. Temperature indices show a higher degree of spatial coherence than precipitation indices, with the majority of statistically significant changes observed at the annual rather than seasonal time periods.

3.2 Introduction

Climate change is having an impact on the frequency and severity of extreme weather events such as heat waves, droughts, high intensity storms, and flash floods (Alexander et al. 2006; IPCC 2012). According to the Intergovernmental Panel on Climate Change, losses from weather-related disasters have increased substantially in recent decades, both at the regional and global scale (IPCC 2014). In Canada, insured losses from major extreme weather events exceeded one billion dollars for five consecutive years between 2009 and 2013, surpassing 8.5 billion over the five-year period (McGillivray 2016). As their frequency increases, extreme events are expected to adversely affect the environment and play an important role in the future of regional agriculture, influencing what and how much is produced within and across years (Weber and Hauer 2003; Kharin et al. 2007; Wreford et al. 2010). To better adapt to challenges of future climate change and mitigate potential adverse effects, more detailed insights into extreme weather need to be made available to regional decision-makers (IPCC 2012). Spatial and temporal characteristics of climate extremes may be investigated by calculating indices derived from available temperature and precipitation observations (Alexander et al. 2006). Assessing changes in these indices and identifying ones that could cause significant problems can provide information for successful implementation of adaptation strategies and mitigation measures (Li et al. 2011).

During the past few years numerous studies have examined changes in extreme weather events at the global (Frich et al. 2002; Alexander et al. 2006; Klein Tank et al. 2009) and regional (Moberg and Jones 2005; Zhang et al. 2005a; Brown et al. 2010; Caesar et al. 2011) scales. It has been suggested that naturally and anthropogenically

caused changes in climate have resulted in more frequent, intense, spatially and temporally variable extreme weather events (IPCC 2012). Frich et al. (2002), Alexander et al. (2006) and Klein Tank et al. (2009) all show that in past decades most parts of the world have experienced a significant decrease in the number of cold extremes and an increase in hot extremes, including a greater number of heat waves. Multiple studies, including those by Alexander et al. (2006) and Frich et al. (2002), have shown that minimum temperatures have been increasing at a greater rate than maximum temperatures, resulting in a decreased daily temperature range. Heavy precipitation events have increased over most areas, and increases in rare precipitation events have been recorded in Europe and North America (IPCC 2014), while the maximum number of consecutive dry days has decreased (Frich et al. 2002). Importantly, it has been noted that there is less spatial coherence and statistical significance in precipitation extremes compared to temperature changes (Alexander et al. 2006).

Climate extremes in Canada have been investigated by Bonsal et al. (2001), Zhang et al. (2001), Vincent and Mekis (2006), and Yagouti et al. (2008) among others. Bonsal et al. (2001) noted a significant increasing trend in annual and seasonal temperature extremes, in both the lower and higher percentiles of the daily minimum and maximum temperature distributions in the 20th century. Similarly, Vincent and Mekis (2006) found there were fewer days with extreme low temperatures and more days with extreme high temperatures in most seasons. As seen in global studies, this warming is characterized by a stronger increase in minimum temperatures as opposed to maximum temperatures, resulting in a significant decrease in the diurnal temperature range (Bonsal et al. 2001; Vincent and Mekis 2006). Analyses of precipitation indices show an increase

in total precipitation and the number of heavy precipitation events as well as a decrease in the maximum number of consecutive dry days (Zhang et al. 2001; Vincent and Mekis 2006). No spatially consistent trends have been detected in the frequency and intensity of precipitation extremes during the past decades, making the spatial coherence of such events significantly lower than that of temperature extremes (Zhang et al. 2001; Vincent and Mekis 2006).

Overall, the frequency of extreme events in Canada, including high intensity storms, freezing rain, and heat waves has increased significantly in the past decades (Chiotti and Lavender 2008), leading to issues such as soil erosion, crop damage, and an increase in livestock fatalities. Research conducted on extreme weather events and their impacts on Canadian agriculture (Motha and Baier 2005; Reid et al. 2007) shows that increases in extreme weather events are already occurring in all regions of the country and this trend is expected to persist into the future. Higher temperatures, lower precipitation, and higher wind speeds are expected to affect the country's western regions, while extreme heat and precipitation events will be causing crop damage in the east (Motha and Baier 2005). Given this lack of spatial coherence in changes and trends in extreme weather events, it is evident that regional and/or single-site analyses are necessary to identify patterns and variability of climate extremes over space and time (Bartholy and Pongracz 2007; Brown et al. 2010; Zhang et al. 2014).

To my knowledge, no studies have been done in eastern Ontario that describe temporal trends in extreme weather indices and spatial variations in these trends. Given the importance of agriculture to the local econom, it is of interest for climate change detection and of practical importance for agricultural producers to know how local

conditions were affected by climate change in the recent past and what potential impacts could be (Qian et al. 2012). Climate change studies suggest that changing agroclimatic conditions in Ontario will result in longer growing seasons, milder winters and fewer frost days, increasing potential crop yields (Reid et al. 2007). Importantly, these benefits may be offset by the increased frequency and intensity of extreme weather events, particularly if they occur at critical periods (Lemmen and Warren 2004; Motha and Baier 2005). Although a variety of studies have analyzed trends in climatic extremes both globally (Frich et al. 2002; Alexander et al. 2006) and regionally (Griffiths and Bradley 2007; Brown et al. 2010), few have examined trends during agriculturally sensitive periods, such as the planting season (PS), the growing season (GS), and the harvesting season (HS). The primary objective of this study is to detect and analyze trends in temperature and precipitation extremes in the region and identify the indices that show the most spatial coherence across eastern Ontario at different temporal scales (annual, PS, GS, and HS). Gaining knowledge on the geographic variation in sensitivity to climate change may contribute to ongoing adaptation efforts and assist practitioners in evaluating and further developing methodologies for climate risk mapping for use by insurance industry and the agricultural community.

3.3 Data and Methods

To account for changes in climate extremes in eastern Ontario over the past five decades, we focused on selecting a study area and data that would represent spatio-temporal variation and provide sufficient detail to allow extreme event indices to be calculated. Trends in main meteorological variables and extreme events along with temporal shifts in the probability of their occurrence were considered. Please recall that a

detailed discussion of methods pertaining to weather station selection, gap filling, indicator selection and calculation as well as trend and probability analysis is provided in Chapter 2.

3.3.1 Study area and weather station data

The study area is located in south-central Canada and covers over 31,000 km^2. The western part of the region, covering just over 40 percent of its total area, is part of the Boreal Shield ecozone, an area characterized by extensive forest coverage, lakes, and bedrock outcrops (Ecological stratification working group 1995). The eastern part of the region supports most agriculture in the area and includes rolling plains that extend from the Ottawa River in the north to the St. Lawrence River in the south. These more fertile lands of the Ottawa and St. Lawrence valleys support multiple agricultural activities and are home to over 1.3 million people (Statistics Canada 2011a). Projections by the Ontario Ministry of Finance (2011) indicate that the population of eastern Ontario is expected to grow by almost 25% over the next 20 years. Climatologically, the lower-lying eastern part of the region has a milder climate than the western part, characterized by warm summers, cool winters and average temperatures of 16 and -7°C for July and January, respectively (Ecological stratification working group 1995). By contrast, the western part, located at higher elevations of the Canadian shield, is about 2°C cooler than the east, with annual total precipitation averaging 950 compared to 850 mm in the Mixedwood Plains (Ecological stratification working group 1995). A significant part of eastern Ontario is located in the North American storm belt, which creates rapid weather changes in the region (Ecological stratification working group 1995).

To characterize climate extremes in eastern Ontario eleven weather stations were selected to represent ten ecodistricts located in the study area (Figure 2.1; Table 2.5). The largest ecodistrict, Algonquin, was split into two parts to adequately capture the differences in climate between its northern and southern parts (Table 2.3). Weather station data were used to characterize broader regions to avoid artefacts from methods to spatially distribute the observations, and because for temperature and (to a lesser extent) precipitation weather station data are representative of much larger regions (Yan et al. 2002; Pfahl and Wernli 2011; Orlowsky and Seneviratne 2014).

Data availability and quality are some of the prerequisites for extreme event analysis (El Kenawy et al. 2011). A quality controlled infilled provincial weather station dataset already existed for the period from 1960 to 2000 (Schroeter et al. 2008). 56 of those stations are located in eastern Ontario, but only15 of them were still in operation in 2010 (Appendix 2). These stations were considered as potential representative stations for eastern Ontario ecodistricts, provided they had been in operation for at least 25 years prior to 2010. Despite being decommissioned prior to 2010, Arnprior Grandon, Kingston A, and Kingston PS weather stations were also considered due to the length of available data series prior to that year.

The remaining stations were evaluated for ecodistrict representativeness using methods adapted from Yan et al. (2002) and Pfahl and Wernli (2011). Time series of average daily temperature, 5th and 95th percentiles of daily mean values in the annual temperature cycle, total monthly precipitation and the 95th percentile of single day precipitation for each month in the baseline period were calculated for all weather stations (Yan et al. 2002; Pfahl and Wernli 2011; Orlowsky and Seneviratne 2014). For

both temperature and precipitation, the time series of potential representative stations were compared to spatially averaged time series of all other stations in each ecodistrict (Yan et al. 2002). The comparison included calculating the Spearman's rank based correlation coefficient and visually assessing the plotted time series (Orlowsky and Seneviratne 2014). Stations with the highest correlation coefficients with all other stations in each ecodistrict were selected as representative stations, provided a consistent record of over 35 years in the study period or 25 or more consecutive years up to 2010 were identified in an ecodistrict. If such a record was not available, a suitable station in close proximity (within 10 km) to the boundary was selected in an adjacent ecodistrict.

3.3.2 Gap filling and quality control

The analysis of extremes is sensitive to the presence of missing values (El Kenawy et al. 2011), and erroneous data could interfere with assessing extremes and affect the reliability of the finalized data series. Therefore, minimum and maximum daily temperature and precipitation data series for selected weather stations were infilled by Dr. Harold Schroeter, following Schroeter et al. (2000; 2008) and error checking was conducted using RClimDex software (Zhang et al. 2015).

3.3.3 Indicator selection and calculation

A summary of 15 extreme event indices that were calculated for selected representative stations in eastern Ontario is presented in Table 2.1. All except HWE and CWE were developed by the Expert Team on Climate Change Detection and Indices (ETCCDI) in a joint effort of the World Meteorological Organization and the World Climate Research Programme (Alexander et al. 2006). Each of the indices provides an account of the intensity, length or frequency of a particular extreme, such as maximum

single day precipitation event (RX1day), a dry spell (CDD), or a heavy precipitation event (R10). The other two indices, the HWE 30°C 'heat alert' threshold (Environment and Climate Change Canada 2015), and the CWE -20°C severe winter weather threshold (Gachon 2005), provide measures that are specific for adaptation needs in the study region.

Some of the percentile indices (TN10p, TX10p, TN90p, and TX90p) are calculated relative to the 1961-1990 base period that is most commonly used in climate literature (EBNFLO Environmental AquaResource Inc 2010). These indices may have artificial discontinuities at the tails of the base period due to sampling error (Zhang et al. 2005b) and overestimate threshold exceedance rates outside the base period. To eliminate this possibility a bootstrapping procedure was performed, as recommended by Zhang et al. (2005b), to make the estimation of threshold exceedance rates for in-base and out-of-base periods comparable.

All of the selected indices are relevant in the eastern Ontario context and have implications for agriculture and other activities in the region. The indices represent the so-called 'moderate extremes' that occur several times per year or season and allow for a more comprehensive statistical analysis than 'severe extremes' that are only observed once every few years (Klein Tank and Können 2003; Moberg and Jones 2005; Alexander et al. 2006).

To check for differing patterns in agriculturally sensitive times of year, extreme weather indices were calculated and analyzed at four different scales within an annual time step: (a) the entire year (Jan-Dec), (b) the planting season (PS, Apr-May), (c) the growing season (GS, May-Sep), and (d) the harvesting season (HS, Sep-Nov).

Changes and trends in basic climate variables were also examined, including: daily minimum temperature, daily maximum temperature and daily total precipitation (PRCPTOT). These variables were analyzed at the annual and seasonal (PS, GS, HS) scales.

3.3.4 Trend analysis

After the indices were calculated for each time series, trend assessment was carried out by means of the rank-based non-parametric Mann-Kendall (MK) test (Mann 1945; Kendall 1975). This method does not assume that the data are normally distributed and is robust to the effect of outliers that are fairly common in climate data series (Caesar et al. 2011; Vincent et al. 2011), which makes it suitable for extremes' analyses. Iterative de-trending and pre-whitening, as suggested by Zhang et al. (2000), was performed to account for potential lag-1 autocorrelation effects in the time series, which can cause false trend detection (Caesar et al. 2011, Yue et al 2002). The magnitude of trends was computed using the Theil-Sen approach (Sen 1968) and their statistical significance was assessed at the 5% level. P-values for each of the calculated indices are provided in Appendix 4.

Trends in two indices, GSL and CWE, could not be calculated seasonally. The former is only reported annually, while the latter did not have a sufficient number of occurrences at seasonal scales to make trend analysis possible.

3.3.5 Probability density functions

To complete the analysis of temporal changes in climate extremes the study period was split into two 25-year intervals, 1961-1985 and 1986-2010, and regional averages were computed for every index as the mean of the indices at individual stations.

Probability density functions (PDFs) were calculated at the annual and seasonal (PS, GS, HS) periods for each index, as well as regional averages of daily minimum and daily maximum temperature and total precipitation.

All calculations and subsequent statistical analyses and graphic representation of results were performed in R (R Core Team 2015) and ArcGIS Desktop version 10.3 (Esri, Redlands, CA, USA).

3.4 Results

3.4.1 Trends in basic meteorological variables

Changes in daily minimum and maximum temperature and total precipitation are shown in Figure 3.1. There has been an increase in all three variables from 1961 to 2010 in eastern Ontario, with daily minimum temperature, daily maximum temperature and total precipitation increasing by 1.52°C, 1.36°C and 140 mm, respectively. Average annual minimum temperature shows a greater increase than average annual maximum temperature, with decadal changes of 0.33 and 0.28°C respectively (Table 3.1).

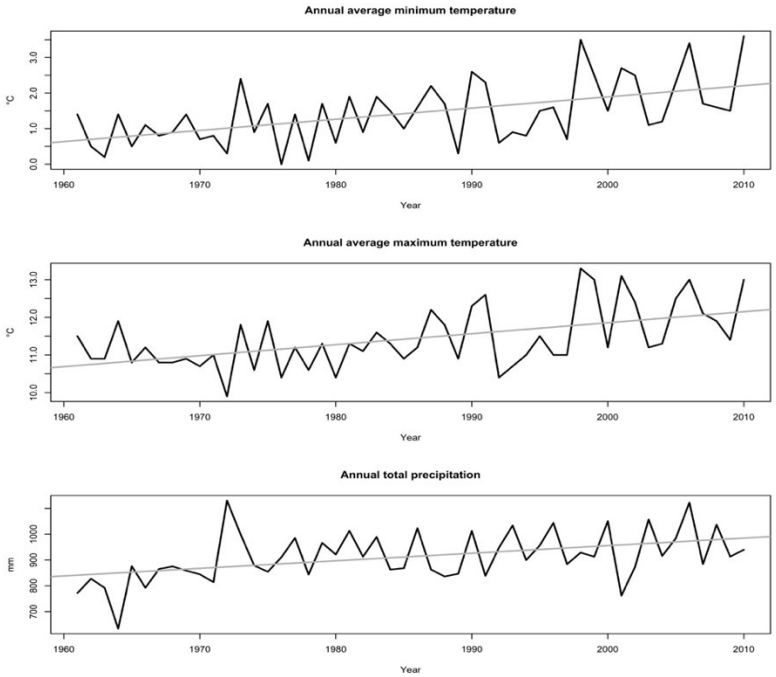


Figure 3.1: Annual average minimum and maximum temperature and total precipitation in eastern Ontario in 1961-2010. Linear trends are shown in grey.

Seasonally, increases in minimum temperature are largest during the growing season, followed by the planting and harvesting seasons, measuring 0.31, 0.30, and 0.18°C, respectively (Tables 3.2, 3.3, and 3.4). Conversely, maximum temperature shows the smallest increase increase during the growing season and greater increases during the planting and harvesting seasons, at 0.18, 0.23, and 0.22°C, respectively (Tables 3.3 and 3.4). The harvesting season is the only time period when increases in maximum temperature are larger than those in minimum temperature (Table 3.4). Average precipitation shows the largest decadal increases during the growing (0.44% or 18.33 mm) and harvesting (0.45% or 11.4 mm) seasons, with smaller increases observed during the planting season (0.4% or 5.97 mm) and annually (0.3% or 27.82 mm) (Tables 3.1 – 3.4). Statistically significant trends in precipitation have been observed annually but are not as coherent as trends in minimum and maximum temperature.

Table 3.1: Trends in climate indices and basic climate variables in eastern Ontario, 1961-2010. Trend analysis was conducted on annual data and significant trends at 95% confidence level are shown in bold. Trend magnitudes are presented as decadal changes, for ease of comparability to other studies. Values for eastern Ontario are averages of ecodistrict trends and have not been assessed for significance.

	Algonquin North	Glengarry Plain	Algonquin South	Napanee - Prince Edward	Smith Falls Plain	Frontenac	Ottawa Valley Plain	Muskrat Lake	Russell and Prescott Plains	North Gower - Winchester Plains	Upper St. Lawrence Plain	eastern ON	Units
HWE	0.38	**1.43**	1.54	0	0	1	0.56	0.53	0.24	0.77	0.38	0.62	days
CWE	**-2.75**	**-2.24**	**-1.89**	**-1.21**	**-2.76**	-0.73	**-2.59**	**-3.89**	-1.26	-0.95	-1.67	-1.99	days
DTR	**-0.08**	-0.04	0	-0.04	-0.03	0	0	-0.08	0	0.03	**-0.19**	-0.04	°C
GSL	**3.33**	**3.57**	2.5	3.08	-0.59	1.43	1	1.98	2.86	1.22	2.73	2.1	days
TN10p	**-1.88**	**-1.9**	**-1.56**	**-1.52**	**-1.44**	**-1.16**	**-1.67**	**-2.65**	**-1.41**	**-1.4**	**-1.65**	-1.66	% days
TX10p	**-1.12**	**-1.6**	**-0.99**	**-1.27**	**-1.09**	**-0.91**	**-1.42**	**-1.01**	**-1.34**	**-1.3**	**-1.21**	-1.21	% days
TN90p	**0.89**	**1**	**0.93**	**0.73**	0.51	0.86	**0.99**	0.23	**1.3**	0.46	**1.6**	0.86	% days
TX90p	**0.79**	**1.2**	**1.34**	0.68	0.61	**1.07**	**0.93**	0.61	**0.9**	**0.83**	0.8	0.89	% days
RX1day	**2.4**	2.29	0.39	0.75	1.45	1.24	1.62	**2.62**	**2.24**	**2.88**	2.99	1.9	mm
RX5day	2.07	3.47	2.13	1.39	**3.74**	**3.75**	**4.9**	2.14	3.33	**3.85**	**3.79**	3.14	mm
SDII	-0.08	-0.03	-0.05	-0.08	0.06	0.03	**0.15**	**-0.19**	0.1	0	-0.14	-0.02	mm/day
R10	0	0.61	0.71	0.24	0.29	0.97	0.54	0.13	**1.51**	**1.85**	0	0.62	days
CDD	0	-0.36	0	0	0	0	0	0	0	0	-0.56	-0.08	days
R95p	6.1	**35**	**20**	9.44	21.85	**22.24**	**28.25**	9.7	**28.44**	**35.61**	14.27	20.99	mm
PRCPTOT	13.17	**36.25**	**29.05**	9.56	9.52	**26.51**	25.85	**24.9**	**42.16**	**56.35**	**32.66**	27.82	mm
AvgTempMin	**0.37**	**0.4**	**0.34**	**0.29**	**0.28**	**0.21**	**0.36**	**0.39**	**0.36**	**0.23**	**0.41**	0.33	°C
AvgTempMax	**0.29**	**0.37**	**0.26**	**0.22**	**0.23**	**0.25**	**0.32**	**0.29**	**0.32**	**0.29**	**0.26**	0.28	°C

Table 3.2: Trends in climate indices and basic climate variables during the planting season in eastern Ontario, 1961-2010. Trend analysis was conducted on annual data and significant trends at 95% confidence level are shown in bold. Trend magnitudes are presented as decadal changes, for ease of comparability to other studies. Values for eastern Ontario are averages of ecodistrict trends and have not been assessed for significance.

	Algonquin North	Glengarry Plain	Algonquin South	Napanee - Prince Edward	Smith Falls Plain	Frontenac	Ottawa Valley Plain	Muskrat Lake	Russell and Prescott Plains	North Gower - Winchester Plains	Upper St. Lawrence Plain	eastern ON	Units
HWE	0	0	0	0	0	0	0	0.08	0	0	0	0.01	days
DTR	-0.09	0.01	0	-0.08	0.01	0	-0.05	0.01	0	0	-0.18	-0.03	°C
TN10p	**-2.18**	**-1.99**	**-1.37**	-0.73	**-1.86**	**-2.72**	**-1.64**	**-2.63**	**-2.74**	**-2.11**	**-2.41**	-2.03	% days
TX10p	-1.02	**-1.36**	-1.08	-1	-1.42	-0.38	**-1.52**	-0.85	**-1.34**	**-1.38**	**-1.56**	-1.17	% days
TN90p	1.16	1.24	1.18	0.43	0.55	0	1.13	-0.1	0	0	**2.13**	0.7	% days
TX90p	1.13	**1.71**	1.59	0.52	0.96	**1.67**	1.17	1.02	1.3	1.49	1.26	1.26	% days
RX1day	0.98	1.39	-1	-0.67	1.73	0.25	1.36	0.66	1.12	1	**1.86**	0.79	mm
RX5day	-0.03	0.18	0.14	-0.09	0	-0.4	0.07	-0.27	-0.29	-0.48	**0.47**	-0.06	mm
SDII	-0.08	0.14	-0.16	-0.29	0.14	0.08	0.06	-0.06	0.13	0.05	0.03	0	mm/day
R10	0.29	0	0	0	0	0	0	0	0.31	**0.48**	0	0.1	days
CDD	-0.16	0	0	0.32	-0.05	0.22	-0.31	-0.21	0	-0.56	-0.56	-0.12	days
R95p	3.09	6.83	-0.76	-2.55	5.64	2.76	4.92	-1.14	6.6	**6.89**	5.92	3.47	mm
PRCPTOT	7.11	6.19	3.42	1.06	4	4.3	6.55	**3.95**	9.47	**10.48**	9.17	5.97	mm
AvgTempMin	**0.44**	**0.39**	0.25	0.16	**0.25**	0.22	**0.31**	**0.33**	**0.31**	0.17	**0.44**	0.3	°C
AvgTempMax	0.24	0.35	0.22	0.06	0.17	0.2	0.27	0.22	0.32	0.3	0.23	0.23	°C

Table 3.3: Trends in climate indices and basic climate variables during the growing season in eastern Ontario, 1961-2010. Trend analysis was conducted on annual data and significant trends at 95% confidence level are shown in bold. Trend magnitudes are presented as decadal changes, for ease of comparability to other studies. Values for eastern Ontario are averages of ecodistrict trends and have not been assessed for significance.

	Algonquin North	Glengarry Plain	Algonquin South	Napanee - Prince Edward	Smith Falls Plain	Frontenac	Ottawa Valley Plain	Muskrat Lake	Russell and Prescott Plains	North Gower - Winchester Plains	Upper St. Lawrence Plain	eastern ON	Units
HWE	0.3	**1.36**	1.52	0	0	1	0.56	0.53	0.23	0.73	0.36	0.6	days
DTR	**-0.15**	-0.09	-0.13	-0.2	-0.08	0	-0.05	-0.13	-0.06	0	**-0.21**	-0.1	°C
TN10p	**-2.36**	**-2.32**	**-1.59**	**-2.68**	**-1.65**	**-1.59**	**-2.25**	**-3.17**	**-2.1**	**-1.5**	**-2.24**	-2.13	% days
TX10p	**-1.47**	**-1.81**	**-0.83**	**-1.24**	**-1.02**	**-1**	**-1.65**	**-0.85**	**-1.52**	**-1.24**	**-1.31**	-1.27	% days
TN90p	**1.44**	**1.19**	1.18	**1.23**	0.26	0.83	**0.91**	-0.57	0.89	-0.39	**1.47**	0.77	% days
TX90p	0.39	1.07	0.47	-0.47	-0.35	0.6	0.18	0	0	0	0	0.17	% days
RX1day	1.43	3.31	-0.03	0.6	-0.05	1.66	1.34	**2.97**	1.58	**2.85**	**2.82**	1.68	mm
RX5day	0.22	**0.19**	0.15	0.12	0	0.14	0.1	0	0.06	0	0.17	0.1	mm
SDII	0.03	0	-0.11	-0.03	0.19	0.18	0.21	-0.1	0.18	0.07	0	0.06	mm/day
R10	0	0.66	0.51	0	0.38	**0.76**	0.48	0	**0.99**	**1.14**	0.47	0.49	days
CDD	0	0	0	0	0	0	0.45	0.23	0	0	0	0.06	days
R95p	5.2	**13.97**	11.02	5	**13.95**	10.33	11.46	8.19	18.14	**18.03**	14.53	11.8	mm
PRCPTOT	8.11	**22.55**	18.37	10.2	12	17.13	**17.5**	**16.69**	**24.03**	**28.85**	**26.2**	18.33	mm
AvgTempMin	**0.42**	**0.4**	**0.29**	**0.39**	**0.25**	**0.16**	**0.32**	**0.33**	**0.35**	**0.12**	**0.39**	0.31	°C
AvgTempMax	**0.24**	**0.32**	0.15	0.07	0.09	0.14	**0.21**	0.17	**0.22**	**0.19**	0.13	0.18	°C

Table 3.4: Trends in climate indices and basic climate variables during the harvesting season in eastern Ontario, 1961-2010. Trend analysis was conducted on annual data and significant trends at 95% confidence level are shown in bold. Trend magnitudes are presented as decadal changes, for ease of comparability to other studies. Values for eastern Ontario are averages of ecodistrict trends and have not been assessed for significance.

	Algonquin North	Glengarry Plain	Algonquin South	Napanee - Prince Edward	Smith Falls Plain	Frontenac	Ottawa Valley Plain	Muskrat Lake	Russell and Prescott Plains	North Gower - Winchester Plains	Upper St. Lawrence Plain	eastern ON	Units
HWE	0	0	0	0	0	0	0	0	0	0	0	0	days
DTR	-0.04	0.11	0.18	0.18	0.05	0	0.14	0	0	**0.06**	-0.03	0.06	°C
TN10p	**-1.32**	**-1.47**	-0.89	-0.33	**-1.25**	-0.69	-0.8	**-2.54**	**-1.27**	-1.23	**-1.18**	-1.18	% days
TX10p	-0.92	**-2.1**	-0.81	**-1.11**	**-1.15**	-1.1	**-1.46**	-0.83	**-1.14**	-1	**-1.4**	-1.18	% days
TN90p	0.52	0.34	0.71	0	0	0	0.58	0	0	-0.56	0.65	0.2	% days
TX90p	0.37	0.41	1.14	0	0	0.55	0	0	0	0	0.35	0.26	% days
RX1day	1.29	2.58	2.13	1.43	1.05	2.73	2	1.07	1	2	2.27	1.78	mm
RX5day	0.31	0	0.11	0	0	0.23	0.09	-0.09	0.32	0.08	0.11	0.11	mm
SDII	-0.15	0.06	0.13	0.07	0.1	0.26	0.23	-0.31	0	-0.07	0	0.03	mm/day
R10	0	0.63	0.13	0	0	0	0	0	0	0	**0.61**	0.12	days
CDD	0	-0.38	0	0	0	0.12	0	0	0	-0.38	-0.26	-0.08	days
R95p	1.43	12	**14.74**	9	8.13	**14.14**	9.63	3.26	8.1	8	**13.57**	9.27	mm
PRCPTOT	5.67	14.71	**15.77**	10.64	3.37	13.87	8	4.95	11.5	**17.78**	**19.12**	11.4	mm
AvgTempMin	**0.24**	**0.26**	0.2	0.06	0.1	0.06	0.19	**0.29**	**0.22**	0.1	**0.27**	0.18	°C
AvgTempMax	0.2	**0.38**	**0.24**	0.2	0.12	0.18	**0.31**	0.16	0.21	0.18	0.2	0.22	°C

Seasonal changes in temperature and precipitation distributions for two 25-year sub-periods are shown in Figures 3.2 – 3.4. Maximum and minimum temperature changes are dominated by shifts to warmer and more variable conditions. For average minimum temperature the greatest increases and changes in variability can be observed during the planting and growing season, with modest increases happening during the harvesting season. Similarly, average maximum temperatures show the most significant changes during the planting and growing seasons, mostly due to increases in higher percentiles of the distribution as well as greater variability. Interestingly, a prominent distributional shift in maximum temperature during the growing season surpasses that of minimum temperature, despite the fact that minimum temperatures are known to change at a greater rate than maximum temperatures. Distributional shifts towards greater total precipitation can be observed during the growing and harvesting seasons, while the planting season shows the least change.

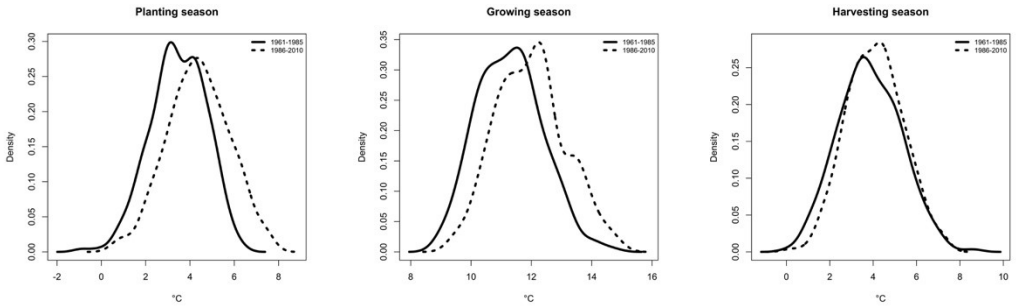


Figure 3.2: Temporal changes in probability distributions of seasonal (PS, GS, HS) average daily minimum temperature in eastern Ontario.

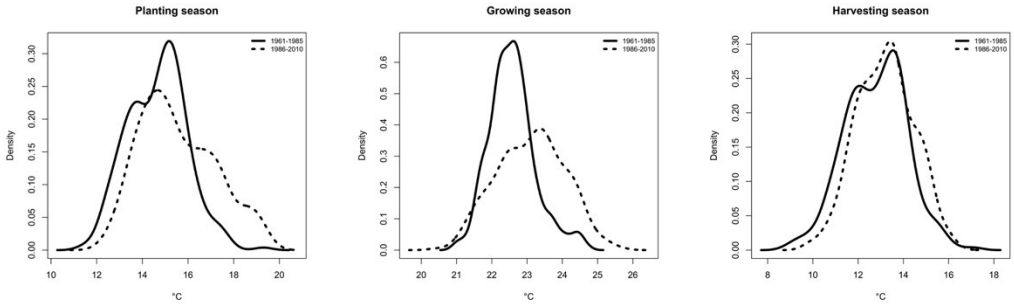


Figure 3.3: Temporal changes in probability distributions of seasonal (PS, GS, HS) average daily maximum temperature in eastern Ontario.

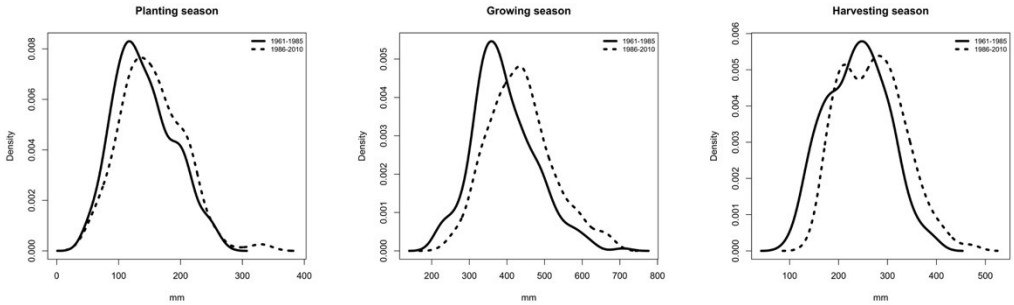


Figure 3.4: Temporal changes in probability distributions of seasonal (PS, GS, HS) total precipitation in eastern Ontario.

3.4.2 Trends in temperature indices

Trends in temperature indices, expressed as change per decade, were calculated annually and seasonally (PS, GS, HS) and are presented in Tables 3.1 – 3.4 for individual ecodistricts and the entire region.

Cold weather extremes (CWE) have decreased by an average of 1.99 days/decade across eastern Ontario, with over half of the ecodistricts showing statistically significant decreases. Increases in hot weather extremes (HWE) are less substantial at 0.62 days/decade on average, with the only significant trend detected in the Glengarry Plain ecodistrict, while Napanee – Prince Edward and Smith Falls Plain ecodistricts exhibit no trend. Growing season length (GSL) shows statistically significant increases in Algonquin North and Glengarry Plain, with an average increase of 2.1 days/decade and only the Smith Falls Plain ecodistrict exhibiting a slight decrease in growing season

length. The number of cool nights (TN10p) and cool days (TX10p) have decreased at all ecodistricts and time periods, being most substantial during the growing season, at 2.13 and 1.27 days/decade for cool nights and cool days respectively. The decrease in cool nights and cool days is statistically significant for all ecodistricts annually and during the growing season and for over half of the ecodistricts during planting and harvesting seasons. Warm nights (TN90p) and warm days (TX90p) exhibit increasing trends across the region, with statistically significant trends present annually for the majority of ecodistricts.

Trends during agriculturally important times of the year are mostly non-significant, implying that significant changes in warm nights and warm days likely occur during the winter months. The largest increase in warm nights (0.77 days/decade) occurred during the growing season, while the largest increase in warm days (1.26 days/decade) was during the planting season. Overall, decreases in cool extremes have been happening at a greater rate than increases in warm extremes, corresponding to a general decline in the daily temperature range (DTR) across the region.

Spatial trends in temperature indices at the annual, PS, GS, and HS time periods are presented in Figures 3.5, 3.6, 3.7, and 3.8, respectively. Cold weather extremes have decreased substantially throughout the region, while hot weather extremes show more variability, with stationary trends (i.e. no notable change) in Napanee – Prince Edward and Smith Falls Plain ecodistricts and the largest increasing trends in South Algonquin and Glengarry Plain (Figure 3.5a and b). Daily temperature range is the least spatially coherent index, with positive, negative and stationary trends present at all time periods except the growing season, when decreases in the DTR are dominant across the region

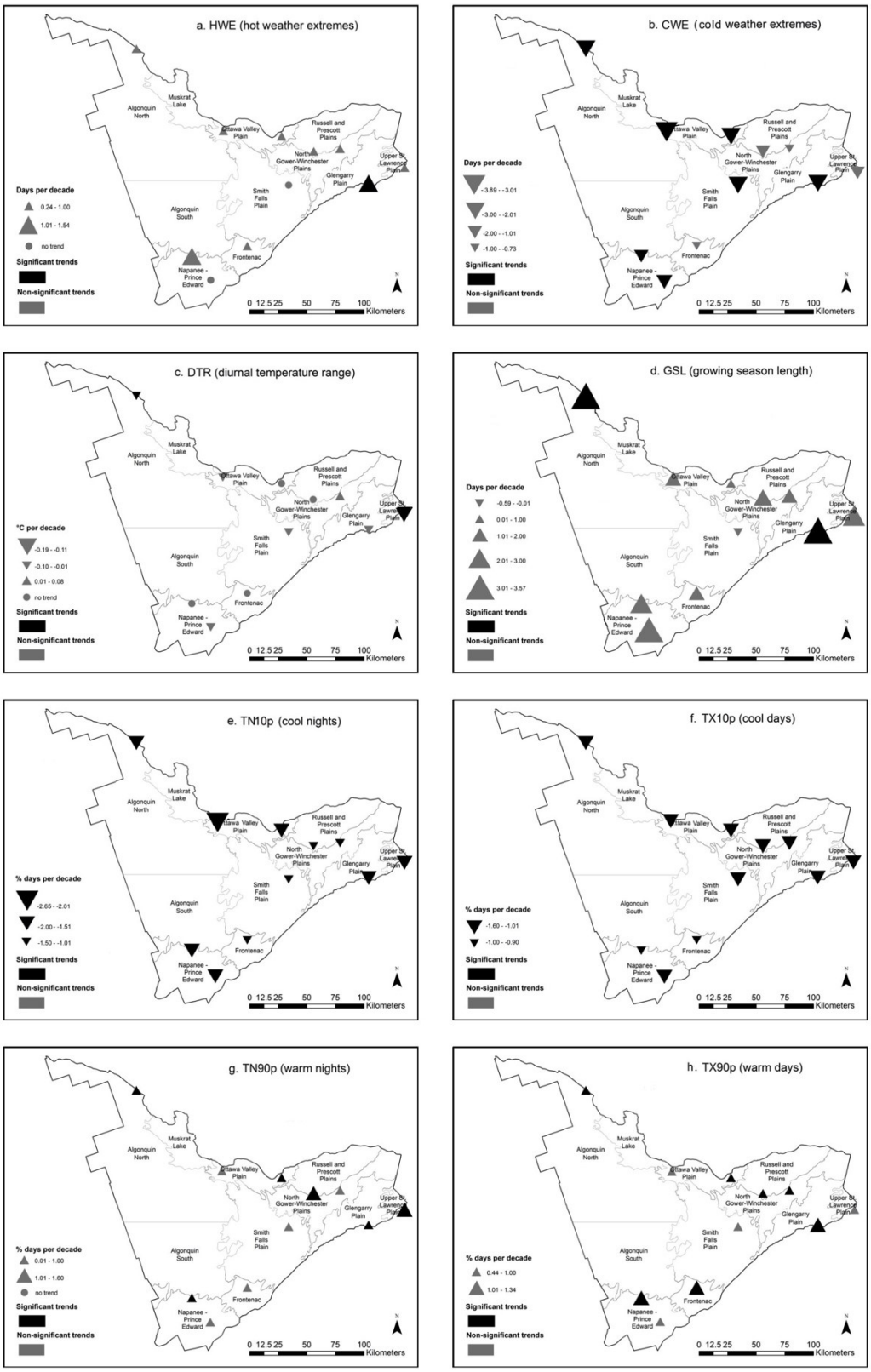


Figure 3.5: Trends in annual temperature indices in eastern Ontario in 1961-2010.

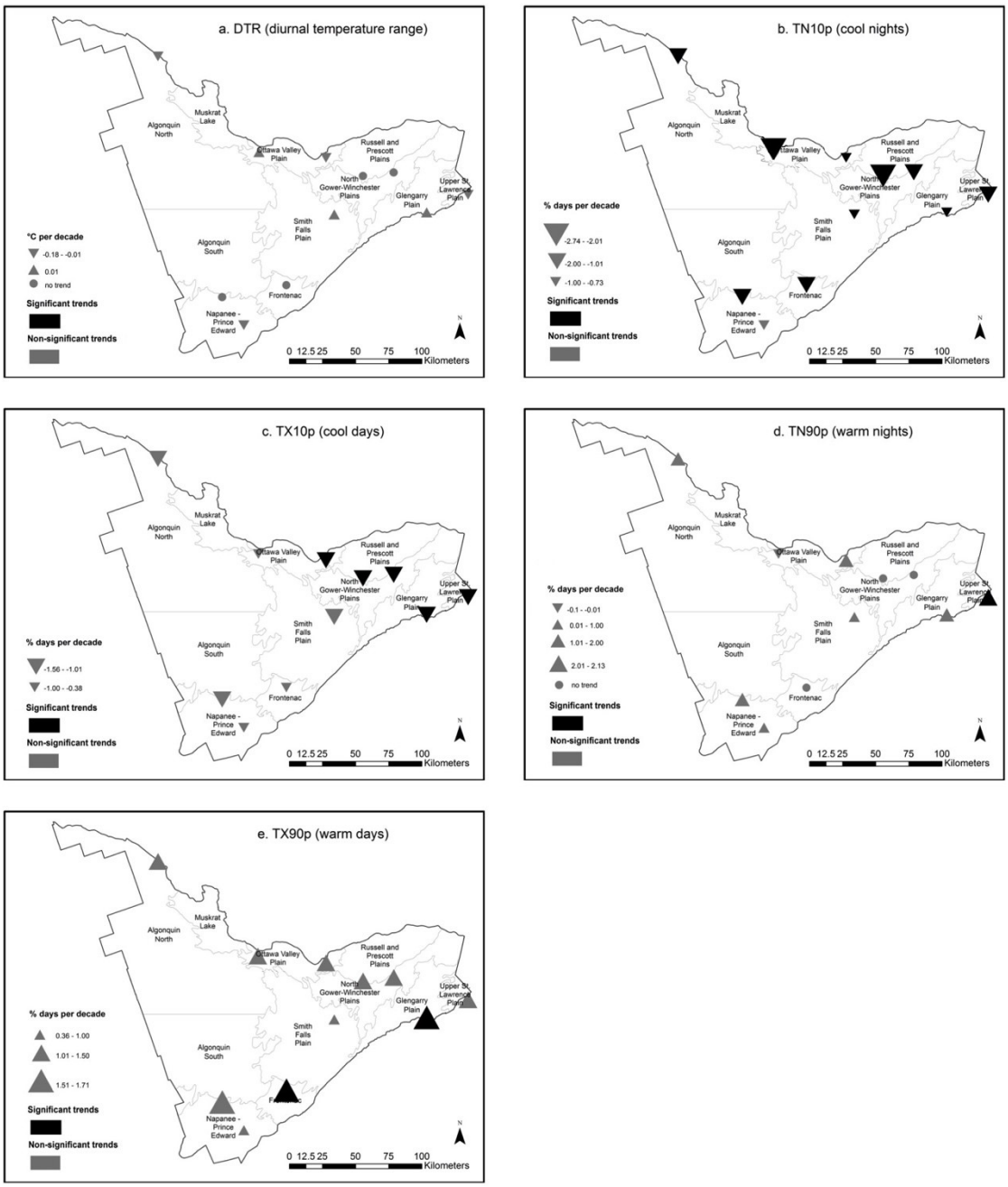


Figure 3.6: Trends in temperature indices during the planting season in eastern Ontario in 1961-2010.

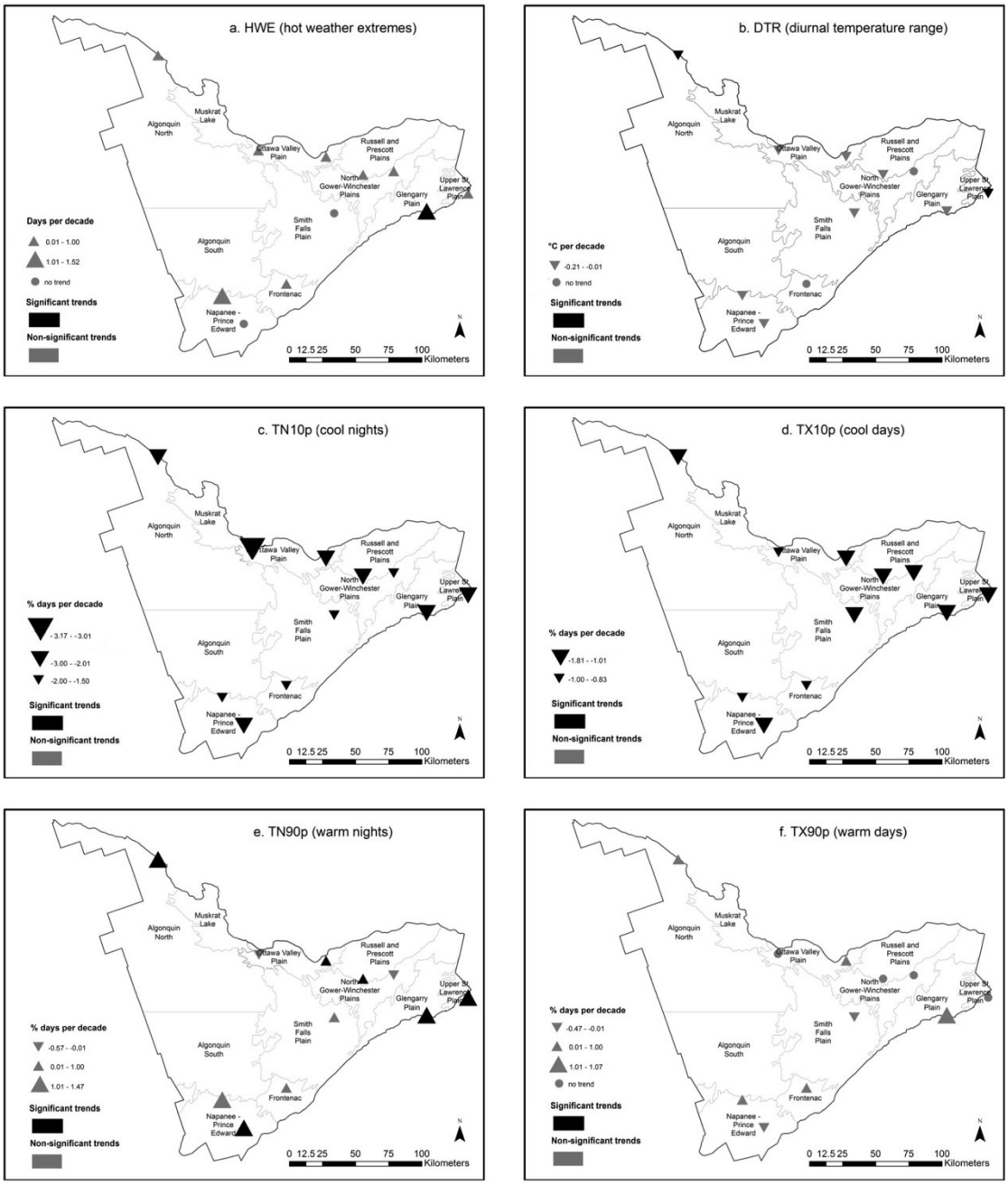


Figure 3.7: Trends in temperature indices during the growing season in eastern Ontario in 1961-2010.

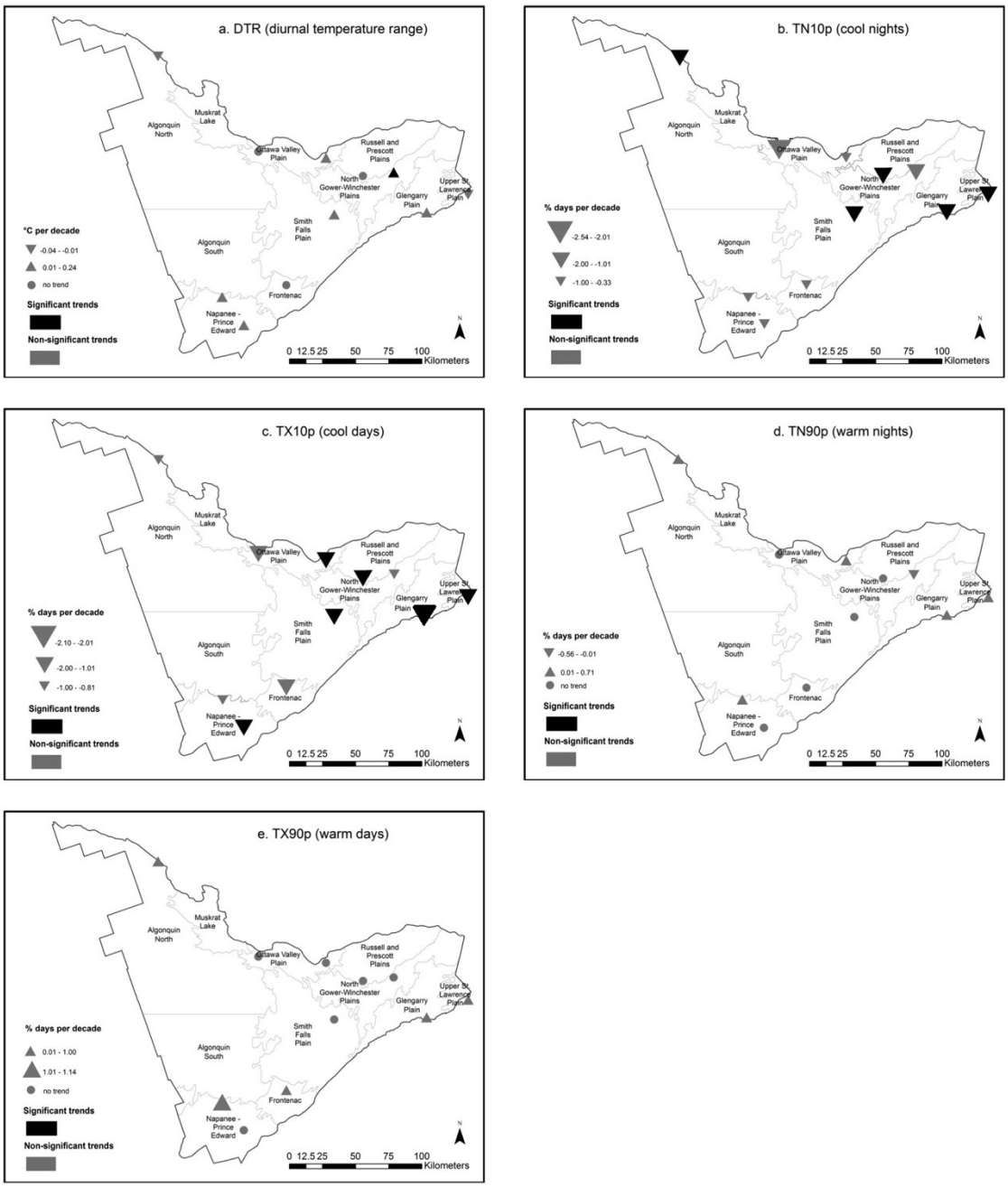


Figure 3.8: Trends in temperature indices during the harvesting season in eastern Ontario in 1961-2010.

(Figures 3.5c, 3.6a, 3.7b, and 3.8a). Growing season length has increased in most of eastern Ontario except the Smith Falls Plain ecodistrict, with the biggest increases occurring in the southern and eastern parts of the region (Figure 3.5d). Indices with the most consistency across eastern Ontario are cool nights and cool days, which have decreased in all ecodistricts and at all time periods, the greatest changes occurring along the St. Lawrence and Ottawa rivers in the eastern part of the region annually and during the planting season (Figures 3.5e and f, 3.6b and c). Warm days and warm nights have increased the most in the southern and eastern parts of the region, respectively, while ecodistricts along the Ottawa River show the least amount of change annually (Figure 3.5g and h). Notably, there has been less spatial coherency during agriculturally sensitive times of year, with stationary and negative trends present in both indices during the planting, growing and especially harvesting seasons (Figures 3.6d and e, 3.7e and f, 3.8d and e). The majority of stationary and negative trends have been observed in North Gower – Winchester Plains, Russell and Prescott Plains, Muskrat Lake and Napanee – Prince Edward ecodistricts.

3.4.3 Trends in precipitation indices

A shift toward a wetter climate has been observed across the region, manifested in greater total precipitation, maximum 1-day and 5-day precipitation amounts (RX1day and RX5day), more heavy precipitation days (R10) and precipitation on very wet days (R95p), as well as a decline in the number of consecutive dry days (CDD), as seen in Tables 3.1-3.4.

Annual trends in RX1day have shown an increase of 1.9 mm/decade, with the greatest growth observed during the harvesting season. Most of the trends are not

statistically significant and there are some negative trends during the planting and growing seasons. At the annual scale, RX5day has increased by 3.11 days/decade; however, seasonal trends have much smaller magnitude and a large number of negative and stationary trends are present during the planting and growing seasons. Statistically significant trends have been observed only annually and during the growing season. R10 has increased by 0.62 days/decade annually but exhibits smaller growth rates at seasonal time periods, most notably the planting season (0.1 days/decade). The majority of trends are not statistically significant and a large number of stationary trends are present during the planting and harvesting seasons. Similarly, precipitation on very wet days shows greater increases (20.99 mm/decade) and more statistically significant trends annually compared to seasonal periods (e.g. 3.47 mm/decade during the planting season). The number of consecutive dry days has decreased at all periods except the growing season, during which a slight increase has been observed. Simple daily intensity index shows the least substantial change and the greatest variability, with positive, negative and stationary trends present at all periods.

Spatial trends in precipitation indices for annual and seasonal (PS, GS, HS) periods are presented in Figures 3.9, 3.10, 3.11, and 3.12.

Maximum 1-day and 5-day precipitation indices are consistently increasing at the annual and harvesting season periods, with particularly strong increases observed in the eastern part of the region (Figures 3.9a and b, 3.12a and b). By contrast, no distinct patterns have been observed among ecodistricts during the planting season, although maximum 5-day precipitation shows an overall decline over time (Figure 3.10b). The number of consecutive dry days and simple daily intensity index have shown the least

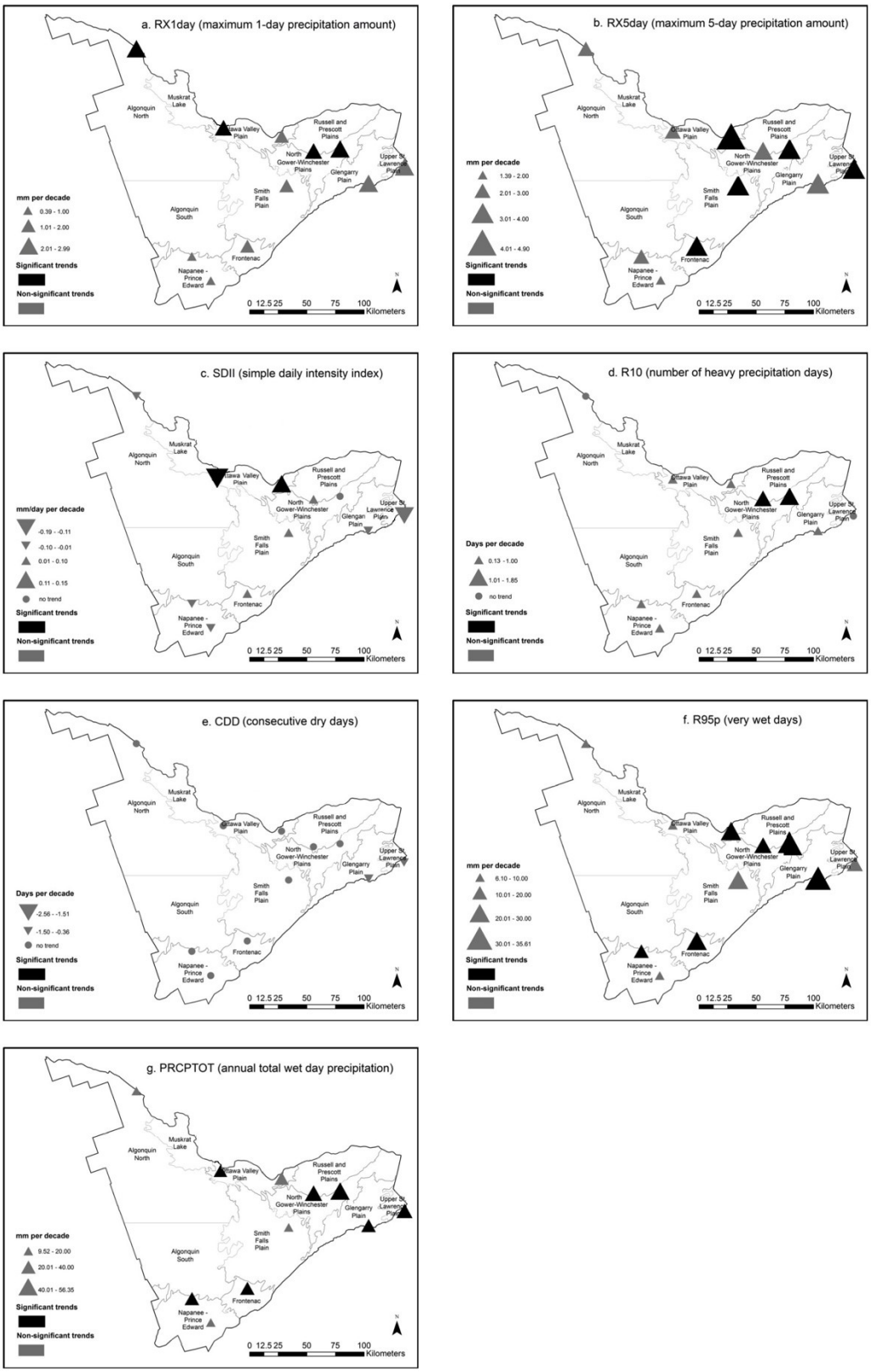


Figure 3.9: Trends in annual precipitation indices in eastern Ontario in 1961-2010.

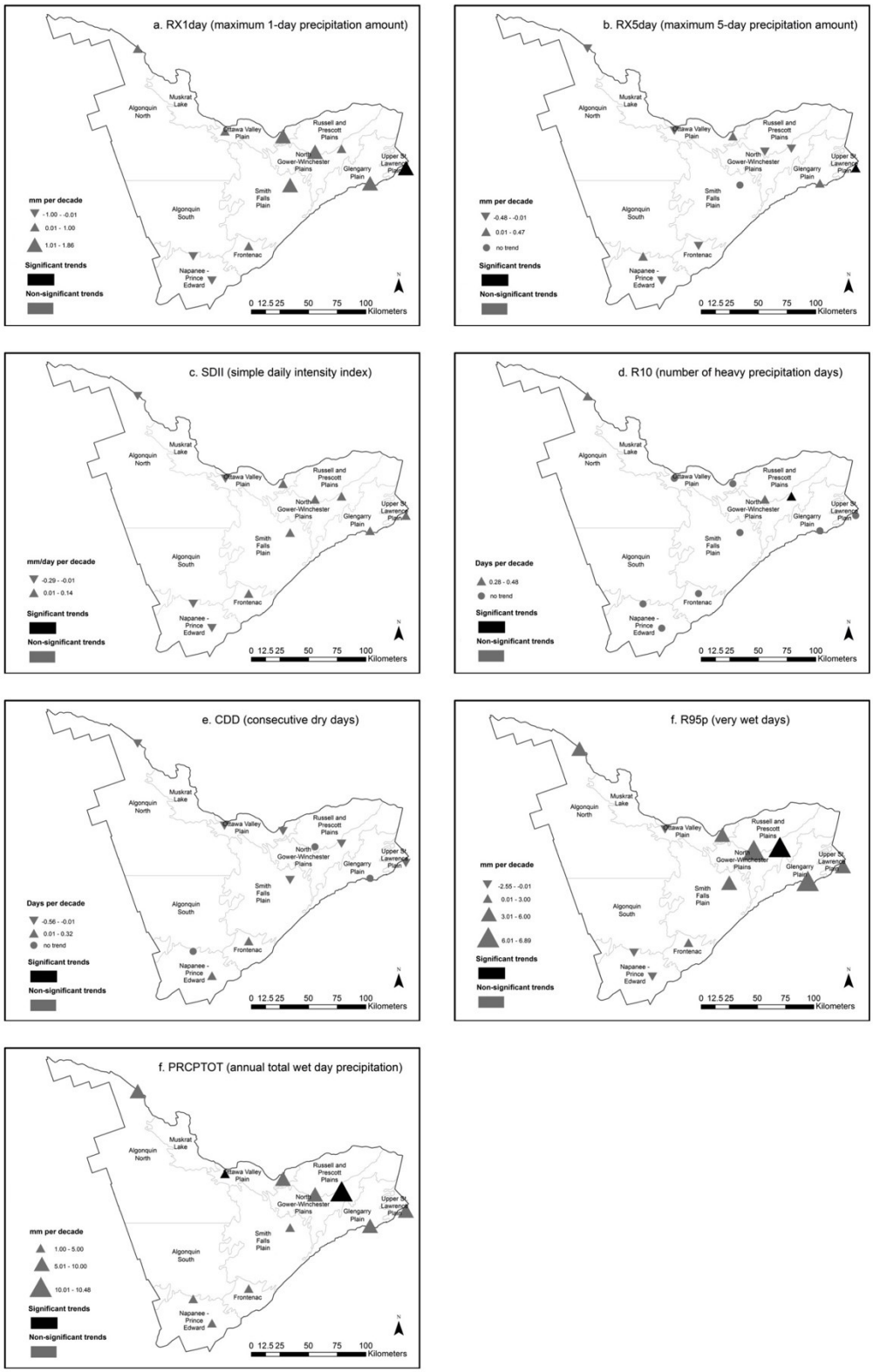


Figure 3.10: Trends in precipitation indices during the planting season in eastern Ontario in 1961-2010.

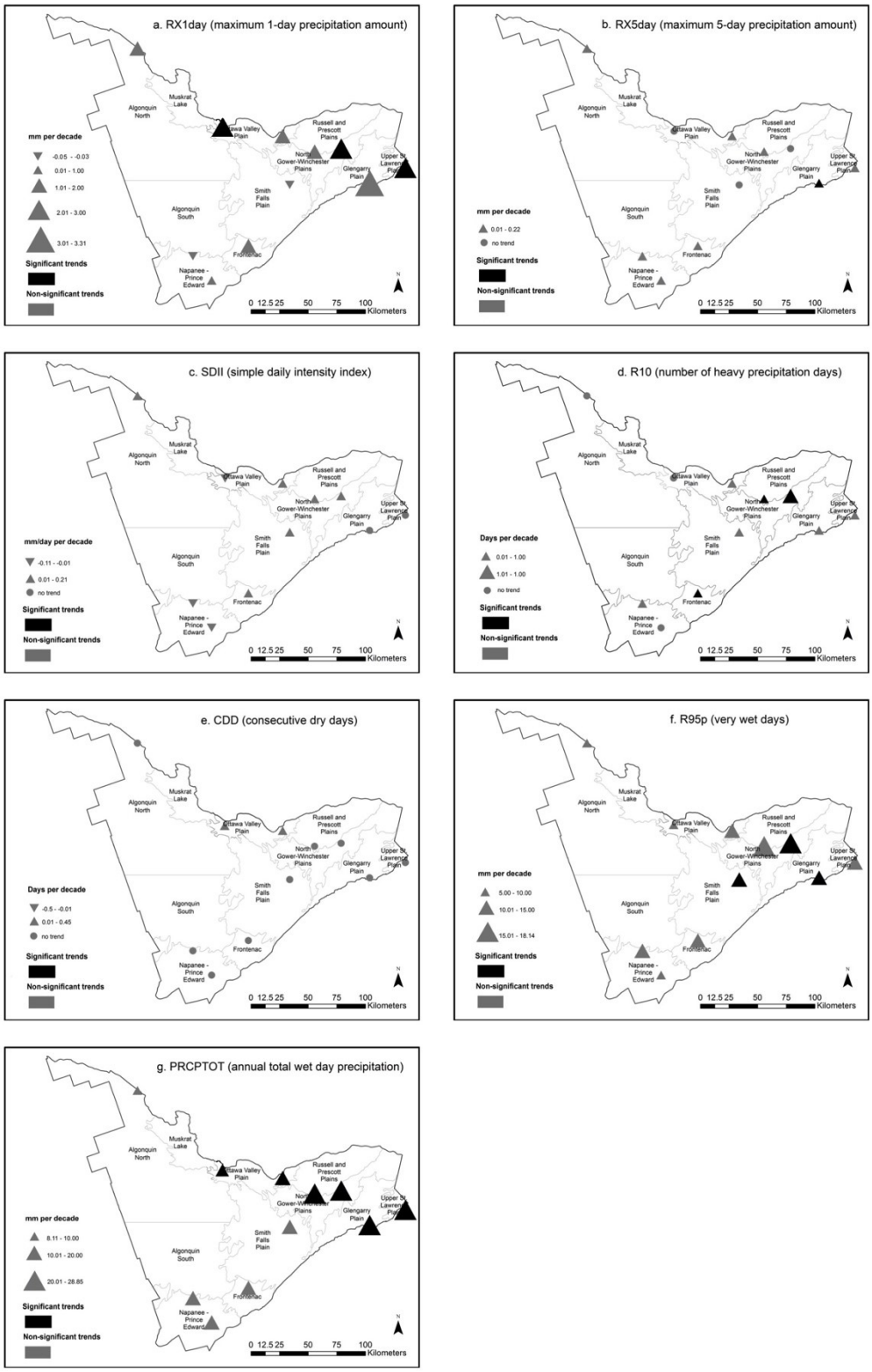


Figure 3.11: Trends in precipitation indices during the growing season in eastern Ontario in 1961-2010.

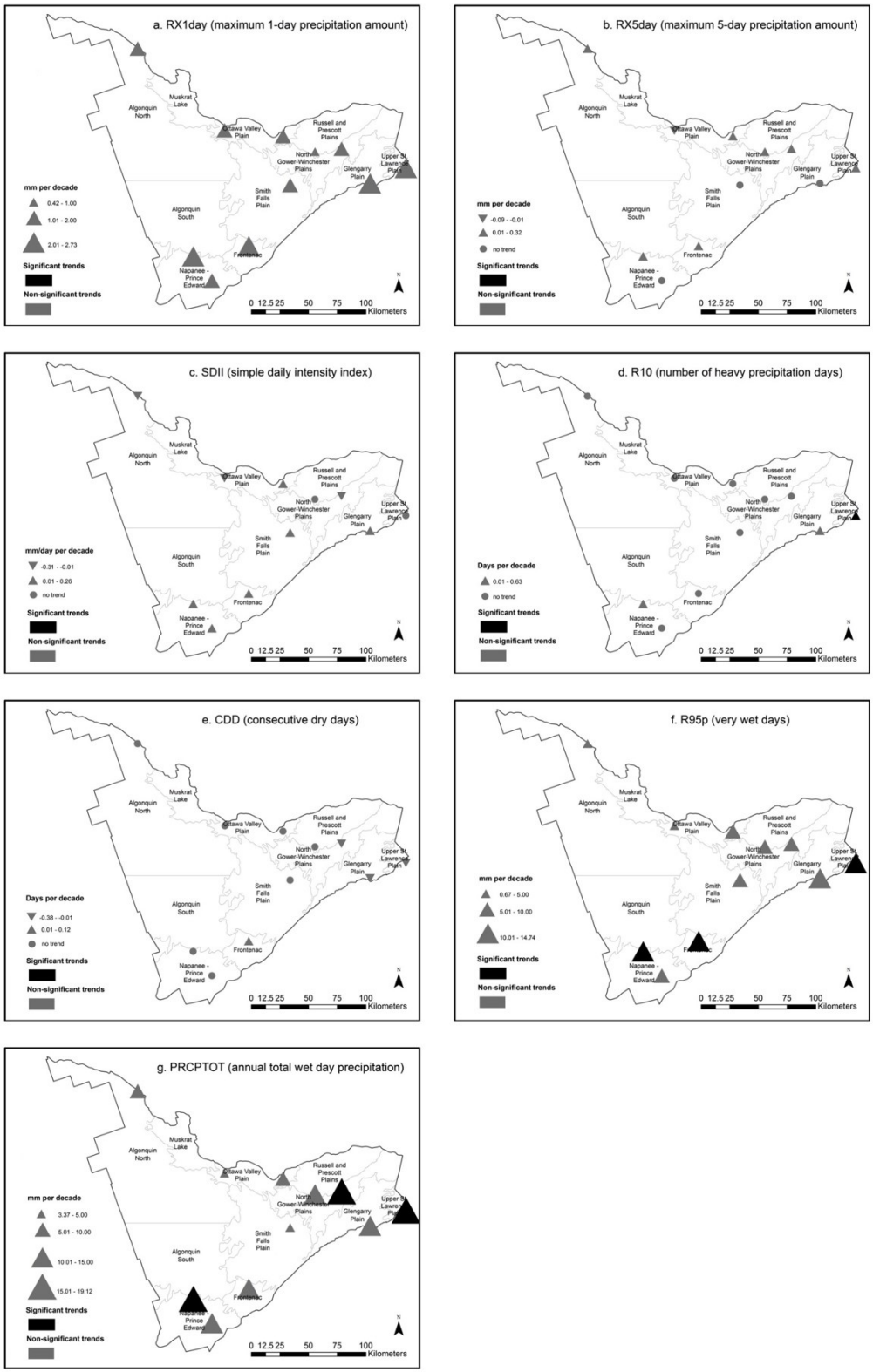


Figure 3.12: Trends in precipitation indices during the harvesting season in eastern Ontario in 1961-2010.

number of significant trends as well as the least spatial coherence, with positive, negative and stationary trends occurring at all time periods (Figures 3.9c and e, 3.10c and e, 3.11c and e, 3.12c and e). The largest increases in heavy precipitation days occur annually and during the growing season; however, most of these trends are not statistically significant (Figures 3.9d and 3.11d). One of the more striking trends was the increase in the number of very wet days, with most of the increases happening in the eastern part of the region annually (Figure 3.9f) and during the growing season (Figures 3.11f). Total precipitation exhibits the largest variability annually, with the biggest increases occurring in North Gower – Winchester Plains, Russell and Prescott Plains, and Glengarry Plains ecodistricts (Figure 3.9g). The most substantial increases in total precipitation during the planting, growing and harvesting seasons also occur in the eastern and southern parts of the region (Figures 3.10g, 3.11g, and 3.12g), in areas located in close proximity to large bodies of water such as the St. Lawrence river and affected by the changing mid-latitudes' storm tracks (Klein Tank et al. 2009). Overall, precipitation indices show fewer statistically significant trends compared to temperature indices and less spatial coherence, especially at seasonal time periods.

3.4.4 PDF functions: multi-decadal summaries

Comparing probability distributions for two sub-periods (Figures 3.13 - 3.16) shows notable decreases in cold weather extremes (CWE) and increases in hot weather extremes (HWE) and growing season length (GSL). Percentile-based indices indicate that the number of cool nights (TN10p) and cool days (TX10p) has declined substantially at the annual, planting and growing season scale, while the decrease during the harvesting season is less pronounced. The number of warm nights (TN90p) and warm days (TX90p)

has increased, with the greatest changes observed at the annual scale. Changes during the planting, growing, and especially harvesting season are less pronounced. Overall, the differences between the distributions of the percentile-based indices indicate that extreme minimum temperature has been increasing faster than extreme maximum temperature. This trend is consistent with the decrease in the daily temperature range (DTR) that has been observed annually and during the planting and growing seasons, while increasing slightly during the harvesting season. A common feature in the distributions of extreme maximum temperature indices across all time periods is increased variability in 1986-2010 compared to 1961-1985.

Precipitation indices show fewer and less pronounced signs of change compared to temperature indices, with most notable changes occurring as increases in short, intense precipitation events. Increases in maximum single-day precipitation (RX1day), very wet days (R95p), and total precipitation (PRCPTOT) have been observed at all time periods and, coupled with decreases in simple daily precipitation intensity (SDII), this implies that there were more days with precipitation in 1986-2010 compared to 1961-1985. The number of heavy precipitation days (R10) and maximum 5-day precipitation amount (RX5day) exhibit minor increases in frequency and magnitude, respectively. The variability of the two indices has increased annually and during the growing season, with few changes during the planting season and a decrease during the harvesting season. The number of consecutive dry days (CDD) shows a minor decrease annually and during the planting and harvesting seasons, and a mostly stationary trend during the growing season. An overall shift toward a warmer and wetter climate has been observed.

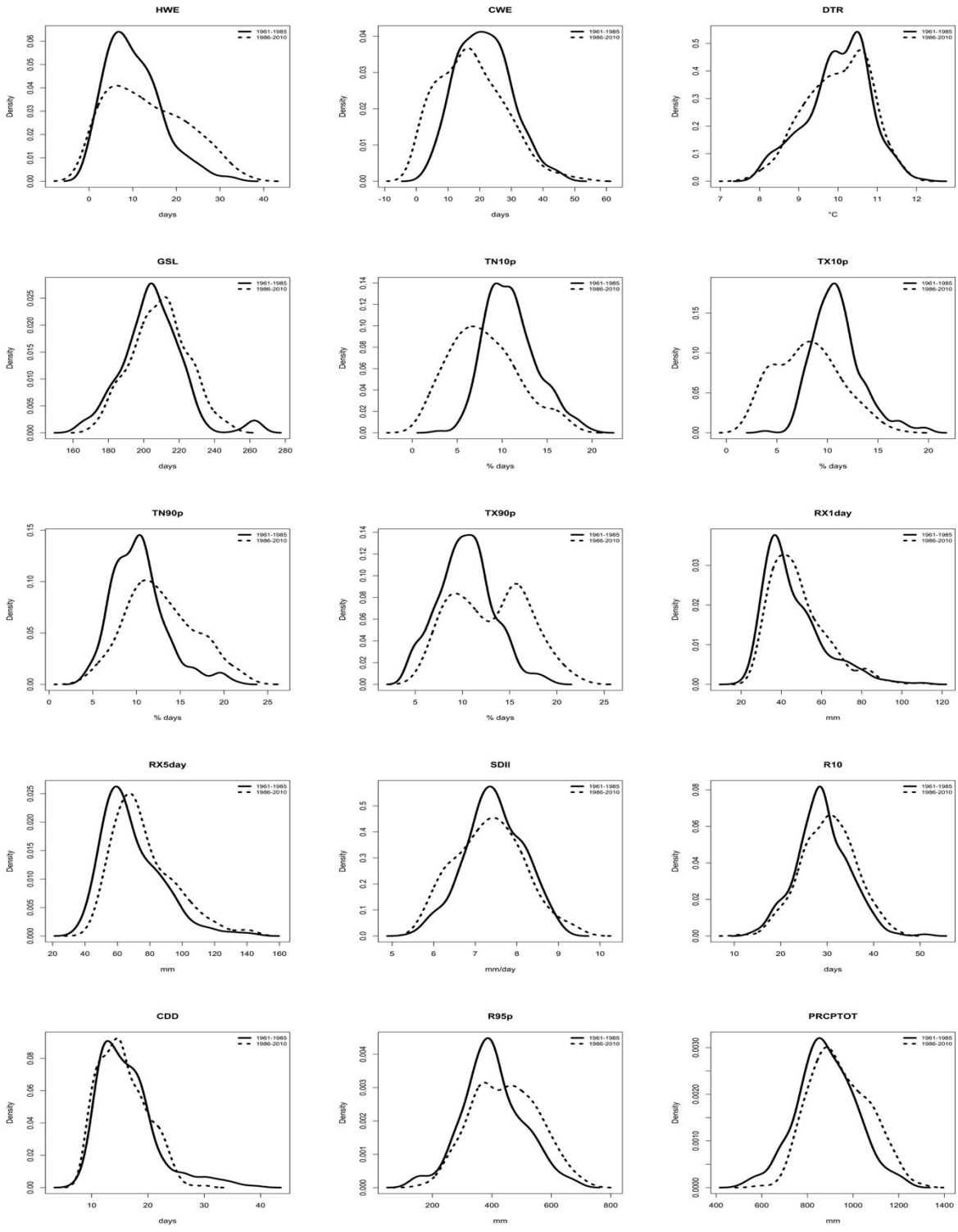


Figure 3.13: Temporal changes in annual probability distributions of extreme event indices in eastern Ontario.

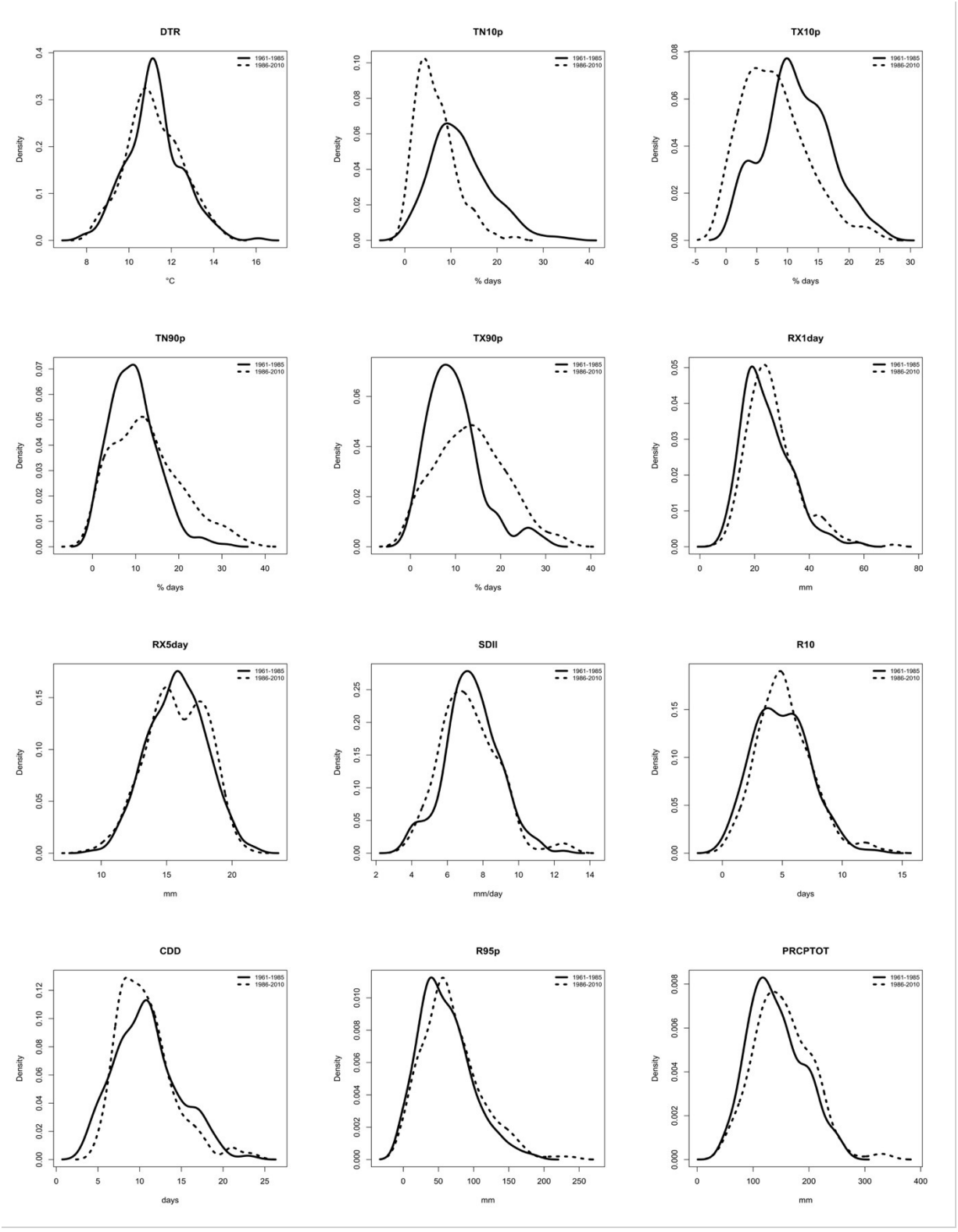


Figure 3.14: Temporal changes in probability distributions of extreme event indices during the planting season in eastern Ontario.

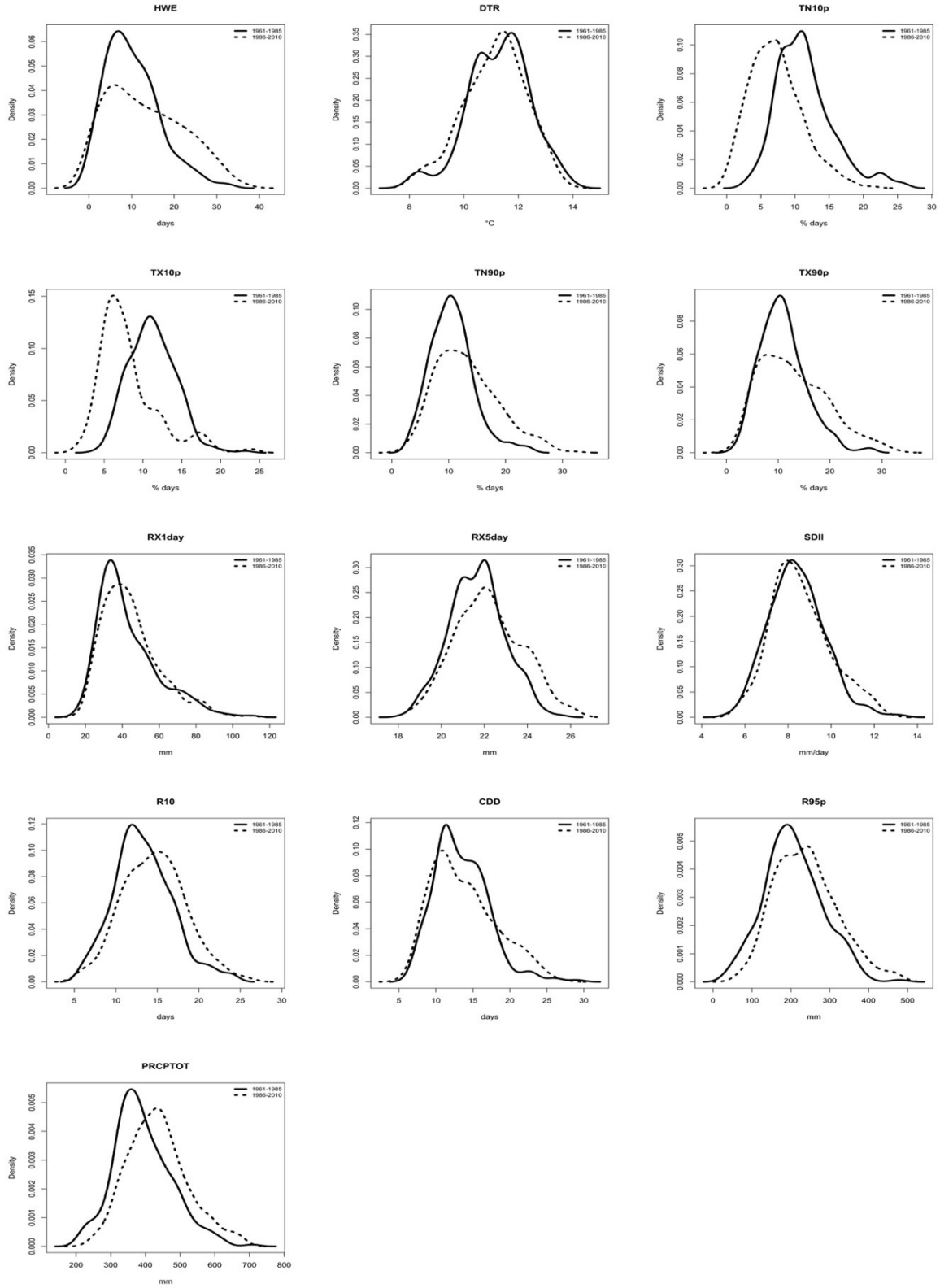


Figure 3.15: Temporal changes in probability distributions of extreme event indices during the growing season in eastern Ontario.

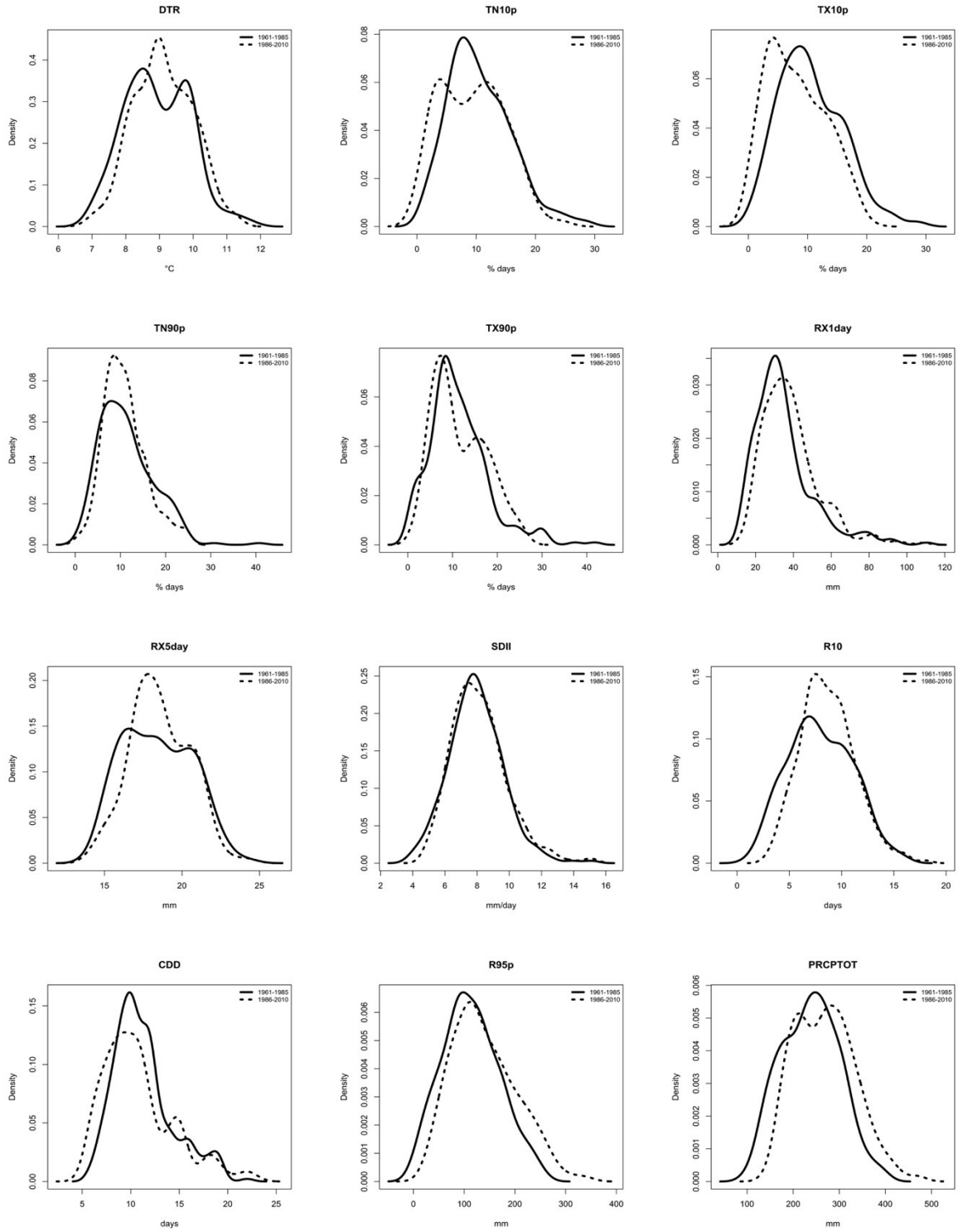


Figure 3.16: Temporal changes in probability distributions of extreme event indices during the harvesting season in eastern Ontario.

3.5 Discussion

This research is one of the first reports to use standard indices to describe trends in climate extremes in eastern Ontario on agriculturally based time periods. The use of data from weather stations representing ten distinct ecodistricts in the region has allowed for a detailed exploration of geographical differences in climate trends within eastern Ontario. It should be kept in mind that few stations are completely free of changes in location, instruments or observing practices that could have an impact on the instrumental record (Insaf et al. 2013); therefore, care should always be taken during result interpretation. Since homogeneity tests and adjustments have not been performed in this research, the discussion focuses more on the overall magnitude and direction of trends as opposed to specific values.

The majority of statistically significant changes in climate extremes in eastern Ontario have been observed at the annual rather than seasonal periods. According to Yan et al. (2002), seasonal temperature and precipitation are known to be more variable from year to year than annual values. Therefore, substantial interannual variations could result in a large number of high magnitude trends not detected as significant using the MK test.

Maximum and minimum temperature changes in the region are dominated by shifts to warmer and more variable conditions. Warmer temperatures and the corresponding increase of the growing season length are expected to be beneficial for agricultural operations in the region; however, related risks such as the spread of pests and diseases adapted to the new, warmer climate are a concern. Changes in interannual variability can impact agricultural productivity and pose increased risks to food security, for instance, by affecting the amplitude and predictability of pest and disease outbreaks

(Gornall et al. 2010). Additionally, increased summer temperatures could result in reduced weight gain in cattle and reduced milk production in dairy cows, as well as heat-related losses for poultry producers (AAFC 2015).

Decreases in cold weather extremes, cool days and cool nights have been consistently larger than increases in hot weather extremes, warm days and warm nights at all time periods. This phenomenon, known as asymmetric warming, has been observed in other parts of Canada (Vincent and Mekis 2006; Yagouti et al. 2008), northeastern United States (Brown et al. 2010), and globally (Frich et al. 2002; Alexander et al. 2006). The results of this investigation are therefore in agreement with earlier global studies showing that it is more accurate to view the world as becoming less cold rather than getting hotter (Alexander et al. 2006).

Changes in precipitation patterns in eastern Ontario have been observed at all time periods. Greater increases in annual values of precipitation indices compared to values during agriculturally relevant seasons are likely an indication of significant increases in winter precipitation. Coupled with increases in air temperature, the likelihood of winter precipitation to fall in the form of rain is high (IPCC 2012). As a result, protective snow cover could be diminished, exposing perennial plants (e.g. forages) to killing frosts (Belanger et al. 2002) and providing a poor opportunity for groundwater recharge prior to the planting season (Sauchyn et al. 2009). Observed increases in total precipitation as well as the amount of heavy precipitation and very wet days during the planting, growing and harvesting seasons could potentially be detrimental to crops and cause disruptions in farm operations. Heavy rains in spring cause planting delays and often result in elevated disease risks, while excessive fall precipitation delays harvesting and has a detrimental

effect on crop quality (Weber and Hauer 2003; Hatfield et al. 2011). Shifts in precipitation distribution and greater amounts of rain falling during high precipitation events result in insufficient water availability and drought conditions at critical crop growth stages (Hatfield and Prueger 2004). Lack of available soil moisture becomes a particularly important issue when air temperature is elevated because this increases moisture retention capacity of air and consequently evaporation, imposing further stress on crops (Sauchyn et al. 2009). Importantly, these changes are particularly prominent in the eastern part of the region where the majority of higher quality agricultural lands are located (Statistics Canada 2011b).

Statistically significant trends in precipitation indices have been observed annually but are not as coherent as trends in temperature indices. This finding is in agreement with other studies (Wulfmeyer and Henning-Mueller 2006; Pfahl and Wernli 2011) that comment on the relation between spatial coherence and large-scale atmospheric forcings that trigger extreme temperature events. In their investigation of the influence of large teleconnection patterns, such as the Arctic Oscillation (AO), the Pacific–North American pattern (PNA), and the El Niño–Southern Oscillation (ENSO) on climatic extremes Griffiths and Bradley (2007) found that the AO was a good predictor of winter temperature extremes in the northeastern United States, a region directly adjacent to our study area. In comparison, the spatial coherence of precipitation extremes, particularly in warmer months, is smaller and corresponds to short-term convective events. At the annual scale, precipitation extremes exhibit greater spatial coherence due to the passage of synoptic-scale low-pressure systems resulting in increased accumulation periods of precipitation (Bacchi and Kottegoda 1995; Pfahl and

Wernli 2011).

3.6 Conclusion

A detailed examination of changes in extreme weather events in 1961-2010 was conducted for eastern Ontario. A suite of descriptive indices of moderate extremes that occur several times per year or season and allow for a comprehensive statistical analysis was selected. Changes in weather conditions were studied at annual and agriculturally significant periods, including the planting, growing and harvesting seasons, making the results valuable for the agricultural community and providing relevant scientific guidance to policy and decision makers in the region.

The analysis of trends and probability distributions of basic temperature and precipitation variables and extreme event indices has shown an increase in warmer and wetter conditions in most parts of the region. The greatest changes in both temperature and precipitation extremes have been observed in the eastern part of the region and along the St. Lawrence River, where most agricultural lands are located. Temperature indices show a higher degree of spatial coherence than precipitation indices, and the majority of statistically significant changes were observed at the annual rather than seasonal periods.

To further improve our understanding of changing extremes in eastern Ontario, it is recommended that future studies address the issue of data homogeneity in weather station time series and evaluate the impacts of changing large-scale systems (e.g. shifts in mid-latitudes' storm tracks) on local climate. To better understand the impacts of weather extremes at agriculturally sensitive times of year, it is recommended that individual crop tolerances are studied to provide information on specific effects of extremes on agricultural crops.

This study improves our understanding of the spatial and temporal trends and variations in temperature and precipitation extremes in eastern Ontario. The results of the study will inform local planners and decision makers on key changes in climate extremes, contribute to ongoing adaptation efforts, and assist practitioners in evaluating and further developing methodologies for climate risk mapping.

Chapter 4. Research paper: "Impacts of extreme weather events on corn (Zea mays) and soybeans (Glycine max): observed trends in key agroclimatic and phenological indices in eastern Ontario, 1961-2010"

4.1 Abstract

Increasing frequency and intensity of extreme weather events are expected to adversely affect crop yields and increase the vulnerability of agricultural producers to climate change. The vulnerability of agricultural systems to adverse weather conditions is closely linked to the characteristics of local farming systems and specific crops that are grown. This study offers a detailed account of spatial and temporal changes in weather conditions from the perspective of two crops, throughout the growing season in eastern Ontario from 1961 to 2010. Crop specific extreme event indices for corn (Zea mays) and soybeans (Glycine max) were developed based on agronomic and climate change literature review, and consultations with local crop experts. A total of 19 phenologically sensitive indices were developed for corn and soybeans (8 and 11, respectively) and were used to characterize the timing and severity of specific crop extreme events for eleven weather stations, selected to represent distinct ecodistricts within the region. Daily temperature and precipitation data were used to calculate agroclimatic indices and extreme event indices associated with critical thresholds at different phenological stages of corn and soybean development. Increases in accumulated crop heat units and growing season length were prominent trends in eastern Ontario. Growing season length increased largely due to an earlier start of the season rather than its later end. Poor seeding conditions became more prevalent over time, particularly during soybean planting season in mid- to late May. More instances of flooding were recorded during early vegetative

stages of corn development. Extreme weather events during critical reproductive stages increased for both corn and soybean, affecting corn during the blister, milk and dough stages and soybeans during the seed development stage. The most significant changes in crop-specific indicators were observed in the eastern part of the region and along the St. Lawrence River, where corn and soybeans are commonly grown.

4.2 Introduction

Climate change, and extreme weather events specifically, present a key threat to the agricultural sector. As their frequency increases, extreme events are expected to adversely affect crop yields and increase the vulnerability of agricultural producers to climate change through higher input costs and decreased profits (Weber and Hauer 2003; Hay 2007; Kharin et al. 2007; Wreford et al. 2010).

Many crops are more sensitive to changes in the frequency of extreme temperature and precipitation events than to changes in mean conditions (Lemmen and Warren 2004). As a result, extreme events such as floods, droughts, intense storms, heat waves, and tornadoes are likely to lead to much greater production losses than other factors related to climate change, such as increases in mean temperature (Motha and Baier 2005; Wreford et al. 2010). The timing of extreme events in relation to stages of plant development has been identified as an important factor by a number of researchers (Lemmen and Warren 2004; Motha and Baier 2005). Responses to extreme events and changes in growing conditions in general differ by crop; therefore, individual crop tolerances must be taken into account when defining critical weather conditions affecting their development, growth, and yield (Gornall et al. 2010).

Much research has been conducted on changes in temperature and precipitation regimes, shifting moisture availability and the effect of these changes on crops, in this region (Chapter 3, this thesis) and elsewhere (e.g. Lemmen and Warren 2004; Bootsma et al. 2005; Motha and Baier 2005). Conversely, only a limited number of studies (notably, Gourdji et al. 2013; Trnka et al. 2014; Ceglar et al. 2016) have assessed yield in relation to intra- and interannual weather extremes and crop sensitivities.

A common approach to analyzing impacts of climate change on crops is the use of process-based models that provide comprehensive information on crop systems as well as potential management practices to adapt to changes in climate (Sauchyn et al. 2009; Laux et al. 2010; Ceglar et al. 2016). However, such models typically omit factors such as extreme events, pest infestations, and disease outbreaks, often resulting in overly optimistic projections of climate change effects on agriculture (Cline 2007; White et al. 2011). Additionally, process models tend to overestimate the use of best management practices and the effectiveness of new technologies (Sauchyn et al. 2009). Moreover, most such models require detailed information on humidity, soil moisture, and other parameters, and their interactions, which are not always available (Ceglar et al. 2016) or introduce new levels of uncertainty when applied across time and space (e.g. Mitchell et al. 2005).

In contrast, agroclimatic indices based on daily weather data provide a variety of ways to detect and assess impacts of temperature and precipitation extremes on crop growth and yield variability (Qian et al. 2010; Izumi and Ramankutty 2016). The use of agroclimatic indices, covering a wide range of crop-specific adverse conditions, can provide valuable regional scale information on the impact of weather extremes on crop

yield (Trnka et al. 2014; 2015). Agroclimatic indices calculated at the regional scale can also be used in conjunction with machine learning techniques and economic models to produce risk estimates of crop production losses (Chavez et al. 2015).

The necessity to conduct regional studies that assess levels of exposure and vulnerability of crops to climate extremes has been identified by the Intergovernmental Panel on Climate Change (IPCC 2012). Although most agricultural areas routinely cope with extreme weather events and their impacts, rates of projected change are expected to exceed the range observed in the past in many areas, while ongoing changes in the frequency and distribution of these events will make more areas exposed to climate extremes (Wreford et al. 2010). Providing farmers and policy makers with knowledge on possible timing and magnitude of extreme weather events will help them prepare better recovery plans and ultimately reduce the impacts of extremes on crop yield, land resources as well as infrastructure (Hay 2007).

Climate change studies suggest that changing agroclimatic conditions in Ontario will result in longer growing seasons, milder winters and fewer frost days, increasing potential crop yields (Reid et al. 2007). Importantly, these benefits may be offset by increased frequency and intensity of extreme weather events, particularly if they occur at critical crop growth stages.

It is of interest for climate change detection and of practical importance for agricultural producers to know how local agroclimatic conditions were affected by climate change historically to determine what the potential impacts could be in the future (Qian et al. 2012). Eastern Ontario experienced a number of extreme weather events in past decades, the most recent being the drought of 2012 that produced a devastating

effect on the region's major crops: corn and soybeans (Agricorp 2012). With recent increases in the total area of land under corn (31% increase between 2006 and 2011) and soybeans (57% increase between 2006 and 2011) reported by Statistics Canada (2011b), the need to adequately assess risks to these crops is growing. Extreme weather events may affect long-term yields if they occur at crucial plant developmental stages, such as germination, seedling emergence, flowering and development of fruits and seeds (soybeans), tasselation and silking (corn), ripening of fruits (soybeans) and grain filling (corn) (Turvey 1999). In addition to affecting crop yield, extreme events may also make the timing of field applications more difficult, thus reducing the efficiency of farm inputs such as fertilizers and pesticides (Motha and Baier 2005).

The main goal of this study is to develop a new set of crop-specific indices that will more clearly identify vulnerabilities of regional crops to weather extremes. Using agronomic and climate change literature and consultations with crop experts, threshold temperature and precipitation values were defined and a set of crop-specific indicators was calculated to investigate the effects of changes in temperature and precipitation conditions on corn and soybeans in eastern Ontario. To distinguish between standard and newly developed indices, they are referred to as agroclimatic and crop-specific (phenological) indices, respectively. This article provides detailed information on changes in frequency, intensity and spatial distribution of key agroclimatic and phenological indices relevant for corn and soybean production in the region. The implications of extreme weather during sensitive periods of corn and soybean development are discussed with respect to potential impacts on yield and identification of

desirable traits. Potential implications (e.g. increased use of irrigation) for adapting to future climate change are considered.

4.3 Data and methods

Regional analysis of changes in agroclimatic and crop-specific extreme weather events from 1961 to 2010 was conducted using daily data from 11 weather stations in eastern Ontario. A detailed discussion of methods pertaining to weather station selection, gap filling, indicator calculation and analysis was provided in Chapter 2.

4.3.1 Study area and weather station data

The study region spans the area of over 31,000 km^2 and covers eight census divisions within the census agricultural district of eastern Ontario. The region is home to over 1.3 million people (Statistics Canada 2011a), with an expected 25% population increase in the next 20 years (Ontario Ministry of Finance 2011). Agriculture is one of the main industries and major land uses in the region, with just under 30% of the total area being used in crop production, livestock operations or agroforestry. Cattle ranching and farming, hay farming, and oilseed and grain farming are the most common farm types that make up approximately 30, 20 and 19 percent of the region's 8,007 farms respectively (Statistics Canada 2011c).

The eastern part of the study area is located on the fertile lands of eastern Ontario, comprising the Ottawa and St. Lawrence valleys (Mixedwood Plains ecozone) and accounting for nearly 60% of the region (Ecological stratification working group 1995). Milder climate, which is influenced by the proximity to the Great Lakes, supports a relatively diversified agricultural sector, although it is dominated by cash crop operations (Statistics Canada 2011d). Less agriculture occurs in the remainder of the region (Boreal

Shield ecozone), where agricultural activity is restricted to livestock and forage due to colder temperatures and less productive soils (Weber and Hauer 2003).

Overall, nearly a third of agricultural lands are used for cultivating corn and soybeans, making them the dominant crops in the region. Corn and soybeans are grown on productive Class 1- 4 lands that make up just over 38% of the region's total land area (Canada Land Inventory 1998). The two crops are mostly grown in the eastern part of the region, where close to 90% of the fertile soils are found (Figure 4.1).

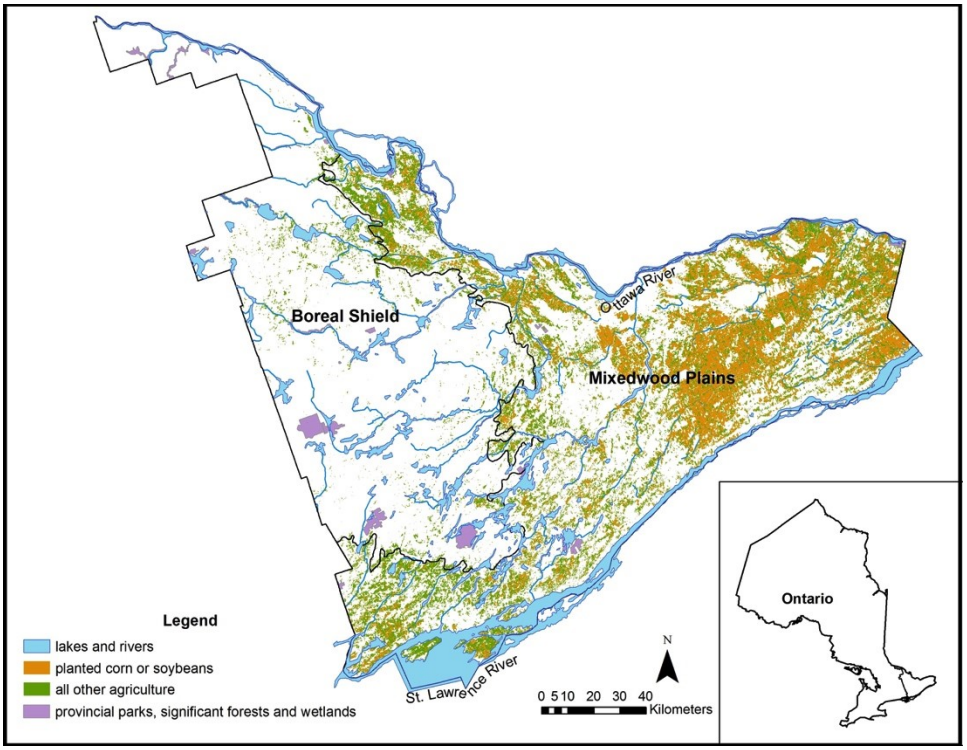


Figure 4.1: Distribution of corn and soybeans in eastern Ontario ecozones. Significant natural features such as lakes, forests and wetlands are shown for reference purposes. Source: AAFC crop inventory 2015

Spatial analysis of observed changes in agroclimatic and phenological extreme event indices was conducted using data from eleven weather stations representing ten ecodistricts within the study area (Table 2.5; Figure 2.1). The largest ecodistrict, Algonquin, was split into two parts and two representative weather stations were selected

to adequately capture the differences in climate between its northern and southern parts (Table 2.3). Using weather station data as opposed to gridded climate data made it possible to avoid issues such as reduced signals of extreme events, which are known to occur during the averaging and interpolating of weather data (Zhang et al. 2011).

Weather station data for temperature and, to a lesser extent, precipitation are representative of much larger regions (Yan et al. 2002; Pfahl and Wernli 2011; Orlowsky and Seneviratne 2014). For this research weather station representativeness was evaluated using methods adapted from Yan et al. (2002) and Pfahl and Wernli (2011), including the production and analysis of smoothed annual temperature cycles, monthly precipitation totals as well as 5th (daily temperature) and 95th (daily temperature and single day precipitation for each month) percentile time series. Stations with the highest correlations with all other stations in each ecodistrict were selected as representative stations. In cases when no stations with a consistent record of over 35 years in the study period or 25 or more consecutive years up to 2010 were located in an ecodistrict, a suitable station in close proximity (within 10 km) to the boundary was selected in an adjacent ecodistrict (Algonquin South, Muskrat Lake) or in an outside the study area portion of the ecodistrict (Upper St. Lawrence Plain).

Infilled datasets for minimum and maximum daily temperature and precipitation data series for selected weather stations were produced following the methodology of Schroeter et al. (2000; 2008). ‘Surrogate’ stations were used to populate data gaps in a ‘target’ station according to criteria about record length, reliability and proximity to the target station. Long-term climatic relationships between ‘surrogate’ stations and the ‘target’ station were determined using climate normal data, with missing values estimated

based on the difference (for temperature) or ratio (for precipitation) established between any pair of stations (Schroeter et al. 2000).

4.3.2 Selection and statistical analysis of agroclimatic indices

To capture agriculturally relevant changes in regional climate between 1961 and 2010 a suite of agroclimatic indices was selected and calculated using formulas given in Table 2.2. This included indices such as growing season length (GSL), growing season start (GSS), growing season end (GSE), and crop heat units (CHU), all of which provide information important for crop growth and are commonly used in climate change impact studies (Bootsma 1994; Qian et al. 2010).

Prior to indicator calculation a number of quality control measures were taken using RClimDex software (Zhang et al. 2015) to detect the presence of any errors that might interfere with assessing extremes and affect the reliability of the finalized data series. Homogeneity checks and adjustments were excluded from quality control measures due to significant uncertainty in methods for homogenizing and adjusting climate data (Caesar et al. 2011; Vincent et al. 2011). A more detailed quantitative assessment of changes in agroclimatic and phenological extreme event indices would warrant an extensive homogeneity testing exercise.

Agroclimatic indices were calculated annually for each of the ecodistricts (Table 2.5), using R (R Core Team 2015). Statistical analysis of results involved trend detection and calculation using non-parametric Mann-Kendall (MK) test (Mann 1945; Kendall 1975). Iterative de-trending and pre-whitening, as suggested by Zhang et al. (2000), was performed prior to trend assessment to account for potential lag-1 autocorrelation effects in the time series, which can cause false trend detection (Caesar et al. 2011, Yue et al.

2002). Statistical significance of detected trends was assessed at the 5% level. Annual indicator values calculated for each ecodistrict were averaged for two 25-year intervals: 1961-1985 and 1986-2010. Mean values and standard deviations (SD) were tabulated. Boxplots were produced to display the distribution of data in each ecodistrict for all indicators and both sub-periods. Maps showing the spatial distribution of the calculated indices were produced for the two time intervals to capture temporal changes in the spatial distribution of the indices. Graphic representation of results was done using R (R Core Team 2015) and ArcGIS Desktop version 10.3 (Esri, Redlands, CA, USA).

4.3.3 Development and calculation of phenological indices

The majority of climate indices used to characterize extreme weather events and assess their frequency and intensity are designed to be applicable in a variety of spatial contexts, from global to regional (Frich et al. 2002; Alexander et al. 2006). These indices, however, are less relevant when there is a need to address specific needs of a particular economic sector such as agriculture (Qian et al. 2010).

In order to capture information regarding when and how often weather conditions are unfavourable throughout the growing season in eastern Ontario, information regarding the sensitivities of locally grown corn and soybeans was collected and used to establish specific thresholds of frost, heat, moisture and drought tolerance. The focus was to identify key periods of vulnerability during the growing season, which are potentially the most damaging to crops (Qian et al. 2010).

Initial analysis of agronomic literature identified that early vegetative and early/mid-reproductive stages (silking and kernel formation in corn, pod formation and seed filling in soybeans) are the most sensitive periods in crop growth cycles (Nielsen

2000; Brevedan and Egli 2003). Farming operations are also important determinants of production, with the greatest weather vulnerabilities occurring during planting and harvesting seasons (Reid et al. 2007). Literature describing the implications of each form of plant stress during vulnerable phenological and operational periods was used to translate extreme weather events into impacts on crop yields by establishing tolerance thresholds to extreme events at critical phenological stages (Hlavinka et al. 2009; Trnka et al. 2014). Selected sources included books, peer-reviewed articles, agronomy reports, and technical papers by government and non-governmental organizations. A total of 94 sources were studied, of which 38 focused on corn, 42 on soybeans, and 14 provided information on both crops. Temperature and precipitation threshold data for different phenological stages were extracted from literature along with yield loss percentages associated with threshold exceedance. Tables 4.1a and 4.1b give detailed summaries of extreme event tolerance thresholds at different crop growth stages as well as associated production effects for corn and soybeans, respectively.

Based on the review, extreme events were characterized as those weather related events resulting in potential yield losses of 20% or more, which resulted in the selection of 8 extreme phenological indicators for corn and 11 for soybeans (Table 4.2). The indices were then validated during informal consultations with regional crop experts that agreed to go over the proposed indices; these experts were researchers and extension workers from federal (AAFC) and provincial (OMAFRA) levels of government, working in eastern Ontario. Phenological indices were calculated annually for each of the ecodistricts (Table 2.5), statistically analysed uing R (R Core Team 2015) and graphically represented using ArcGIS Desktop version 10.3 (Esri, Redlands, CA, USA).

Table 4.1: Extreme event tolerance thresholds and associated production effects at different crop growth stages of (a) corn and (b) soybeans. CHU estimates were provided by OMAFRA (2009b).
(a)

Growth Stage	CHU requirements	Extreme events tolerance and thresholds	Production effects	Sources
VE (emergence)	180 CHU	Drought conditions slow and stop germination. Repeated wetting and drying decrease seed viability at this stage. Soil temperature of less than 10°C delays emergence. Corn ususlly emerges in 8-10 days at 16-18°C, and 18 to 20 days at 10-13°C.	If 25% of the stand emerged 7-10 days late, losses are 7%; if 25-50% emerged 21 days late the losses are 10%; if more than 50% emerged 21 days late the losses are 20%, equivalent to losses due to late planting. Less than 125 CHUs by May 14 significantly delays emergence. Planting past May 10 adds 1% to the yield loss per day in May (2% in June).	Ritchie et al. 1993; Nielsen 2000; OMAFRA 2009a; Abendroth et al. 2011
V1	330 CHU			
V4	630 CHU	Frost <= -2C damages corn leaves.	Leaf killing frost (-2°C) up to V6 stage results in yield losses of up to 8%.	Kumudini and Tollenaar 1998
V6	680 CHU	Growing point is at or above ground; corn is more susceptible to frost injury. Temperature below 0°C adversly affects plant growth, may kill plants. Flood tolerance while the growing point is below ground is very low.	Flooding (P>=8mm for 5+ days)up until the V6 stage kills plants within 48 hrs at temperatures less than 25°C, and within 24 hrs at temperatures greater than 25°C.	Nielsen 2000; OMAFRA 2009a
V8	930 CHU	Multi-day drought (CDD > 10) prior to and during the tasseling stage is harmful for corn; after V8 plants can survive being submerged in water for 8+ days, but are more suceptible to disease and suffer poor root development.	Frost at V8 or greater results in 40-50% yield loss if >70% of leaves are dead, 15-30% decrease if 30-50% of leaves are dead.	Carter 1995; Coulter 2000
V12	1,270 CHU		CDD >10 and CHUs between 600 and 1300 results in 10 to 20% yield loss; Average yield loss per day during drought stress is 3%.	Claassen and Shaw 1970
VT (tasseling)	1,310 CHU	Pollen viability is reduced by drought and high temperatures. Temperatures of above 35°C (during endosperm cell division) are lethal to corn pollen viability and result in reduced kernel growth rate and final kernel size. Evapotranspiration demands (8mm a day) and drought sensitivity are high.	Average yield loss per day during drought stress is 3%.	Shaw 1988; Rhoads and Bennett 1990; Kumudini and Tollenaar 1998; Nielsen 2000; Sanchez et al. 2014
R1 (silking)	1,480 CHU	Pollination occurs, environmental stresses at this time are very detrimental to yield. Evapotranspiration requirements during pollination are approximately 8 mm per day.	CDD >10 in the last 2 weeks of July (CHUs between 1300 and 1600) result in yield loss up to 50%; Average yield loss per day during drought stress is 7%.	Brouwer and Heibloem 1986; Schoper et al. 1987
R2 (blister)	1,825 CHU	Water required at this stage 55 mm. Evapotranspiration demands are 6.5mm per day.	Average yield loss per day during drought stress is 4%. Corn plants that are weakened by heat and drought stress are more susceptible to damage from insects and diseases and have poor nutrient uptake.	Claassen and Shaw 1970; Lauer 2006
R3 (milk)	2,000 CHU	Water required at this stage 60 mm. Temperatures above 30°C impair cell division and amyloplast replication in corn kernels, reducing yields.	Average yield loss per day during drought stress is 4%; 6 days of 33°C or more result in 4% decrease in yield in addition to reduction due to drought stress.	Shaw 1988; Rhoads and Bennett 1990
R4 (dough)	2,165 CHU	Water required at this stage 10 mm, evepotranspiration requirements ar 6.5mm per day. Killing frost may cause yield losses of 25%-40%. 50% reduction in photosynthesis and grain filling at temperatures between 0 and 2°C. Temperatures below -2°C result in irreversible damage to stalks and husks causing yield loss.	Average yield loss per day during drought stress is 4%. Yield loss due to frost damage (-2°C) to ear shanks during late dough can reach 50% -60%. Frost damage to leaves (-1-2°C) results in yield losses up to 35%.	Nielsen 2000; Lauer 2004; OMAFRA 2009a
R5 (dent)	2,475 CHU	Frost<=-1°C damages leaves. Evapotranspiration demands is 6.5mm per day, with at least 20 mm of water required for stress-free development during the dent stage.	Average yield loss per day during drought stress is 3%. Yield loss due to frost damage (-2°C) to ear shanks during early and late dent can reach 20% and 5% respectively. Frost damage to leaves (-1-2°C) results in yield losses between 3 and 26%.	Claassen and Shaw 1970; Staggenborg et al. 1996
R6 (maturity)	2,800 CHU			

(b)

Growth Stage	Days required to reach stage (after seeding)	Extreme events tolerance and thresholds	Production effects	Sources
VE (emergence)	12	Excessive or insifficient soil moisture hinders soybean seed germination. At VE and VC stages soybeans have some tolerance to temperature of -1-2°C for short periods of time.	Planting on May 24 or June 7 (as opposed to May 10) reduces yield by 8 and 15%, respectively. A 3-day delay in planting results in a 1-day delay in maturity. Drought stress during seedling emergence can lead to low plant populations and, ultimately, lower yields.	Ball et al. 2001; OMAFRA 2009; Robinson et al. 2009; Board and Kahlon 2011; University of Wisconsin 2012
VC (unifoliate)	20	Growing point is above ground, plant can be killed by frost (below -2°C), if both the stem and the growing point are damaged.	Frost below -2°C causes plant death (percentage of yield loss corresponds to percentage of plants killed).	OMAFRA 2009
V2 (second trifoliate)	26	Frost tolerance is low at 0°C. Soybeans are susceptible to damage from waterlogging at early vegetative stages.	Temperature below 0°C causes plant death. 3 days of flooding (waterlogging) result in 20% yield loss; 6 days of flooding result in 93% loss.	Sullivan et al.2001; VanToai et al. 2010; Board and Kahlon 2011
V3 (third trifoliate)	34			
V4 (fourth trifoliate)	40	Soybeans are sensitive to night time temperature of less than 10°C.	Two days of waterlogging reduces yield by 18%. Cool night time temperatures during late vegetative stages reduce yield by up to 25%.	Fehr and Caviness 1977; Board and Kahlon 2011
V5 (5th trifoliate)	46			
V6 (6th trifoliate)	50			
R1 (beginning bloom)	55	Temperature between 1 and 10°C during this time results in yield reduction. Temperature over 29-30°C during the day (Tmax) ad 22-24°C at night (Tmin) causes delays in plant development and results in yield reduction. The effects are especially severe if soil moisture is limited - less than 75mm of rain accumulated prior to flowering results in decreased yields. Soybean pollen viability is reduced at temperatures above 30°C, reaching complete failure at 47°C. Frost sensitivity is high (0°C).	Cool temperatures (<= 10°C) during this time result in yield reduction of up to 25% due to decreased seed size. Night temperature of 24°C reduces yields by 10% compared to the optimum T of 16-18°C. Exposure to high temperatures of 38°C during the day and 30°C at night can reduce pollen production and germination by 34 and 56%, respectively, compared to a more favourable regime of 30°C during the day and 22°C at night. Frost between R1 and R5 can reduce yields by up to 80%.	Seddigh and Joliff 1984; Staggenborg et al. 1996; Morrison et al. 2006; Salem et al. 2007; OMAFRA 2009; Berglund 2011; Board and Kahlon 2011
R2 (full bloom)	65	Temperature of less than 10°C affects pollen production. Water requirements are hight at 70mm during the full bloom stage.	2 days of waterlogging reduces yield by 26%. 4 days of moisture stress result in 19% yield decrease at R3 and 8% at R1.	Wright et al. (no date); VanToai et al. 1994; Westgate and Peterson 1993; VanToai et al. 2010
R3 (beginning pod)	75	Cool temperatures at this stage are detrimental to seed development. Moisture deficit during pod filling is detrimental to soybeans. Seed fill for the cool temperature regime (18°C during day and 13°C during night) is low and and maturity is delayed.	If maturity is delayed there are more chances that the plant could be killed by frost.	
R4 (full pod)	85	Frost tolerance is -1°C. Each mm of precipitation during R4 and R5 stages is responsible for generating nearly 25 kg/ha of seed yield. Required water amount is 80mm. Temperature over 33°C has a detrimental effect on soybeans during seed filling. Soybean's ability to compensate for the effects of environmental stresses once favourable conditions return decreases significantly.	4 days of water stress result in 36% yield decrease.	Ritchie et al. 1994; Egli 2010
R5 (beginning seed)	95		Greatest frost related losses occur at R5 stage. Frost (-1°C) can reduce yields by 65%. One or two weeks of water stress (40% of required water) beginning at R6 can reduce the yield by up tp 23 and 37%, respectively. Continuous water stress after R6 results in yield losses as high as 39%. Temperature of 33°C during R5 to R7 results in 22% yield loss, temperature of 35°C - results in 38% yield loss. A 1.3% decrease in soybean yield has been observed per 1°C increase in mean temperature. During severe water stress at the same stages, these temperatures result in 42% and 64% yield loss respectively. Just water stress (at optimum temperature of 27-29°C) results in 38-47% yield loss.	Sedigh and Joliff 1984; Wright et al. (no date); Baker et al. 1989; Dornbos and Mullen 1991; Pan 1996; Staggenborg et al. 1996; Thomas 2001; Brevadan and Egli 2003; Boote et al. 2005; Lobell and Field 2007; Berglund 2011; Hatfield et al. 2011
R6 (full seed)	115		Frost can reduce yields by as much as 37%. Freezing temperatures of -1°C during seed development result in yield losses of 24 to 65% .	Saliba et al. 1982; Wright et al. (no date); Staggenborg et al. 1996; Berglund 2011
R7 (beginning maturity)	120	Frost tolerance is medium at -1°C. Temperatures over 31°C have a negative impact on soybeans.	Frost can reduce yields by 11%. However, a frost between R6 and R7 may or may not affect yield, depending on the temperature and duration of the freeze. Excessive heat during the ripening of soybeans (≥ 31°C for 3 consecutive days) leads to diminished oil production.	Wright et al. (no date); Staggenborg et al. 1996; Berglund 2011
R8 (Full maturity)	130+			

4.4 Results

4.4.1. Phenological indices

The developed suite of phenological indices is presented in Table 4.1. The indices capture the occurrence of specific conditions at critical crop growth stages or agricultural operation periods and can be used to provide important information on changes in crop-specific extreme weather events in the context of warming climate. CHU accumulation for corn-specific indices began on the sowing date; similarly, the sowing date marked the starting point of soybean growth period. For the purposes of this research seeding dates were set on the 7th day following the end of the period with unfavourable conditions during the planting season. In years when unfavourable seeding conditions were not detected, target planting dates for corn and soybeans were set as May 1 and May 10, respectively (OMAFRA 2009a).

Six of the corn-specific and three of the soybean-specific indices (highlighted in bold, Table 4.2) were observed in the weather record for eastern Ontario over the 50-year study period. The remaining indices (two for corn and seven for soybeans) showed no occurrences in any ecodistrict, and therefore were omitted from subsequent analysis. Tables showing annual averages and standard deviations of indices occurring multiple times per year (poor seeding conditions (corn and soy), early flooding (corn and soy), early killing frost (corn), fall killing frost (corn)) are provided in Section 4.4.3 for the 1961-1985 and 1986-2010 sub-periods. Similarly, annual averages and the total number of occurrences for indices that could, by definition, occur only once a year (pollination drought, R2 drought, R3 drought, and R4 drought (corn), pod filling drought and seed development drought (soybeans)) are provided in Section 4.4.3. Maps showing changes

Table 4.2: Definitions of crop-specific extreme event indices used in the study.

Index name	Definition	Units
Corn:		
Poor seeding conditions	**Weekly precipitation 30% greater than weekly mean precipitation (between April 23 and May 20)**	**weeks/year**
Early flooding	**Weekly precipitation 30% greater than weekly mean precipitation with 1 to 780 accumulated CHUs**	**weeks/year**
Pollination drought	**CDD >10 with 1,301 to 1,600 accumulated CHUs**	**annual occurrence (Yes or No)**
R2 (blister) drought	**P<45mm with 1,601 to 1,825 accumulated CHUs**	**annual occurrence (Yes or No)**
R3 (milk) drought	**P<45mm with 1,826 to 2,000 accumulated CHUs**	**annual occurrence (Yes or No)**
Early killing frost	Tmin <=-2°C with 2,165 to 2,475 accumulated CHUs	days/year
R4 (dough) drought	**P<8mm with 2,001 to 2,165 accumulated CHUs**	**annual occurrence (Yes or No)**
Fall killing frost	Tmin <=-2°C with 2,476 to 2,600 accumulated CHUs	days/year
Soybeans:		
Poor seeding conditions	**Weekly precipitation 30% greater than weekly mean precipitation (weeks between May 7 and June 10)**	**weeks/year**
Spring killing frost	Tmin <0°C 26 to 50 days after seeding	days/year
Early flooding	Precipitation 30% greater than weekly precipitation 25 to 45 days after seeding	weeks/year
Cool nights	Tmin <10°C for 5+ days 45-55 days after seeding	annual occurrence (Yes or No)
Warm nights	Tmin>=24°C 55 to 100 days after seeding	days/year
Mid-season flooding	Precipitation >90mm 60 to 80 days after seeding	annual occurrence (Yes or No)
Pod filling drought	**Precipitation <10mm 81 to 95 days after seeding**	**annual occurrence (Yes or No)**
Early killing frost	Tmin <-1°C between 90 and 100 days after seeding	days/year
Extreme heat	Mean Tmax>33°C 95-120 days after seeding	days/year
Fall killing frost	Tmin <-1°C 101 to 110 days after seeding;	days/year
Seed development drought	**P<5mm 96-115 days after seeding**	**annual occurrence (Yes or No)**

in the spatial distribution of detected indices over time can be found in Section 4.4.3, with the exception of early killing frost (corn), fall killing frost (corn), and early flooding (soybeans) that occur in 1-2 ecodistricts in the 1961-1985 sub-period and have no occurrences in 1986-2010.

4.4.2 Historic trends in agroclimatic indices

Annual changes in key agroclimatic indices in eastern Ontario are shown in Figure 4.2. The growing season increased over the past five decades, mostly due to an earlier start of the warm period and to a lesser extent due to its later end. In addition to the longer growing season, a considerable increasing trend in annual crop heat units was observed.

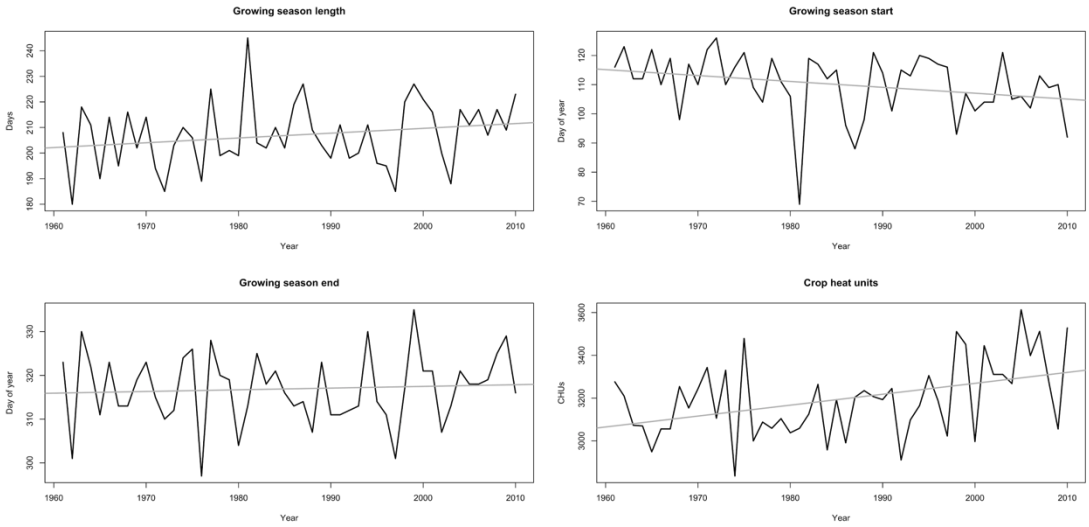


Figure 4.2: Annual agroclimatic indices in eastern Ontario in 1961-2010. Linear trends are shown in grey.

Decadal non-linear trends in agroclimatic indices showed increases in crop heat units, growing season length and, to a lesser extent, growing season end as well as decreases in growing season start (Table 4.3). In general, both GSL and CHU showed strong increasing trends across the region. The growing season in eastern Ontario increased by 2.08 days per decade, with increases observed in all ecodistricts except

Table 4.3: Trends in agroclimatic indices in eastern Ontario, 1961-2010. Trend analysis was conducted on annual data and significant trends at 95% confidenece level are shown in bold. Trend magnitudes are presented as decadal changes, for ease of comparability to other studies. Values for eastern Ontario are averages of ecodistrict trends and have not been assessed for significance.

	Algonquin North	Glengarry Plain	Algonquin South	Napanee - Prince Edward	Smith Falls Plain	Frontenac	Ottawa Valley Plain	Muskrat Lake	Russell and Prescott Plains	North Gower - Winchester Plains	Upper St. Lawrence Plain	eastern ON	Units
GSL	**3.33**	**3.57**	2.5	3.08	-0.59	1.43	1	1.71	2.86	1.22	2.73	2.08	days
GSS	**-3.74**	**-2.29**	-2.14	-1.43	-0.85	-2.27	-1.74	-1.53	**-3.21**	-1.58	**-2.33**	-2.1	days
GSE	-1.43	2.19	0.69	**2.22**	-1.35	0.37	-0.94	0	0	0	0	0.16	days
CHU	**79.39**	**81.83**	**56.07**	**56.97**	**52.89**	42.97	**50**	**95.86**	**72.42**	31	**60.49**	61.8	crop heat units

Table 4.4: Annual mean ±SD of key agroclimatic indices in eastern Ontario for 1961-1985 and 1986-2010 sub-periods.

Ecodistrict name	**Growing season length (days/year)**		**Growing season start (DOY)**		**Growing season end (DOY)**		**Crop heat units (CHU/year)**	
	1961-1985	**1985-2010**	**1961-1985**	**1985-2010**	**1961-1985**	**1985-2010**	**1961-1985**	**1985-2010**
Algonquin North	190 ± 14.54	198 ± 13.29	121 ± 10.81	111 ± 11.5	312 ± 11.55	308 ± 10.01	2858 ± 187.07	3091 ± 189.8
Glengarry Plain	210 ± 16.69	218 ± 14.22	112 ± 14.61	106 ± 11.44	321 ± 10.8	325 ± 11.28	3359 ± 163.85	3552 ± 212.52
Algonquin South	210 ± 17.38	212 ± 15.91	110 ± 15.93	105 ± 11.7	319 ± 9.97	318 ± 11.12	3108 ± 220.25	3193 ± 223.81
Smith Falls Plain	204 ± 18.3	203 ± 13.49	111 ± 14.45	110 ± 10.58	315 ± 11.4	312 ± 11.53	2989 ± 152.19	3124 ± 191.59
Napanee - Prince Edward	216 ± 14.67	221 ± 16	108 ± 13.11	106 ± 12.45	324 ± 10.88	328 ± 9.95	3373 ± 186.56	3481 ± 217.81
Frontenac	212 ± 17.3	215 ± 14.34	110 ± 15.05	105 ± 11.35	322 ± 10.66	322 ± 10.14	3308 ± 214.39	3400 ± 210.71
Ottawa Valley Plain	206 ± 12.31	209 ± 14.45	113 ± 7.86	106 ± 10.89	318 ± 9.75	315 ± 11.15	3194 ± 152.66	3316 ± 197.87
Muskrat Lake	199 ±14.2	203 ± 12.22	114 ±7.87	111 ± 8.91	313 ± 11.93	315 ± 10.83	2924 ± 189.31	3155 ± 186.02
Russell and Prescott Plains	200 ± 15.53	209 ± 13.21	115 ± 9	106 ± 10.65	314 ± 13.4	316 ± 10.67	3021 ± 182.66	3196 ± 166.26
North Gower - Winchester Plains	199 ± 14.91	203 ± 13.58	116 ± 7.89	110 ± 10.12	314 ± 11.48	313 ± 12.19	3063 ± 179.77	3069 ± 211.22
Upper St. Lawrence Plain	207 ± 15.48	212 ± 14	112 ± 14.28	106 ± 11.56	319 ± 9.45	318 ± 11.22	3193 ± 132.58	3323 ± 221.9
eastern Ontario	204 ± 6.51	207 ± 6.43	114 ± 2.79	109 ± 1.6	318 ± 4.01	317 ± 5.95	3126 ± 174.52	3264 ± 162.48

Smith Falls Plain, where a decrease of 0.59 days per decade was detected. The largest increases in GSL were noted in the eastern part of the region and along the St. Lawrence River. The increase in GSL is attributable to the earlier onset of the season, as no pronounced lengthening was detected at the end of season (GSE). The start of the growing season advanced in all ecodistricts, averaging 2.1 days and ranging from 0.85 to 3.74 days per decade. The most prominent advances in GSS were observed in the eastern part of the study area (Russell and Prescott plains, Upper St. Lawrence Plain); however, a significant decrease of 3.74 days per decade was detected in Algonquin North. Averaging at 0.16 days per decade, growing season end showed the highest spatial variation in eastern Ontario, with trends ranging from -1.43 to 2.22 days per decade in Algonquin North and Napanee – Prince Edward, respectively. The most consistent trends were observed for CHUs, with accumulated crop heat units increasing in all ecodistricts, averaging at 61.8 CHUs and ranging from 31 to 95.86 CHUs per decade. Shifts in CHUs were greatest in the Muskrat Lake ecodistrict and in the southern part of the region, along the St. Lawrence River. The majority of statistically significant trends were observed in crop heat units, where nine ecodistricts demonstrated increases. In contrast, only 1, 2, and 4 ecodistricts showed statistically significant trends for GSE, GSL, and GSS respectively. Changes in average values and variances of agroclimatic indices observed in two 25-year intervals in the study period are presented in Table 4.4. Boxplots displaying the distribution of data in each ecodistrict for all indicators and both sub-periods can be found in Appendix 5. In agreement with trend discussion above, GSL and CHU values

increased, while GSS shifted to earlier dates and GSE did not exhibit a coherent pattern across the region. Variances decreased in 9 ecodistricts for GSL and 7 ecodistricts for GSS. Contrastingly, GSE and CHU indices showed more variability over time, with increased variances in 6 and 8 ecodistricts respectively.

Indicator values for the two sub-periods were mapped to demonstrate changes in the spatial distribution of the indices (Figures 4.3 and 4.4). Shifts to a warmer climate were observed throughout eastern Ontario, with the majority of changes occurring in the southern and eastern parts of the region.

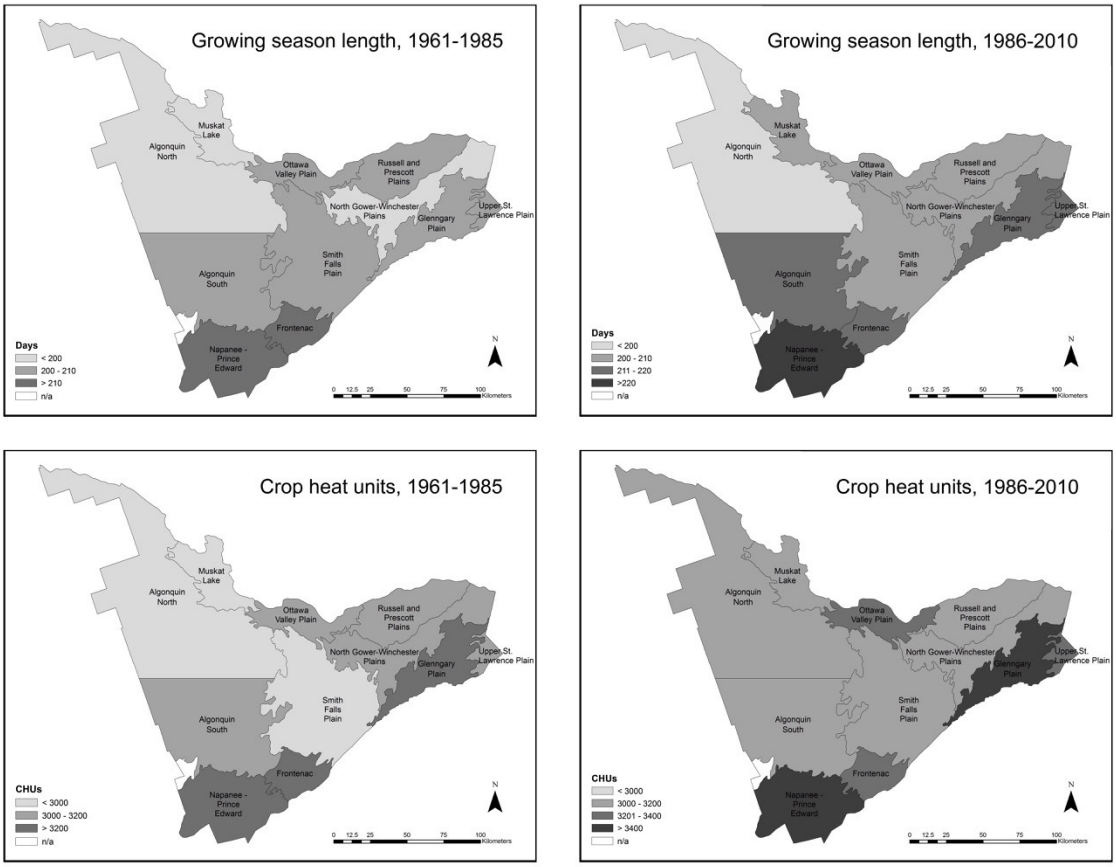


Figure 4.3: Average annual values in GSL and CHU indices in eastern Ontario ecodistricts in 1961-1985 and 1986-2010.

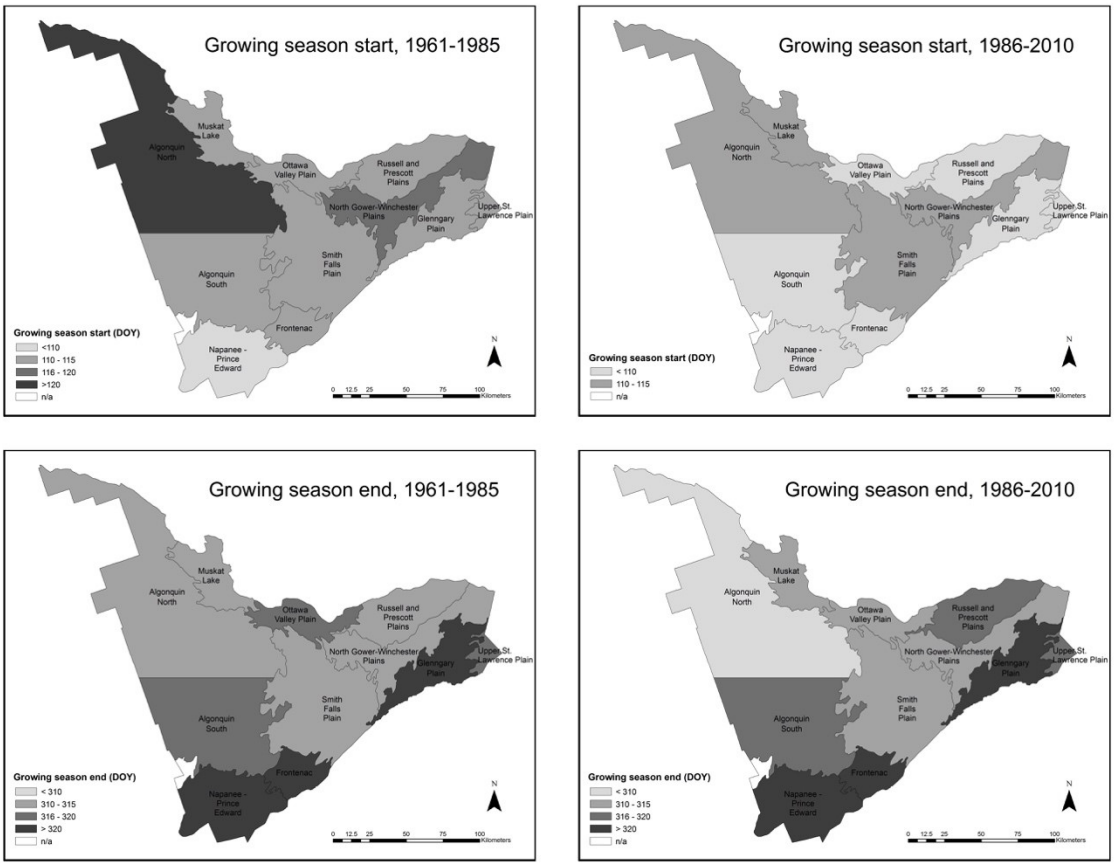


Figure 4.4: Average annual values in GSS and GSE indices in eastern Ontario ecodistricts in 1961-1985 and 1986-2010.

4.4.3 Historic trends in corn indices

Eight indices were calculated to assess spatial and temporal changes in corn-specific extreme events in eastern Ontario (Table 4.2). Average values and standard deviations were reported for indices related to wet conditions (poor seeding conditions, early flooding) and frost (early killing frost, fall killing frost), observed during the 1961-1985 and 1986-2010 sub-periods (Table 4.5). Sub-period totals were calculated for dry weather extreme event indices (pollination drought, R2 (blister) drought, R3 (milk) drought, R4 (dough) drought) that could, by definition, occur not more than once a year (Table 4.5). Spatial changes in indicator values are shown in Figures 4.5 and 4.6.

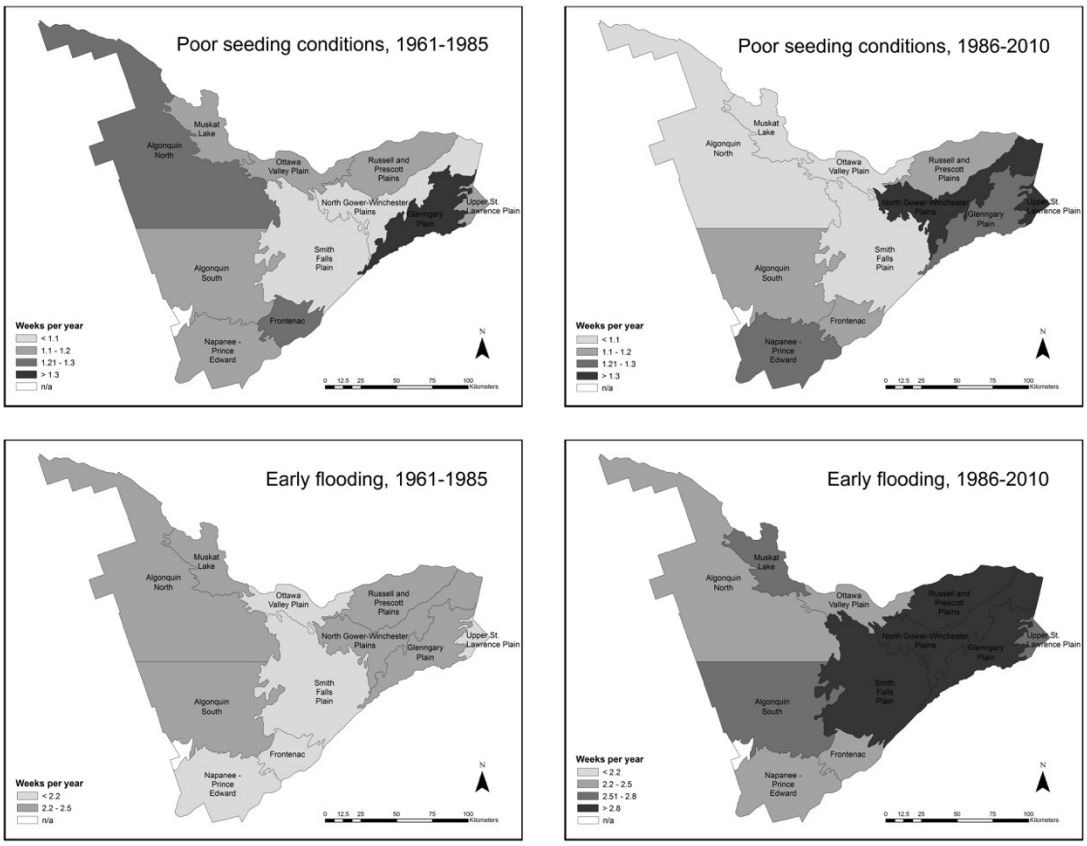


Figure 4.5: Average annual values in poor seeding conditions and early flooding indices for corn in eastern Ontario ecodistricts in 1961-1985 and 1986-2010.

Table 4.5: Select corn-specific phenological indices for 1961-1985 and 1986-2010 sub-periods. Indices of events occurring multiple times per year are presented as annual mean ±SD. Indices of events occurring (by definition) not more than once a year are presented as period totals.

Ecodistrict name	**Poor seeding conditions (weeks/year)**		**Early flooding (weeks/year)**		**Pollination drought (occurrence/time peiod)**		**R2 drought (occurrence/time period)**		**R3 drought (occurrence/time period)**		**Early killing frost (days/year)**		**R4 drought (occurrence/time period)**		**Fall killing frost (days/year)**	
	1961-1985	**1985-2010**	**1961-1985**	**1985-2010**	**1961-1985**	**1986-2010**	**1961-1985**	**1986-2010**	**1961-1985**	**1986-2010**	**1961-1985**	**1986-2010**	**1961-1985**	**1986-2010**	**1961-1985**	**1986-2010**
Algonquin North	1.28 ± 0.98	1.04 ± 0.84	2.32 ± 0.9	2.32 ± 1.07	2	2	4	5	20	22	0.08 ± 0.28	0	23	23	0.6 ± 2.6	0
Glengarry Plain	1.32 ± 1.11	1.28 ± 0.84	2.29 ± 1.37	2.84 ± 1.11	0	0	6	5	20	18	0	0	19	20	0	0
Algonquin South	1.12 ± 0.93	1.12 ± 0.97	2.2 ± 1.38	2.52 ± 1.29	5	3	7	6	22	23	0.04 ± 0.2	0	21	23	0	0
Smith Falls Plain	1.08 ± 1.04	1 ± 0.82	1.96 ± 1.4	2.84 ± 1.34	3	2	2	3	21	20	0	0	23	23	0	0
Napanee - Prince Edward	1.2 ± 0.91	1.24 ± 1.01	2.16 ± 1.31	2.2 ± 1.55	3	1	3	9	20	23	0	0	21	25	0	0
Frontenac	1.24 ± 0.97	1.2 ± 1	2 ± 1.38	2.48 ± 1.19	2	2	6	5	22	21	0	0	20	20	0	0
Ottawa Valley Plain	1.2 ± 1.15	1 ± 0.87	2 ± 1.38	2.32 ± 1.14	1	1	5	5	19	20	0	0	23	21	0	0
Muskrat Lake	1.16 ± 0.94	1.08 ± 0.86	2.28 ± 1.24	2.68 ± 1.44	1	4	2	7	23	19	0	0	24	24	0	0
Russell and Prescott Plains	1.12 ± 1.13	1.16 ± 0.8	2.4 ± 1.53	2.84 ± 1.52	1	1	2	5	19	22	0	0	21	23	0	0
North Gower - Winchester Plains	1.04 ± 0.93	1.32 ± 0.85	2.2 ± 1.55	3 ± 1.38	1	1	1	4	17	21	0	0	20	23	0	0
Upper St. Lawrence Plain	1.12 ± 1.36	1.32 ± 1.14	2.13 ± 1.55	2.62 ± 1.24	2	0	3	5	20	20	0	0	19	21	0	0

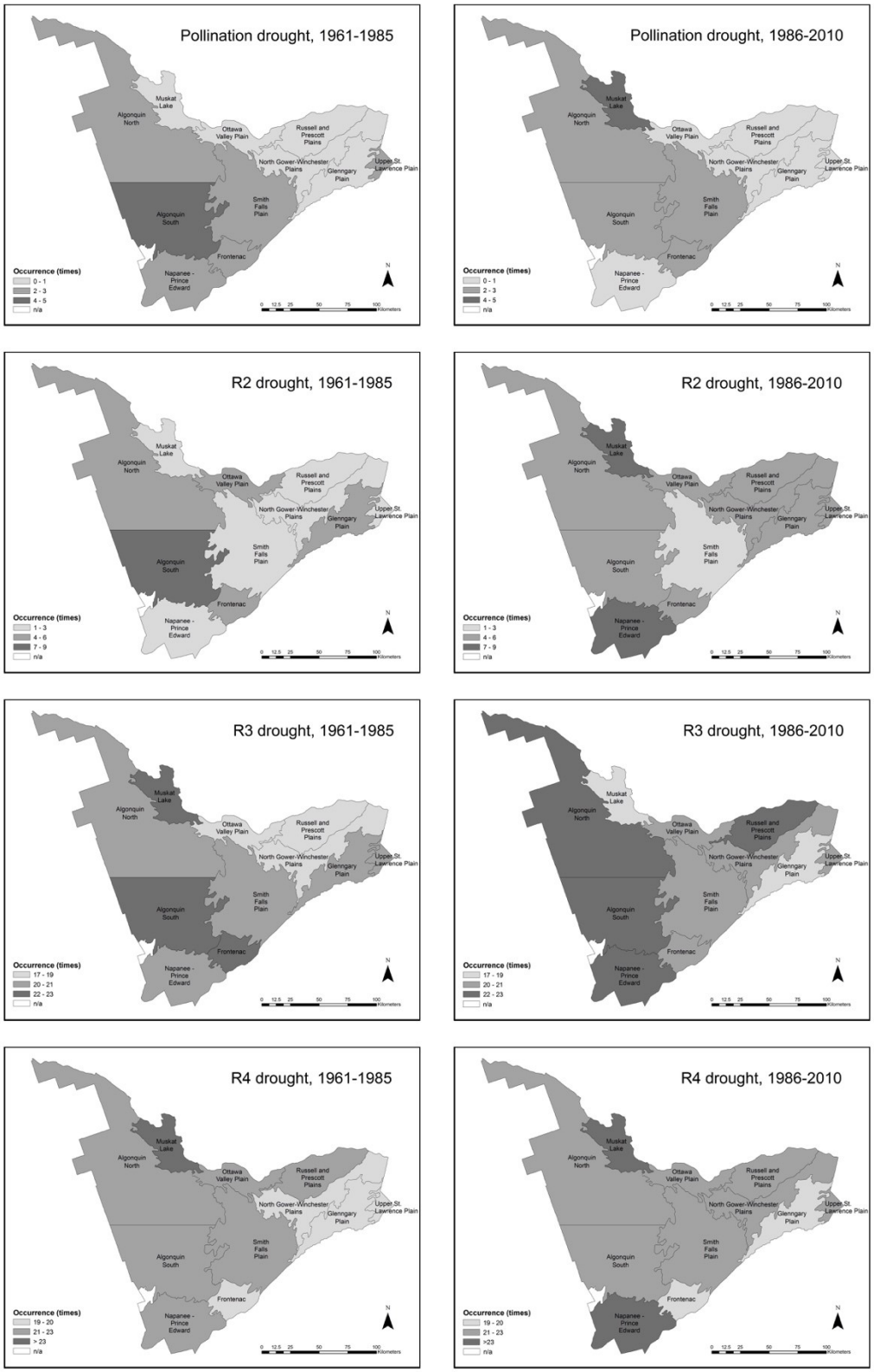


Figure 4.6: Average annual values in drought indices for corn in eastern Ontario ecodistricts in 1961-1985 and 1986-2010.

Boxplots displaying the distribution of data in each ecodistrict for all indicators and both sub-periods can be found in Appendix 5.

Poor seeding conditions for corn were observed during the average of 1.17 and 1.16 weeks per year during 1961-1985 and 1986-2010 sub-periods, respectively (Figure 4.5), resulting in an average seeding delay of 2.6 and 2.4 days (Table 4.6). Seeding delay was calculated as the difference between the actual seeding date (1 week following the end of poor seeding conditions) and the target seeding date (May 1). Note the increasing variance in seeding delay, particularly in ecodistricts in the southern part of the region, along the St. Lawrence River. Changes in poor seeding conditions observed in individual ecodistricts did not display spatial coherence, with increases and decreases found in four and six ecodistricts, respectively, and one ecodistrict (Algonquin South) showing no change between the study sub-periods. The number of weeks with early flooding increased in all ecodistricts, averaging 2.2 and 2.6 weeks per year in the first and second half of the study period respectively. The range of values increased from 2-2.3 to 2.2-3 weeks per year in 1961-1985 and 1986-2010 respectively, while the variance observed in individual ecodistricts mostly decreased. Spatially, the greatest changes occurred in the eastern part of the region, where the longest flooding periods were recorded.

Pollination drought occurrences ranged from 0 to 5 in 1961-1985 and 0 to 4 in 1986-2010, averaging 1.9 and 1.5 in the two sub-periods respectively. Over half (6) of the ecodistricts showed no change in dry conditions during pollination, while 4 and 1 of the ecodistricts exhibited decreasing and increasing trends, respectively. Spatially, pollination drought was more prevalent in the western part of the study area and less common in the eastern part. On average, drought during the blister (R2) stage of corn

Table 4.6: Average annual seeding delay ±SD for corn and soybean crops in eastern Ontario ecodistricts for 1961-1985 and 1986-2010 sub-periods.

Ecodistrict name	Corn seeding delay (days)		Soybean seeding delay (days)	
	1961-1985	1985-2010	1961-1985	1985-2010
Algonquin North	3.16±5.29	1.6±3.15	6.84±4.55	4.88±2.65
Glengarry Plain	2.79±5.75	2.92±5.29	8.24±6.08	6.56±5.28
Algonquin South	2.12±4.43	2.24±5.52	6.84±4.55	6.56±4.09
Smith Falls Plain	2.64±4.91	1.32±2.41	6.28±4.43	6.84±5.69
Napanee - Prince Edward	3.2±5.89	3.72±6.48	7.4±5.25	6.28±4.02
Frontenac	2.12±4.29	2.96±5.99	7.4±4.91	6.56±4.57
Ottawa Valley Plain	2.72±5.19	1.88±4.37	7.4±6.12	5.72±3.79
Muskrat Lake	2.76±5.21	1.64±4.16	6.84±4.55	5.72±4.3
Russell and Prescott Plains	2.64±4.79	2.64±5.2	6.28±4.43	6.28±5.22
North Gower - Winchester Plains	2.12±4.29	2.4±4.88	6.28±4.43	6.84±5.32
Upper St. Lawrence Plain	2.74±5.88	2.71±4.07	6.84±4.98	7.12±6.06

growth increased from 3.7 to 5.4 occurrences in 1961-1985 and 1986-2010, ranging from 1 to 7 and from 3 to 9 in the two sub-periods, respectively. R2 drought became more common in 7 out of 11 ecodistricts, while remaining constant in 1 and decreasing in 3 ecodistricts. Most increases occurred in the eastern part of the study area and along the St. Lawrence River, with the greatest change detected in Napanee – Prince Edward ecodistrict. Occurrences of dry conditions during the milk (R3) stage increased from 20.4 to 20.8 in the two sub-periods, ranging from 17 to 23 and 18 to 23 in 1961-1985 and 1986-2010, respectively. Increases occurred in the majority of ecodistricts, with the exception of Muskrat Lake, Glengarry Plain, Smith Falls Plain, and Frontenac and have been the largest in North Gower – Winchester Plains. Dough (R4) stage drought occurrences ranged from 19 to 24 and 20 to 25, averaging at 21.3 and 22.4 during 1961-1985 and 1986-2010 sub-periods, respectively. Ten ecodistricts exhibited stationary or increasing trends in R4 drought, with the largest increase observed in Napanee – Prince Edward ecodistrict, and the only decrease detected in Ottawa Valley Plain.

Early killing frost was observed twice in Algonquin North and once in Algonquin South ecodistrict in the first half of the study period. Central and eastern ecodistricts were

not affected by early killing frost in 1961-2010. Fall killing frost occurred fifteen times in Algonquin North in 1961-1985, with thirteen out of fifteen fall frost occurrences recorded during a cold spell in October 1974. Similar to early killing frost, no instances of fall killing frost were observed in any of the ecodistricts during the second half of the study period.

4.4.4 Historic trends in soybean indices

A total of 11 indices were calculated to assess spatial and temporal changes in soybean-specific extreme events in eastern Ontario (Table 4.2). Four of the indices were observed during the 1961-1985 and 1986-2010 sub-periods; average values and standard deviations were reported for poor seeding conditions and early flooding, and sub-period totals were calculated for pod filling drought and seed development drought that could not, by definition, occur more than once a year (Table 4.7). Spatial changes in indicator values are shown in Figure 4.7. Boxplots displaying the distribution of data in each ecodistrict for all indicators and both sub-periods can be found in Appendix 5.

Poor seeding conditions became more prevalent over time, increasing by an average of 0.18 weeks per year in the more recent 1986-2010 sub-period compared to 1961-1985 (Table 4.7). Interestingly, there was very little overlap between the indicator ranges in the first and second half of the study period, with poor conditions lasting 1.28-1.52 and 1.48-1.96 weeks per year, respectively, resulting in an average seeding delay of 7 and 6.3 days (Table 4.6). Seeding delay was calculated as the difference between the actual seeding date (1 week following the end of poor seeding conditions) and the target seeding date (May 10). Similarly to seeding delay in corn, variance increased in ecodistricts along the St. Lawrence River and decreased in ecodistricts along the Ottawa

Table 4.7: Select soybean-specific phenological indices for 1961-1985 and 1986-2010 sub-periods. Indices of events occurring multiple times per year are presented as annual mean ±SD. Indices of events occurring (by definition) not more than once a year are presented as period totals.

Ecodistrict name	**Poor seeding conditions (weeks/year)**		**Early flooding (weeks/year)**		**Pod filling drought (occurrence/time period)**		**Seed development drought (occurrence/time period)**	
	1961-1985	**1986-2010**	**1961-1985**	**1986-2010**	**1961-1985**	**1986-2010**	**1961-1985**	**1986-2010**
Algonquin North	1.44 ± 0.77	1.64 ± 0.91	0	0	21	21	23	23
Glengarry Plain	1.52 ± 1.05	1.84 ± 0.85	0	0	25	22	19	24
Algonquin South	1.44 ± 0.96	1.92 ± 1	0	0	23	24	20	24
Smith Falls Plain	1.32 ± 0.9	1.76 ± 0.97	0	0	24	19	20	25
Napanee - Prince Edward	1.36 ± 0.95	1.48 ± 1.05	0	0	22	22	23	24
Frontenac	1.48 ± 1.05	1.84 ± 1.03	0	0	24	21	20	25
Ottawa Valley Plain	1.36 ± 0.95	1.56 ± 0.92	0	0	24	21	15	24
Muskrat Lake	1.36 ± 0.81	1.8 ± 1.08	0	0	24	22	19	24
Russell and Prescott Plains	1.48 ± 1.05	1.8 ± 0.96	0.04 ± 0.2	0	23	21	19	24
North Gower - Winchester Plains	1.28 ± 1.1	1.96 ± 0.98	0.04 ± 0.2	0	23	22	19	24
Upper St. Lawrence Plain	1.36 ± 1.08	1.88 ± 1.13	0	0	20	21	22	24

River. No substantial changes in variability were detected, with both increases and decreases in SD recorded in different ecodistricts; however, the increase in indicator

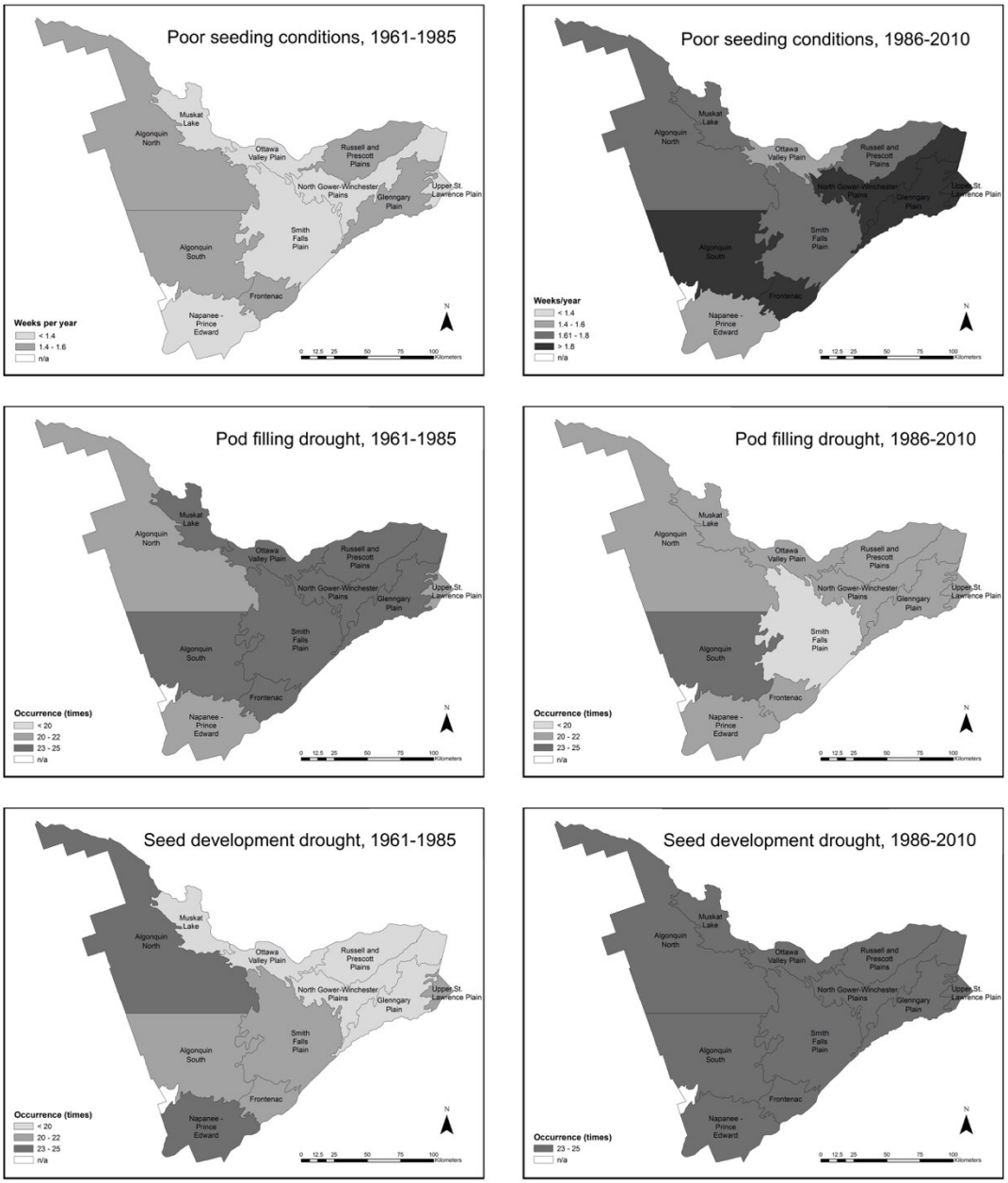


Figure 4.7: Average annual values in soybean-specific extreme event indices in eastern Ontario ecodistricts in 1961-1985 and 1986-2010.

range points showed greater spatial variability at the regional scale. Poor seeding conditions lasted the longest along the St. Lawrence River and increased the most in Upper St. Lawrence Plain and North Gower – Winchester Plains ecodistricts. Only two

instances of early flooding were recorded, both occurring in 1977 in adjacent ecodistricts: Prescott and Russell Plains and North Gower – Winchester Plains. Early flooding conditions were not observed in the 1986-2010 sub-period.

Dry conditions during pod filling and seed development were observed during most years in the study period. Pod filling drought showed a slight decrease in occurrence over time, whereas seed development drought became more frequent. Spatially, changes in dry conditions during pod filling remained stable or showed a slight increase in the western part of eastern Ontario, and decreased in the central and eastern parts of the study area, being most substantial in the Smith Falls Plain ecodistrict (Figure 4.7). All ecodistricts except Algonquin North showed increases in dry conditions during seed development period, with the greatest shift observed in Ottawa Valley Plain.

4.5 Discussion

Increases in growing season length and accumulated crop heat units represent some of the dominant trends in the region. This, and the fact that growing season length has increased largely due to an earlier start of the season rather than its later end, is in agreement with other studies done in Canada, as well as research from the American Midwest (Qian et al. 2012; Hatfield et al. 2015). Longer and warmer growing seasons and fewer instances of fall frost during crop maturing stages are expected to benefit the quality and quantity of crop yield and have a positive impact on agricultural production activities (Bootsma et al. 2005; Shen et al. 2005). Selecting later maturing varieties and expanding production to lands that are currently unsuitable for growing corn and soybeans could be some of the advantages of a longer and warmer growing season in the region (Bootsma et al. 2011). Given that corn and soybean yields could increase by 0.6

and 0.13 t ha $^{-1}$ respectively with every 100 CHUs (Bootsma et al. 2005), increases in CHUs observed in eastern Ontario over the past five decades have the potential to raise yields by up to 2.4 (corn) and 0.52 (soybeans) t ha $^{-1}$. It should be noted, that increases in temperature, although beneficial for growing season length and available crop heat units, could become a limiting factor both directly and indirectly, through their relation to evapotranspiration as well as higher risks of crop diseases and pest damages (Pearson et al. 2008; Qian and Gameda 2010; Bootsma et al. 2011). Chen and McCarl (2001) point out a link between increased temperature and precipitation and greater use and cost of pesticides for a number of crops, including corn and soybeans. According to Rosenzweig et al. (2002), overuse of pesticides could result in increased resistance among pests and elimination of protective predators.

Taking advantage of the full growing season is important for high crop yields; therefore timely planting is crucial. Poor weather conditions during the planting season, in particular excess soil moisture and flooding, can delay planting and negatively affect crop yield (OMAFRA 2009a). Slight overall increases in poor seeding conditions for corn were observed in the study period; however, the trends were not uniform across the region, with the eastern part of the study area, where the majority of corn fields are located, experiencing the greatest increases. This could be of concern to corn growers, knowing that when corn planting is delayed, yield reductions averaging about 7% per week of delay can be expected (OMAFRA 2009a). Poor seeding conditions during soybean planting season were even more prevalent than those affecting corn planting, lasting the longest along the St. Lawrence River and increasing the most in Upper St. Lawrence Plain and North Gower – Winchester Plains, ecodistricts where soybeans are

commonly grown. Since soybean development is photoperiod sensitive and reproductive stages are accelerated by shorter days, soybean yields are less affected by planting delay than corn yields, with yield losses averaging 4% per week of planting delay (OMAFRA 2009a).

Flooding conditions were frequently observed during early stages of corn development, increasing over time, averaging 2.36 weeks in the study period and affecting key corn producing areas in the eastern part of the region. Detrimental effects of flooding occurring during this period include plant death due to lack of oxygen available to the plant, hindered root development, increased potential for bacterial diseases as well as losses of nitrogen through denitrification and leaching (Nielsen 2000; Hatfield et al. 2015). In addition to crop damage, increased precipitation and flooding before the crop is fully established can lead to soil erosion and degradation as well as movement of applied pesticides into nearby water bodies (Hatfield et al. 2015).

An increase in 'drought' periods during critical reproductive stages of corn and soybean development was observed in eastern Ontario over the study period and is expected to be a major limiting factor in their development, putting constraints on crop yield potential and resulting in greater yield variability (Pearson et al. 2008; Qian and Gameda 2010; Bootsma et al. 2011). Dry conditions are a significant threat because the majority of land in eastern Ontario is not irrigated (Statistics Canada 2011e) and will be particularly detrimental for crops grown on soils with low water holding capacity (Hatfield et al. 2015).

Overall, it is likely that increases in growing season length and more frequent moisture and heat stresses will require the development and planting of crop varieties that

have greater tolerance to stresses while capturing opportunities for higher yields (Pearson et al. 2008).

4.6 Conclusion

This study provides detailed information on spatial and temporal trends in select agroclimatic and crop-specific extreme event indices in eastern Ontario from 1961 to 2010. The indicators were calculated using data from eleven weather stations representing distinct ecodistricts in the study area. Increases in growing season length and accumulated crop heat units along with greater frequencies of flooding and drought events at critical crop development stages were observed, the most significant changes occurring in key crop producing parts of the region.

Knowledge of shifts in agroclimatic and crop-specific extreme event indices can be useful to the agricultural community, for instance by being applied in cultivar breeding and selection to capture regional changes in temperature and moisture regimes. The results of this study can improve the knowledge and skills of farmers and decision makers, inform adaptation responses, allowing growers to capitalize on the benefits of the changing conditions and reduce the vulnerability of the agricultural sector to climate change by adjusting cropping operations, pesticide and fertilizer application and, possibly, introducing new water management technologies (Kulshreshtha et al. 2010; Calanca et al. 2011).

Further research on potential future changes in the studied indicators is recommended and expected to assist in the development of effective adaptation strategies to reduce the impact of extreme weather on agricultural operations and crop yield.

Chapter 5. Conclusion

Analyses of impacts of extreme weather events on agricultural systems, and specifically on crop development and yield, are limited; yet they provide crucial information to farmers and decision makers, allowing them to make informed management decisions and ultimately increasing the resilience of the agricultural sector to climate change and improving food security. Three types of extreme weather indices were considered in this research, providing information on changes in generic, agroclimatic, and crop-specific extreme events in eastern Ontario from 1961 to 2010. Generic extreme weather indices were calculated and analyzed in Chapter 3, while agroclimatic and crop-specific indices were the focus of Chapter 4 of this thesis. The study brought together physical aspects of weather extremes and crop production to identify events that are most damaging to the agricultural system in eastern Ontario. Daily temperature and precipitation data for eleven stations, representing distinct ecodistricts in the region, were used to calculate the indices. Trends in the indices were calculated and assessed for statistical significance to provide information on temporal changes in weather extremes in eastern Ontario. The spatial distribution of trends and changes in indices was also investigated.

A detailed examination of changes in extreme weather events in 1961-2010, conducted for eastern Ontario, is provided in Chapter 3, with changes in weather conditions studied at annual and agriculturally significant periods, including the planting, growing, and harvesting seasons. An increase in warmer and wetter conditions in most parts of the region was observed, with the greatest changes in both temperature and precipitation extremes occurring in the eastern part of the region and along the St.

Lawrence River, where most agricultural lands are located. Temperature indices show a higher degree of spatial coherence than precipitation indices, with the majority of statistically significant changes observed at the annual rather than seasonal periods.

Critical temperature and precipitation thresholds for corn and soybeans at different phenological stages were identified and used to develop a set of nineteen crop-specific extreme event indices that were the focus of Chapter 4. The defined indices are specific to the needs of corn and soybeans and bear direct relevance to agricultural productivity. Increases in growing season length and accumulated crop heat units along with greater frequencies of flooding and drought events at critical crop development stages were observed, with the most significant changes occurring in key crop producing parts of the region.

The study provides a detailed characterization of the region's changing climate, including past trends in mean temperature and precipitation values as well as extreme events, and the production of regionally explicit data on the impacts of extreme events on corn and soybeans. No prior assessment of this kind has previously been conducted for eastern Ontario. Moreover, the development and analysis of crop-specific indices, in addition to providing valuable data to farmers and decision-makers in the region, can serve as a guideline to those attempting similar research in other regions.

There are a number of uncertainties related to the rate and magnitude of expected changes and the response of crops and society to these changes (Wreford et al. 2010). Regional studies, such as this one, help better understand some of the impacts of weather extremes and sensitivities of local agricultural systems to these changes. However, presently there are limitations in available weather data, both due to possible data

inhomogeneities as well as limited spatial coverage of the weather station network. Given that the majority of trends in calculated indices show coherent patterns, we can conclude that the observed results are reflecting historic changes. It should be noted, however, that exact trend values may be somewhat distorted due to the fact that data homogenization was not performed as part of this study.

To further improve our understanding of changing extremes in eastern Ontario, it is recommended that future studies address the issue of data homogeneity across available weather station time series and evaluate the impacts of changing large-scale systems on local climate. Additionally, further research on potential future changes in the studied indicators is recommended and expected to assist in the development of effective adaptation strategies to reduce the impact of extreme weather on agricultural operations and crop yield. This is particularly important, given that risks associated with extreme heat and precipitation events as well as other extremes are expected to further increase in the changing climate (IPCC 2014). Lastly, a study of multiple intra-annual stresses affecting crop systems would provide crucial information on potential cumulative effects of various extremes.

It is expected that the results of the research will contribute to ongoing adaptation efforts and assist practitioners in evaluating and further developing methodologies for climate risk mapping for use by insurance industry and the agricultural community. Detailed interpretation of these data will allow farmers and policy makers to better understand extreme weather events, identify opportunities and threats to crop production and make informed decisions on modifying agricultural practices (e.g. making adjustments to the cropping calendar, choosing new crop varieties, changing irrigation

and pesticide application schedules) and developing tools to support strategic planning and adaptive policy development.

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Appendix 1: ETCCDI and Gachon indices of extreme weather events

ETCCDI indices:

Index ID	Index name	Definition	Units
Temperature:			
FD	Frost days	Count of days where TN (daily minimum temperature) < 0°C	days
SU	Summer days	Count of days where TX (daily maximum temperature) > 25°C	days
ID	Icing days		days
TR	Tropical nights		days
GSL	Growing season length	Annual (1st Jan to 31st Dec) count between first span of at least 6 days with TMean > 5°C and first span after 1st July of 6 days with TMean < 5°C	days
TXx	n/a	Monthly maximum value of daily maximum temperature	°C
TNx	n/a	Monthly maximum value of daily minimum temperature	°C
TXn	n/a	Monthly minimum value of daily maximum temperature	°C
TNn	n/a	Monthly minimum value of daily minimum temperature	°C
TN10p	Cool nights	Percentage of days when TMin < 10th percentile	% days
TX10p	Cool days	Percentage of days when TMax < 10th percentile	% days
TN90p	Warm nights	Percentage of days when TMin > 90th percentile	% days
TX90p	Warm days	Percentage of days when TMax > 90th percentile	% days
WSDI	Warm spell duration index	Count of days in a span of at least six days where TX > 90th percentile	days
CSDI	Cold spell duration index	Count of days in a span of at least six days where TN > 10th percentile	days
DTR	Diurnal temperature range	Annual mean difference between TMax and TMin	°C
Precipitation:			
RX1day	Max 1-day precipitation amount	Annual maximum 1-day precipitation	mm
RX5day	Max 5-day precipitation amount	Annual maximum 5-day precipitation	mm
SDII	Simple daily intensity index	Annual total precipitation divided by the number of wet days (PRCP >=1.0mm) in the year	mm/day
R10mm	Heavy precipitation days	Annual count of days when PRCP >=10mm	days
R20mm	Very heavy precipitation days	Count of days where RR ≥ 20 mm	days
Rnnmm	n/a	Count of days where RR ≥ user-defined threshold in mm	days
CDD	Consecutive dry days	Maximum number of consecutive days with PRCP<1mm	days
CWD	Consecutive wet days		days
R95pTOT	Very wet days	Annual total PRCP when daily PRCP > 95th percentile	mm
R99pTOT	Extremely wet days	Annual total PRCP when daily PRCP > 99th percentile	mm
PRCPTOT	Annual total wet day precipitation	Annual total PRCP in wet days (daily PRCP >=1mm)	mm

Source: ETCCDI/CRD Climate Change Indices (2009) Definitions of the 27 core indices. http://etccdi.pacificclimate.org/list_27_indices.shtml. Accessed 10 February 2016

Gachon indices:

Index name	Definition	Units
Temperature:		
Cold extremes	Number of days where Tmin <-20°C	days
Hot extremes	Number of days where Tmax >28°C	days
Cool days	Count of days in the 10th percentile of daily Tmax	days
Warm days	Count of days in the 90th percentile of daily Tmax	days
Cool nights	Count of days in the 10th percentile of daily Tmin	days
Warm nights	Count of days in the 90th percentile of daily Tmin	days
Percentage of warm days	Percentage of days Tmax >90th percentile (1961-1990 baseline period)	% days
Percentage of cool nights	Percentage of days Tmin <10th percentile (1961-1990 baseline period)	% days
Frost season length	Tmean <0°C more than 5 days and Tmean >0°C more than 5 days	days
Growing season length	Tmean >5°C more than 5 days and Tmean <5°C more than 5 days	days
Percentage of days with freeze and thaw cycle	Percentage of days when Tmax >0°C and Tmin <0°C	% days
Diurnal temperature range	Mean of diurnal temperature range	°C
Precipitation:		
Wet days	Percentage of days when precipitation >= 1 mm	% days
Very wet days	Count of days in the 90th percentile of rainday amount (Threshold=1 mm)	days
Percentage of very wet days	Percentage of days when precipitation >90th percentile (1961-1990 baseline period)	% days
Max 3-day precipitation amount	Maximum 3-day precipitation total	mm
Simple daily intensity index	Sum of daily precipitation/number of wet days	mm
Consecutive dry days	Maximum number of days when precipitation <1 mm	days

Source: Gachon P (2005) A first evaluation of the strength and weaknesses of statistical downscaling methods for simulating extremes over various regions of eastern Canada. Environment Canada

Appendix 2: List of operating weather stations in eastern Ontario, 1961-2010

ClimateID	Station Name	Province	Latitude	Longitude	Elevation (m)	Start Year	End Year	Ecodistrict
6100285	Appleton	ONT	45.19	-76.11	133	1992	2010	Smith Falls Plain
6100345	Arnprior Grandon	ONT	45.42	-76.37	106.7	1959	1999	Ottawa Valley Plain
6100398	Avonmore	ONT	45.17	-74.97	91.4	1976	2006	Glengarry Plain
6100521	Barrett Chute	ONT	45.25	-76.77	160	1950	1968	Algonquin
6100558	Barry's Bay	ONT	45.43	-77.67	289.6	1976	1982	Algonquin
6100720	Bellrock	ONT	44.48	-76.78	146.3	1957	1978	Algonquin
6100971	Brockville PCC	ONT	44.6	-75.67	96	1965	2010	Smith Falls Plain
6101260	Carp	ONT	45.3	-75.98	114.3	1960	1975	Ottawa Valley Plain
6101265	Cataraqui TS	ONT	44.37	-76.62	144.8	1960	1995	Napanee-Prince Edward
6151309	Centerville	ONT	44.4	-76.91	150	1985	2010	Napanee-Prince Edward
6101335	Chalk River AECL	ONT	46.05	-77.37	121.9	1960	2010	Algonquin
6101440	Chats Falls	ONT	45.47	-76.23	93.9	1950	1992	Ottawa Valley Plain
6101494	Chenaux	ONT	45.58	-76.68	84.1	1950	1990	Muskrat Lake
6101502	Chesterville 2	ONT	45.02	-75.2	85	1983	1997	Glengarry Plain
6101555	Claybank	ONT	45.42	-76.4	106.7	1961	1994	Ottawa Valley Plain
6161662	Cloyne ONT Hydro	ONT	44.82	-77.18	283.5	1967	1981	Algonquin
6101820	Combermere	ONT	45.37	-77.62	286.5	1956	2009	Algonquin
6101874	Cornwall	ONT	45.02	-74.75	64	1950	2010	Glengarry Plain
6101901	Cornwall ON Hydro	ONT	45.03	-74.8	76.2	1954	2007	Glengarry Plain
6101920	Crow Lake	ONT	44.73	-76.6	173.7	1972	1991	Algonquin
6101958	Dalhousie Mills	ONT	45.32	-74.47	68.6	1968	2004	Upper St. Lawrence Plain
6101962	Dalkeith PYM	ONT	45.43	-74.58	76.2	1978	1987	North Gower-Winchester Plains
6101986	Delta	ONT	44.62	-76.13	97.5	1969	1994	Smith Falls Plain
6102009	Des Joachims	ONT	46.18	-77.7	129.5	1950	1977	Algonquin
6102J13	Drummond Centre	ONT	45.03	-76.25	145	1984	2010	Smith Falls Plain
6102531	Foymount	ONT	45.33	-77.3	426.7	1956	1974	Algonquin
6102832	Glen Gordon	ONT	45.17	-74.53	53.3	1967	1999	Upper St. Lawrence Plain
6102808	Glenburnie	ONT	44.33	-76.5	114.3	1972	1999	Napanee-Prince Edward
6102840	Gloucester Kettles	ONT	45.35	-75.55	76.2	1975	1982	Russell and Prescott Plains
6102857	Godfrey	ONT	44.57	-76.63	160	1981	2003	Algonquin
6103367	Hartington IHD	ONT	44.43	-76.69	160	1967	2010	Napanee-Prince Edward
6103390	Hawkesbury	ONT	45.62	-74.63	45.7	1950	1963	Russell and Prescott Plains
6103470	Hinchinbrooke	ONT	44.58	-76.68	180.4	1961	1973	Algonquin
6153935	Kaladar	ONT	44.65	-77.12	214.7	1998	2010	Algonquin
6104025	Kemptville	ONT	45	-75.63	99.4	1928	1997	Smith Falls Plain
6104027	Kemptville CS	ONT	45	-75.63	99.4	1997	2010	Smith Falls Plain
6104146	Kingston A	ONT	44.22	-76.6	92.4	1930	1996	Napanee-Prince Edward
6104175	Kingston PS	ONT	44.24	-76.48	76.5	1960	2010	Napanee-Prince Edward
6104725	Lyndhurst Shawmere	ONT	44.52	-76.08	86.9	1976	2010	Frontenac
6104882	Mallorytown Landing	ONT	44.45	-75.87	83.8	1977	1991	Frontenac
6105460	Morrisburg	ONT	44.92	-75.19	81.7	1913	2008	Glengarry Plain
615NNPL	Napanee	ONT	44.23	-76.97	80	1987	2001	Napanee-Prince Edward
6105576	Navan	ONT	45.43	-75.52	76.2	1973	1974	Russell and Prescott Plains
6105976	Ottawa CDA	ONT	45.38	-75.72	79.2	1889	2010	Ottawa Valley Plain
6106000	Ottawa Macdonald-Cartier Int'l	ONT	45.32	-75.67	114	1938	2010	North Gower-Winchester Plains
6106090	Ottawa NRC	ONT	45.45	-75.62	97.5	1951	1984	Ottawa Valley Plain
6106369	Pembroke SE	ONT	45.75	-76.98	148	1999	2004	Muskat Lake
6106398	Petawawa A	ONT	45.95	-77.32	130.1	1970	2010	Algonquin
610FC98	Petawawa Hoffman	ONT	45.88	-77.25	153	1993	2010	Algonquin
6107002	Renfrew	ONT	45.48	-76.7	129.5	1968	1996	Muskrat Lake
6107133	Rideau Ferry	ONT	44.85	-76.15	129.5	1948	1969	Algonquin
6107247	Russell	ONT	45.26	-75.36	76.2	1954	2010	Russell and Prescott Plains
6107836	Smiths Falls TS	ONT	44.88	-76	114.3	1982	1989	Smith Falls Plain
6107955	South Mountain	ONT	44.97	-75.48	84.7	1960	1996	Smith Falls Plain
6107276	St. Albert	ONT	45.29	-75.06	80	1986	2010	North Gower-Winchester Plains
6108027	Stewartville	ONT	45.4	-76.5	131.1	1950	1969	Ottawa Valley Plain
6109558	Wolfe Island	ONT	44.15	-76.53	90	1986	1996	Napanee-Prince Edward

Source: Environment and Climate Change Canada (2016) Historical data. http://climate.weather.gc.ca/historical_data/search_historic_data_e.html. Accessed 10 April 2016

Appendix 3: R scripts

3.1. Extreme weather event indices calculation

```
# This script calculates extreme event indices
# for each representative weather station

file_list<-c('CHALKRIVER', 'CORNWALL', 'HARTINGTON','KINGSTON',
 'KEMPTVILLE','LYNDHURST', 'OTTAWACDA', 'ARNPRIOR',
 'RUSSELL','STALBERT', 'STANICET')

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


# Global settings for quality control
# Remove NA cells from calculations
NARM <- TRUE
# Round precision in digits
ROUNDDIGITS <- 1

# Calculation periods initialization
PlantingSeason <- 4:5
GrowingSeason <- 5:9
HarvestingSeason <- 9:11

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

getName <- function(period) {
  if (length(period) == 1) {
    return (monthNames[period])
  } else if (period == PlantingSeason) {
    return ("PS")
  } else if (period == GrowingSeason) {
    return ("GS")
  } else if (period == HarvestingSeason) {
    return ("HS")
  }
  return ("ERROR - PERIOD")
}


base_path<-"~/Documents/Rproj/MSc indices calculation/"
setwd(base_path)

calculateRX1 <- function(InputTable) {
```

```
# Calculating RX1

  print("RX1")

  # Create result table
  result_rx1<-data.frame()
  # Calculating yearly
  i<-first_year
  while (i <= last_year) {
    InputTableYearTrim <-
InputTable[as.numeric(format(as.Date(InputTable$Date,"%Y-%m-
%d"),format="%Y")) ==i, ]
    result_rx1<-rbind(result_rx1, c(i,
max(with(InputTableYearTrim,Precipitation), na.rm = NARM)))
    i <- i + 1
  }
  # Calculating RX1 yearly + seasonally (PS, GS, HS)
  for (m in seasonPeriods) {
    i<-first_year
    InputTableSeasonTrim<-
InputTable[as.numeric(format(as.Date(InputTable$Date,"%Y-%m-
%d"),format="%m")) %in% m,]
    while (i <= last_year) {
      InputTableYearTrim <-
InputTableSeasonTrim[as.numeric(format(as.Date(InputTableSeasonT
rim$Date,"%Y-%m-%d"),format="%Y")) ==i, ]
      result_rx1<-rbind(result_rx1, c(paste0(getName(m), "_", i),
max(with(InputTableYearTrim,Precipitation), na.rm = NARM)))
      i <- i + 1
    }
  }
  # Calculating RX1 decadally
  for (m in periods) {
    # Trim input to month m
    InputTableMonthTrim<-
InputTable[as.numeric(format(as.Date(InputTable$Date,"%Y-%m-
%d"),format="%m")) %in% m,]
    #Trim table to 1960s
    InputTableMonth60sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1961 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=1970,]
    #Trim table to 1970s
    InputTableMonth70sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1971 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=1980,]
```

```
    #Trim table to 1980s
    InputTableMonth80sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1981 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=1990,]
    #Trim table to 1990s
    InputTableMonth90sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1991 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=2000,]
    #Trim table to 2000s
    InputTableMonth00sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=2001 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=2010,]
    rx1_60s<-max(with(InputTableMonth60sTrim,Precipitation),
na.rm = NARM)
    rx1_70s<-max(with(InputTableMonth70sTrim,Precipitation),
na.rm = NARM)
    rx1_80s<-max(with(InputTableMonth80sTrim,Precipitation),
na.rm = NARM)
    rx1_90s<-max(with(InputTableMonth90sTrim,Precipitation),
na.rm = NARM)
    rx1_00s<-max(with(InputTableMonth00sTrim,Precipitation),
na.rm = NARM)
    rx1_baseline<-max(with(InputTableMonthTrim,Precipitation),
na.rm = NARM)
    result_rx1<-rbind(result_rx1, c(paste0(getName(m), "_1960s"),
rx1_60s))
    result_rx1<-rbind(result_rx1, c(paste0(getName(m), "_1970s"),
rx1_70s))
    result_rx1<-rbind(result_rx1, c(paste0(getName(m), "_1980s"),
rx1_80s))
    result_rx1<-rbind(result_rx1, c(paste0(getName(m), "_1990s"),
rx1_90s))
    result_rx1<-rbind(result_rx1, c(paste0(getName(m), "_2000s"),
rx1_00s))
    result_rx1<-rbind(result_rx1, c(paste0(getName(m),
"_baseline"), rx1_baseline))
  }

  colnames(result_rx1)[1:2]<-c("Period","RX1")
  return (result_rx1)
}

calculateRX5 <- function(InputTable) {
```

```
  # Calculating RX5

print("RX5")

  # Create result table
  result_rx5<-data.frame()
  # Creating intermediate table (InputTableTrim) for RX5
 calculation
  InputTableTrim <- InputTable[,2:4]
  j<-5
  InputTableTrim[1,1] <- 0
  InputTableTrim[2,1] <- 0
  InputTableTrim[3,1] <- 0
  InputTableTrim[4,1] <- 0
  # Infilling first column of InputTableTrim with the
 precipitation in corresponding 5-day windows
  while(j<=nrow(InputTableTrim)) {
    InputTableTrim[j,1] <- ((InputTableTrim[j-4,2]) +
                            (InputTableTrim[j-3,2]) +
                            (InputTableTrim[j-2,2]) +
                            (InputTableTrim[j-1,2]) +
                            (InputTableTrim[j,2]))
    j<-j+1
  }
  # Caclulating RX5 yearly
  i<-first_year
  while (i <= last_year) {
    InputTableYearTrim <-
 InputTableTrim[as.numeric(format(as.Date(InputTableTrim$Date,"%Y
 -%m-%d"),format="%Y")) ==i, ]
    result_rx5<-rbind(result_rx5, c(i,
 max(InputTableYearTrim[,1], na.rm = NARM)))
    i <- i + 1
  }
  # Calculating RX5 seasonally (PS, GS, HS)
  for (m in seasonPeriods) {
    i<-first_year
    InputTableSeasonTrim<-
 InputTable[as.numeric(format(as.Date(InputTable$Date,"%Y-%m-
 %d"),format="%m")) %in% m,]
    while (i <= last_year) {
      InputTableYearTrim <-
 InputTableSeasonTrim[as.numeric(format(as.Date(InputTableSeasonT
 rim$Date,"%Y-%m-%d"),format="%Y")) ==i, ]
      result_rx5<-rbind(result_rx5, c(paste0(getName(m), "_", i),
 max(InputTableYearTrim[,1], na.rm = NARM)))
      i <- i + 1
    }
  }
  # Calculating RX5 decadally
  for (m in periods) {
```

```
    # Trim input to month m
    InputTableMonthTrim<-
InputTableTrim[as.numeric(format(as.Date(InputTableTrim$Date,"%Y
-%m-%d"),format="%m")) %in% m,]

    #Trim table to 1960s
    InputTableMonth60sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1961 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=1970,]
    #Trim table to 1970s
    InputTableMonth70sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1971 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=1980,]
    #Trim table to 1980s
    InputTableMonth80sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1981 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=1990,]
    #Trim table to 1990s
    InputTableMonth90sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1991 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=2000,]
    #Trim table to 2000s
    InputTableMonth00sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=2001 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=2010,]

    rx5_60s<-max(InputTableMonth60sTrim[,1], na.rm = NARM)
    rx5_70s<-max(InputTableMonth70sTrim[,1], na.rm = NARM)
    rx5_80s<-max(InputTableMonth80sTrim[,1], na.rm = NARM)
    rx5_90s<-max(InputTableMonth90sTrim[,1], na.rm = NARM)
    rx5_00s<-max(InputTableMonth00sTrim[,1], na.rm = NARM)
    rx5_baseline<-max(InputTableMonthTrim[,1], na.rm = NARM)
    result_rx5<-rbind(result_rx5, c(paste0(getName(m), "_1960s"),
rx5_60s))
    result_rx5<-rbind(result_rx5, c(paste0(getName(m), "_1970s"),
rx5_70s))
    result_rx5<-rbind(result_rx5, c(paste0(getName(m), "_1980s"),
```

```
rx5_80s))
    result_rx5<-rbind(result_rx5, c(paste0(getName(m), "_1990s"),
rx5_90s))
    result_rx5<-rbind(result_rx5, c(paste0(getName(m), "_2000s"),
rx5_00s))
    result_rx5<-rbind(result_rx5, c(paste0(getName(m),
"_baseline"), rx5_baseline))
  }

  colnames(result_rx5)[1:2]<-c("Period","RX5")
  return (result_rx5)
}

calculateCDD <- function(InputTable) {

  # Calculating CDD

print("CDD")

  #Create result table
  result_cdd<-data.frame()
  # Write date to InputTableTrim 1st column
  InputTableTrim<-InputTable[,3:4]
  # Add column with value 1 if the day is dry, 0 otherwise. This
will be the second column of result_cdd_i
  InputTableTrim<-
cbind(InputTableTrim,ifelse(InputTable$Precipitation<1,1,0))
  # Add column with 0 value in all cells
  InputTableTrim<-cbind(InputTableTrim,
rep(0,nrow(InputTableTrim)))
  # Add one more column with the date
  # Special processing for the first day
  InputTableTrim[1,4]<-InputTableTrim[1,3]
  # Iterate starting from the second row
  j<-2
  while(j<=nrow(InputTableTrim)) {
    # Put value to the cell in row j, column 3
    # If the day is dry (value of the cell in column 2 is not 0)
    # the value is calculated as ("value of the cell in row (j-
1), column 3" + 1)
    # InputTableTrim[j-1,3]
    # If the day is wet, than the value is 0

    InputTableTrim[j,4]<-ifelse(InputTableTrim[j,3],
InputTableTrim[j-1,4]+1, 0)
    # Proceed to the next day
    j<-j+1
  }
  colnames(InputTableTrim)[1:4] <- c("tmp", "Date",
"Precipitation", "cdd")
  # Calculating CDD yearly
  i<-first_year
```

```
  while (i <= last_year) {
    InputTableYearTrim <-
InputTableTrim[as.numeric(format(as.Date(InputTableTrim$Date,"%Y
-%m-%d"),format="%Y")) ==i, ]
    cdd_yearly<-max(InputTableYearTrim[,4], na.rm = NARM)
    result_cdd<-rbind(result_cdd, c(i, cdd_yearly))
    i <- i + 1
  }
  # Calculating CDD seasonally (PS, GS, HS)
  for (m in seasonPeriods) {
    i<-first_year
    InputTableSeasonTrim<-
InputTableTrim[as.numeric(format(as.Date(InputTableTrim$Date,"%Y
-%m-%d"),format="%m")) %in% m,]
    while (i <= last_year) {
      InputTableYearTrim <-
InputTableSeasonTrim[as.numeric(format(as.Date(InputTableSeasonT
rim$Date,"%Y-%m-%d"),format="%Y")) ==i, ]
      cdd_yearly<-max(InputTableYearTrim[,4], na.rm = NARM)
      result_cdd<-rbind(result_cdd, c(paste0(getName(m), "_", i),
cdd_yearly))
      i <- i + 1
    }
  }
  # Calculating CDD decadally
  for (m in periods) {
    # Trim input to month m
    InputTableMonthTrim<-
InputTableTrim[as.numeric(format(as.Date(InputTableTrim$Date,"%Y
-%m-%d"),format="%m")) %in% m,]
    #Trim table to 1960s
    InputTableMonth60sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1961 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=1970,]
    #Trim table to 1970s
    InputTableMonth70sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1971 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=1980,]
    #Trim table to 1980s
    InputTableMonth80sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1981 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=1990,]
    #Trim table to 1990s
```

```
    InputTableMonth90sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1991 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=2000,]
    #Trim table to 2000s
    InputTableMonth00sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=2001 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=2010,]

    cdd_60s<-max(InputTableMonth60sTrim[,4], na.rm = NARM)
    cdd_70s<-max(InputTableMonth70sTrim[,4], na.rm = NARM)
    cdd_80s<-max(InputTableMonth80sTrim[,4], na.rm = NARM)
    cdd_90s<-max(InputTableMonth90sTrim[,4], na.rm = NARM)
    cdd_00s<-max(InputTableMonth00sTrim[,4], na.rm = NARM)
    cdd_baseline<-max(InputTableMonthTrim[,4], na.rm = NARM)
    result_cdd<-rbind(result_cdd, c(paste0(getName(m), "_1960s"),
cdd_60s))
    result_cdd<-rbind(result_cdd, c(paste0(getName(m), "_1970s"),
cdd_70s))
    result_cdd<-rbind(result_cdd, c(paste0(getName(m), "_1980s"),
cdd_80s))
    result_cdd<-rbind(result_cdd, c(paste0(getName(m), "_1990s"),
cdd_90s))
    result_cdd<-rbind(result_cdd, c(paste0(getName(m), "_2000s"),
cdd_00s))
    result_cdd<-rbind(result_cdd, c(paste0(getName(m),
"_baseline"), cdd_baseline))
  }

  colnames(result_cdd)[1:2]<-c("Period","CDD")
  return (result_cdd)
}

calculateR10 <- function(InputTable) {

# Calculating R10

print("R10")

  #Create result table
  result_r10<-data.frame()
  # Trim input table to days with precipitation >= 10
  InputTableTrim<-InputTable[InputTable$Precipitation >= 10,]
  # Calculating R10 yearly
  i<-first_year
  while (i <= last_year) {
    InputTableYearTrim <-
```

```
InputTableTrim[as.numeric(format(as.Date(InputTableTrim$Date,"%Y
-%m-%d"),format="%Y")) ==i, ]
    result_r10<-rbind(result_r10, c(i, nrow(InputTableYearTrim)))
    i <- i + 1
  }
  # Calculating R10 seasonally (PS, GS, HS)
  for (m in seasonPeriods) {
    i<-first_year
    InputTableSeasonTrim<-
InputTableTrim[as.numeric(format(as.Date(InputTableTrim$Date,"%Y
-%m-%d"),format="%m")) %in% m,]
    while (i <= last_year) {
      InputTableYearTrim <-
InputTableSeasonTrim[as.numeric(format(as.Date(InputTableSeasonT
rim$Date,"%Y-%m-%d"),format="%Y")) ==i, ]
      result_r10<-rbind(result_r10, c(paste0(getName(m), "_", i),
nrow(InputTableYearTrim)))
      i <- i + 1
    }
  }
  # Calculating R10 decadally
  for (m in periods) {
    # Trim input to month m
    InputTableMonthTrim<-
InputTableTrim[as.numeric(format(as.Date(InputTableTrim$Date,"%Y
-%m-%d"),format="%m")) %in% m,]
    #Trim table to 1960s
    InputTableMonth60sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1961 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=1970,]
    #Trim table to 1970s
    InputTableMonth70sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1971 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=1980,]
    #Trim table to 1980s
    InputTableMonth80sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1981 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=1990,]
    #Trim table to 1990s
    InputTableMonth90sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1991 &
```

```
as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=2000,]
    #Trim table to 2000s
    InputTableMonth00sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=2001 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=2010,]
    r10_60s<-nrow(InputTableMonth60sTrim)
    r10_70s<-nrow(InputTableMonth70sTrim)
    r10_80s<-nrow(InputTableMonth80sTrim)
    r10_90s<-nrow(InputTableMonth90sTrim)
    r10_00s<-nrow(InputTableMonth00sTrim)
    r10_baseline<-nrow(InputTableMonthTrim)
    result_r10<-rbind(result_r10, c(paste0(getName(m), "_1960s"),
r10_60s))
    result_r10<-rbind(result_r10, c(paste0(getName(m), "_1970s"),
r10_70s))
    result_r10<-rbind(result_r10, c(paste0(getName(m), "_1980s"),
r10_80s))
    result_r10<-rbind(result_r10, c(paste0(getName(m), "_1990s"),
r10_90s))
    result_r10<-rbind(result_r10, c(paste0(getName(m), "_2000s"),
r10_00s))
    result_r10<-rbind(result_r10, c(paste0(getName(m),
"_baseline"), r10_baseline))
  }
  colnames(result_r10)[1:2]<-c("Period","R10")
  return (result_r10)
}

calculateSDII <- function(InputTable) {

  # Calculating SDII

  print("SDII")

  #Create result table
  result_sdii<-data.frame()
  # Trim input table to days with precipitation >= 1
  InputTableTrim<-InputTable[InputTable$Precipitation >= 1,]
  # Calculating SDII yearly
  i<-first_year
  while (i <= last_year) {
    InputTableYearTrim <-
InputTableTrim[as.numeric(format(as.Date(InputTableTrim$Date,"%Y
-%m-%d"),format="%Y")) ==i, ]
    result_sdii<-rbind(result_sdii, c(i,
round(sum(InputTableYearTrim$Precipitation,
na.rm=NARM)/nrow(InputTableYearTrim), digits = ROUNDDIGITS)))
    i <- i + 1
```

```
  }
  # Calculating SDII seasonally (PS, GS, HS)
  for (m in seasonPeriods) {
    i<-first_year
    InputTableSeasonTrim<-
InputTableTrim[as.numeric(format(as.Date(InputTableTrim$Date,"%Y
-%m-%d"),format="%m")) %in% m,]
    while (i <= last_year) {
      InputTableYearTrim <-
InputTableSeasonTrim[as.numeric(format(as.Date(InputTableSeasonT
rim$Date,"%Y-%m-%d"),format="%Y")) ==i, ]
      result_sdii<-rbind(result_sdii, c(paste0(getName(m), "_",
i), round(sum(InputTableYearTrim$Precipitation,
na.rm=NARM)/nrow(InputTableYearTrim), digits = ROUNDDIGITS)))
      i <- i + 1
    }
  }
  # Calculating SDII decadally
  for (m in periods) {
    # Trim input to month m
    InputTableMonthTrim<-
InputTableTrim[as.numeric(format(as.Date(InputTableTrim$Date,"%Y
-%m-%d"),format="%m")) %in% m,]
    #Trim table to 1960s
    InputTableMonth60sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1961 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=1970,]
    #Trim table to 1970s
    InputTableMonth70sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1971 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=1980,]
    #Trim table to 1980s
    InputTableMonth80sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1981 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=1990,]
    #Trim table to 1990s
    InputTableMonth90sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1991 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=2000,]
    #Trim table to 2000s
```

```
    InputTableMonth00sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=2001 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=2010,]
    sdii_60s<-round(sum(InputTableMonth60sTrim$Precipitation,
na.rm=NARM)/nrow(InputTableMonth60sTrim), digits=ROUNDDIGITS)
    sdii_70s<-round(sum(InputTableMonth70sTrim$Precipitation,
na.rm=NARM)/nrow(InputTableMonth70sTrim), digits=ROUNDDIGITS)
    sdii_80s<-round(sum(InputTableMonth80sTrim$Precipitation,
na.rm=NARM)/nrow(InputTableMonth80sTrim), digits=ROUNDDIGITS)
    sdii_90s<-round(sum(InputTableMonth90sTrim$Precipitation,
na.rm=NARM)/nrow(InputTableMonth90sTrim), digits=ROUNDDIGITS)
    sdii_00s<-round(sum(InputTableMonth00sTrim$Precipitation,
na.rm=NARM)/nrow(InputTableMonth00sTrim), digits=ROUNDDIGITS)
    sdii_baseline<-round(sum(InputTableMonthTrim$Precipitation,
na.rm=NARM)/nrow(InputTableMonthTrim), digits=ROUNDDIGITS)
    result_sdii<-rbind(result_sdii, c(paste0(getName(m),
"_1960s"), sdii_60s))
    result_sdii<-rbind(result_sdii, c(paste0(getName(m),
"_1970s"), sdii_70s))
    result_sdii<-rbind(result_sdii, c(paste0(getName(m),
"_1980s"), sdii_80s))
    result_sdii<-rbind(result_sdii, c(paste0(getName(m),
"_1990s"), sdii_90s))
    result_sdii<-rbind(result_sdii, c(paste0(getName(m),
"_2000s"), sdii_00s))
    result_sdii<-rbind(result_sdii, c(paste0(getName(m),
"_baseline"), sdii_baseline))
  }
  colnames(result_sdii)[1:2]<-c("Period","SDII")
  return (result_sdii)
}

calculateExtremeTemps <- function(InputTable) {

  # Calculating HWE, CWE

  print("HWE, CWE")

  #Create result table
  result_extremes<-data.frame()
  # Trim input to days with TempMax >= 30 for HWE
  InputTableTrimHWE<-InputTable[InputTable$TempMax >= 30,]
  # Trim input to days with TempMin <= -20 for CWE
  InputTableTrimCWE<-InputTable[InputTable$TempMin <= -20,]
  # Calculating HWE and CWE yearly
  i<-first_year
  while (i <= last_year) {
    InputTableYearTrimHWE <-
InputTableTrimHWE[as.numeric(format(as.Date(InputTableTrimHWE$Da
```

```
te,"%Y-%m-%d"),format="%Y")) ==i, ]
    InputTableYearTrimCWE <-
InputTableTrimCWE[as.numeric(format(as.Date(InputTableTrimCWE$Da
te,"%Y-%m-%d"),format="%Y")) ==i, ]
    result_extremes<-rbind(result_extremes, c(i,
nrow(InputTableYearTrimHWE), nrow(InputTableYearTrimCWE)))
    i <- i + 1
  }
  # Calculating HWE and CWE yearly + seasonally (PS, GS, HS)
  for (m in seasonPeriods) {
    i<-first_year
    InputTableSeasonTrimHWE<-
InputTableTrimHWE[as.numeric(format(as.Date(InputTableTrimHWE$Da
te,"%Y-%m-%d"),format="%m")) %in% m,]
    InputTableSeasonTrimCWE<-
InputTableTrimCWE[as.numeric(format(as.Date(InputTableTrimCWE$Da
te,"%Y-%m-%d"),format="%m")) %in% m,]
    while (i <= last_year) {
      InputTableYearTrimHWE <-
InputTableSeasonTrimHWE[as.numeric(format(as.Date(InputTableSeas
onTrimHWE$Date,"%Y-%m-%d"),format="%Y")) ==i, ]
      InputTableYearTrimCWE <-
InputTableSeasonTrimCWE[as.numeric(format(as.Date(InputTableSeas
onTrimCWE$Date,"%Y-%m-%d"),format="%Y")) ==i, ]
      result_extremes<-rbind(result_extremes,
c(paste0(getName(m), "_", i), nrow(InputTableYearTrimHWE),
nrow(InputTableYearTrimCWE)))
      i <- i + 1
    }
  }
  # Calculating HWE and CWE decadally
  for (m in periods) {
    # Trim input to month m
    InputTableMonthTrimHWE<-
InputTableTrimHWE[as.numeric(format(as.Date(InputTableTrimHWE$Da
te,"%Y-%m-%d"),format="%m")) %in% m,]
    InputTableMonthTrimCWE<-
InputTableTrimCWE[as.numeric(format(as.Date(InputTableTrimCWE$Da
te,"%Y-%m-%d"),format="%m")) %in% m,]
    #Trim table to 1960s
    InputTableMonth60sTrimHWE<-
InputTableMonthTrimHWE[as.numeric(format(as.Date(InputTableMonth
TrimHWE$Date,"%Y-%m-%d"),format="%Y")) >=1961 &

as.numeric(format(as.Date(InputTableMonthTrimHWE$Date,"%Y-%m-
%d"),format="%Y")) <=1970,]
    InputTableMonth60sTrimCWE<-
InputTableMonthTrimHWE[as.numeric(format(as.Date(InputTableMonth
TrimCWE$Date,"%Y-%m-%d"),format="%Y")) >=1961 &

as.numeric(format(as.Date(InputTableMonthTrimCWE$Date,"%Y-%m-
%d"),format="%Y")) <=1970,]
```

```
    #Trim table to 1970s
    InputTableMonth70sTrimHWE<-
InputTableMonthTrimHWE[as.numeric(format(as.Date(InputTableMonth
TrimHWE$Date,"%Y-%m-%d"),format="%Y")) >=1971 &

as.numeric(format(as.Date(InputTableMonthTrimHWE$Date,"%Y-%m-
%d"),format="%Y")) <=1980,]
    InputTableMonth70sTrimCWE<-
InputTableMonthTrimCWE[as.numeric(format(as.Date(InputTableMonth
TrimCWE$Date,"%Y-%m-%d"),format="%Y")) >=1971 &

as.numeric(format(as.Date(InputTableMonthTrimCWE$Date,"%Y-%m-
%d"),format="%Y")) <=1980,]
    #Trim table to 1980s
    InputTableMonth80sTrimHWE<-
InputTableMonthTrimHWE[as.numeric(format(as.Date(InputTableMonth
TrimHWE$Date,"%Y-%m-%d"),format="%Y")) >=1981 &

as.numeric(format(as.Date(InputTableMonthTrimHWE$Date,"%Y-%m-
%d"),format="%Y")) <=1990,]
    InputTableMonth80sTrimCWE<-
InputTableMonthTrimCWE[as.numeric(format(as.Date(InputTableMonth
TrimCWE$Date,"%Y-%m-%d"),format="%Y")) >=1981 &

as.numeric(format(as.Date(InputTableMonthTrimCWE$Date,"%Y-%m-
%d"),format="%Y")) <=1990,]
    #Trim table to 1990s
    InputTableMonth90sTrimHWE<-
InputTableMonthTrimHWE[as.numeric(format(as.Date(InputTableMonth
TrimHWE$Date,"%Y-%m-%d"),format="%Y")) >=1991 &

as.numeric(format(as.Date(InputTableMonthTrimHWE$Date,"%Y-%m-
%d"),format="%Y")) <=2000,]
    InputTableMonth90sTrimCWE<-
InputTableMonthTrimCWE[as.numeric(format(as.Date(InputTableMonth
TrimCWE$Date,"%Y-%m-%d"),format="%Y")) >=1991 &

as.numeric(format(as.Date(InputTableMonthTrimCWE$Date,"%Y-%m-
%d"),format="%Y")) <=2000,]
    #Trim table to 2000s
    InputTableMonth00sTrimHWE<-
InputTableMonthTrimHWE[as.numeric(format(as.Date(InputTableMonth
TrimHWE$Date,"%Y-%m-%d"),format="%Y")) >=2001 &

as.numeric(format(as.Date(InputTableMonthTrimHWE$Date,"%Y-%m-
%d"),format="%Y")) <=2010,]
    InputTableMonth00sTrimCWE<-
InputTableMonthTrimCWE[as.numeric(format(as.Date(InputTableMonth
TrimCWE$Date,"%Y-%m-%d"),format="%Y")) >=2001 &

as.numeric(format(as.Date(InputTableMonthTrimCWE$Date,"%Y-%m-
%d"),format="%Y")) <=2010,]
```

```
    result_extremes<-rbind(result_extremes, c(paste0(getName(m),
"_1960s"), nrow(InputTableMonth60sTrimHWE),
nrow(InputTableMonth60sTrimCWE)))
    result_extremes<-rbind(result_extremes, c(paste0(getName(m),
"_1970s"), nrow(InputTableMonth70sTrimHWE),
nrow(InputTableMonth70sTrimCWE)))
    result_extremes<-rbind(result_extremes, c(paste0(getName(m),
"_1980s"), nrow(InputTableMonth80sTrimHWE),
nrow(InputTableMonth80sTrimCWE)))
    result_extremes<-rbind(result_extremes, c(paste0(getName(m),
"_1990s"), nrow(InputTableMonth90sTrimHWE),
nrow(InputTableMonth90sTrimCWE)))
    result_extremes<-rbind(result_extremes, c(paste0(getName(m),
"_2000s"), nrow(InputTableMonth00sTrimHWE),
nrow(InputTableMonth00sTrimCWE)))
    result_extremes<-rbind(result_extremes, c(paste0(getName(m),
"_baseline"), nrow(InputTableMonthTrimHWE),
nrow(InputTableMonthTrimCWE)))
  }
  colnames(result_extremes)[1:3]<-c("Period","HWE", "CWE")
  return (result_extremes)
}

calculateDTR <- function(InputTable) {

# Calculating DTR

print("DTR")

  #Create result table
  result_dtr<-data.frame()
  # Calculating DTR yearly
  i<-first_year
  while (i <= last_year) {
    InputTableYearTrim <-
InputTable[as.numeric(format(as.Date(InputTable$Date,"%Y-%m-
%d"),format="%Y")) ==i, ]
    result_dtr<-rbind(result_dtr, c(i,
round(mean(with(InputTableYearTrim,TempMax - TempMin), na.rm =
NARM), digits=ROUNDDIGITS)))
    i <- i + 1
  }
  # Calculating DTR yearly + seasonally (PS, GS, HS)
  for (m in seasonPeriods) {
    i<-first_year
    InputTableSeasonTrim<-
InputTable[as.numeric(format(as.Date(InputTable$Date,"%Y-%m-
%d"),format="%m")) %in% m,]
    while (i <= last_year) {
      InputTableYearTrim <-
InputTableSeasonTrim[as.numeric(format(as.Date(InputTableSeasonT
```

```
rim$Date,"%Y-%m-%d"),format="%Y")) ==i, ]
      result_dtr<-rbind(result_dtr, c(paste0(getName(m), "_", i),
round(mean(with(InputTableYearTrim,TempMax - TempMin), na.rm =
NARM), digits=ROUNDDIGITS)))
      i <- i + 1
    }
  }
  # Calculating DTR decadally
  for (m in periods) {
    # Trim input to month m
    InputTableMonthTrim<-
InputTable[as.numeric(format(as.Date(InputTable$Date,"%Y-%m-
%d"),format="%m")) %in% m,]
    #Trim table to 1960s
    InputTableMonth60sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1961 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=1970,]
    #Trim table to 1970s
    InputTableMonth70sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1971 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=1980,]
    #Trim table to 1980s
    InputTableMonth80sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1981 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=1990,]
    #Trim table to 1990s
    InputTableMonth90sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1991 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=2000,]
    #Trim table to 2000s
    InputTableMonth00sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=2001 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=2010,]

    result_dtr<-rbind(result_dtr, c(paste0(getName(m), "_1960s"),
round(mean(with(InputTableMonth60sTrim,TempMax - TempMin), na.rm
= NARM), digits=ROUNDDIGITS)))
```

```
    result_dtr<-rbind(result_dtr, c(paste0(getName(m), "_1970s"),
round(mean(with(InputTableMonth70sTrim,TempMax - TempMin), na.rm
= NARM), digits=ROUNDDIGITS)))
    result_dtr<-rbind(result_dtr, c(paste0(getName(m), "_1980s"),
round(mean(with(InputTableMonth80sTrim,TempMax - TempMin), na.rm
= NARM), digits=ROUNDDIGITS)))
    result_dtr<-rbind(result_dtr, c(paste0(getName(m), "_1990s"),
round(mean(with(InputTableMonth90sTrim,TempMax - TempMin), na.rm
= NARM), digits=ROUNDDIGITS)))
    result_dtr<-rbind(result_dtr, c(paste0(getName(m), "_2000s"),
round(mean(with(InputTableMonth00sTrim,TempMax - TempMin), na.rm
= NARM), digits=ROUNDDIGITS)))
    result_dtr<-rbind(result_dtr, c(paste0(getName(m),
"_baseline"), round(mean(with(InputTableMonthTrim,TempMax -
TempMin), na.rm = NARM), digits=ROUNDDIGITS)))
  }
  colnames(result_dtr)[1:2]<-c("Period","DTR")
  return (result_dtr)
}

calculateGSL <- function(InputTable, first_year, last_year) {

# Calculating GSL

print("GSL")
  #Create result table
  result_gsl<-data.frame()

  #Initialize index i with first_year
  i<-first_year
  # And iterate year-by-year
  while(i<=last_year) {
    # Create data frame for year 'i' and cdd  == 1
    InputTableTrim<-
InputTable[as.numeric(format(as.Date(InputTable$Date,"%Y-%m-
%d"),format="%Y"))==i,]
    result_gsl_i<-InputTableTrim[,3:4]
    result_gsl_i<-
cbind(result_gsl_i,apply(InputTableTrim[,c("TempMin","TempMax")]
,1,mean))
    result_gsl_i<-cbind(result_gsl_i, rep(0,nrow(result_gsl_i)))
    j<-6
    countNA<-0
    while(j<=nrow(result_gsl_i)) {
      if (!is.na(result_gsl_i[j,3]) & !is.na(result_gsl_i[j-1,3])
&
          !is.na(result_gsl_i[j-2,3]) & !is.na(result_gsl_i[j-
3,3]) &
          !is.na(result_gsl_i[j-4,3]) & !is.na(result_gsl_i[j-
5,3])) {
        if (((result_gsl_i[j-1,4] > 0) |
             ((result_gsl_i[j,3] > 5) & (result_gsl_i[j-1,3] > 5)
```

```
&
              (result_gsl_i[j-2,3] > 5) & (result_gsl_i[j-3,3] >
5) &
              (result_gsl_i[j-4,3] > 5) & (result_gsl_i[j-5,3] >
5)))&
            !((result_gsl_i[j,3]<5) & (result_gsl_i[j-1,3]<5) &
              (result_gsl_i[j-2,3]<5) & (result_gsl_i[j-3,3]<5) &
              (result_gsl_i[j-4,3]<5) & (result_gsl_i[j-5,3]<5) &
j >= 183))
          result_gsl_i[j,4]<-1
      } else {
        countNA <- countNA + 1
        result_gsl_i[j,4]<-result_gsl_i[j-1,4]
      }
      j<-j+1
    }
    if (countNA > 0) {
      print(paste0("Year ", i, " has ", countNA, " days for which
NAs affected calculation"))
    }
    result_gsl<-rbind(result_gsl,c(i, sum(result_gsl_i[,4], na.rm
= NARM)))
    i<-i+1
  }

  gsl_60s<-c()
  gsl_70s<-c()
  gsl_80s<-c()
  gsl_90s<-c()
  gsl_00s<-c()
  gsl_baseline<-c()

  result<-data.frame()
  i<-1
  # And iterate year-by-year
  # Output GSL yearly
  while(i<=nrow(result_gsl)) {
    gsl_baseline <-c(gsl_baseline, result_gsl[i, 2])
    year <- result_gsl[i, 1]
    result <- rbind(result, c(year, result_gsl[i,2]))
    if (year >= 1961 && year <= 1970) {
      gsl_60s <-c(gsl_60s, result_gsl[i,2])
    } else if (year >= 1971 && year <= 1980) {
      gsl_70s <-c(gsl_70s, result_gsl[i,2])
    } else if (year >= 1981 && year <= 1990) {
      gsl_80s <-c(gsl_80s, result_gsl[i,2])
    } else if (year >= 1991 && year <= 2000) {
      gsl_90s <-c(gsl_90s, result_gsl[i,2])
    } else if (year >= 2001 && year <= 2010) {
      gsl_00s <-c(gsl_00s, result_gsl[i,2])
    }
    i<-i+1
```

```
  }
  # Output GSL yearly + seasonally (PS, GS, HS)
  for (m in seasonPeriods) {
    i<-first_year
    while (i <= last_year) {
      result<-rbind(result, c(paste0(getName(m), "_", i), 0))
      i <- i + 1
    }
  }
  # Output GSL decadally
  for (m in periods) {
    result<-rbind(result, c(paste0(getName(m), "_1960s"),
 round(mean(gsl_60s, na.rm = NARM), digits=0)))
    result<-rbind(result, c(paste0(getName(m), "_1970s"),
 round(mean(gsl_70s, na.rm = NARM), digits=0)))
    result<-rbind(result, c(paste0(getName(m), "_1980s"),
 round(mean(gsl_80s, na.rm = NARM), digits=0)))
    result<-rbind(result, c(paste0(getName(m), "_1990s"),
 round(mean(gsl_90s, na.rm = NARM), digits=0)))
    result<-rbind(result, c(paste0(getName(m), "_2000s"),
 round(mean(gsl_00s, na.rm = NARM), digits=0)))
    result<-rbind(result, c(paste0(getName(m), "_baseline"),
 round(mean(gsl_baseline, na.rm = NARM), digits=0)))

  }
  colnames(result)[1:2]<-c("Period","GSL")
  return (result)
}

calculateTotals <- function(InputTable, first_year, last_year) {
```

```
# Calculating Basic Climate variables:
# mean TempMin, mean TempMax, total Precipitation

print("Totals")

  #Create result table
  result_totals<-data.frame()
  i<-first_year
  # Calculate totals yearly
  while (i <= last_year) {
    InputTableYearTrim <-
InputTable[as.numeric(format(as.Date(InputTable$Date,"%Y-%m-
%d"),format="%Y")) ==i, ]
    InputTablePrecipitationTrim <-
InputTableYearTrim[InputTableYearTrim$Precipitation >=1, ]
    result_totals<-rbind(result_totals, c(i,
round(mean(InputTableYearTrim$TempMin), digits=ROUNDDIGITS),

round(mean(InputTableYearTrim$TempMax), digits=ROUNDDIGITS),

round(sum(InputTablePrecipitationTrim$Precipitation),
digits=ROUNDDIGITS)))
    i <- i + 1
  }
  # Calculate totals yearly + seasonally (PS, GS, HS)
  for (m in seasonPeriods) {
    i<-first_year
    InputTableSeasonTrim<-
InputTable[as.numeric(format(as.Date(InputTable$Date,"%Y-%m-
%d"),format="%m")) %in% m,]
    while (i <= last_year) {
      InputTableYearTrim <-
InputTableSeasonTrim[as.numeric(format(as.Date(InputTableSeasonT
rim$Date,"%Y-%m-%d"),format="%Y")) ==i, ]
      InputTablePrecipitationTrim <-
InputTableYearTrim[InputTableYearTrim$Precipitation >=1, ]
      result_totals<-rbind(result_totals, c(paste0(getName(m),
"_", i), round(mean(InputTableYearTrim$TempMin),
digits=ROUNDDIGITS),

round(mean(InputTableYearTrim$TempMax), digits=ROUNDDIGITS),

round(sum(InputTablePrecipitationTrim$Precipitation),
digits=ROUNDDIGITS)))

      i <- i + 1
    }
  }
  # Calculate totals decadally
  for (m in periods) {
    # Trim input to month m
    InputTableMonthTrim<-
```

```
InputTable[as.numeric(format(as.Date(InputTable$Date,"%Y-%m-
%d"),format="%m")) %in% m,]
    #Trim table to 1960s
    InputTableMonth60sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1961 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=1970,]
    #Trim table to 1970s
    InputTableMonth70sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1971 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=1980,]
    #Trim table to 1980s
    InputTableMonth80sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1981 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=1990,]
    #Trim table to 1990s
    InputTableMonth90sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=1991 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=2000,]
    #Trim table to 2000s
    InputTableMonth00sTrim<-
InputTableMonthTrim[as.numeric(format(as.Date(InputTableMonthTri
m$Date,"%Y-%m-%d"),format="%Y")) >=2001 &

as.numeric(format(as.Date(InputTableMonthTrim$Date,"%Y-%m-
%d"),format="%Y")) <=2010,]

    result_totals<-rbind(result_totals, c(paste0(getName(m),
"_1960s"), round(mean(InputTableMonth60sTrim$TempMin),
digits=ROUNDDIGITS),

round(mean(InputTableMonth60sTrim$TempMax), digits=ROUNDDIGITS),

round(sum(InputTableMonth60sTrim$Precipitation),
digits=ROUNDDIGITS)))
    result_totals<-rbind(result_totals, c(paste0(getName(m),
"_1970s"), round(mean(InputTableMonth70sTrim$TempMin),
digits=ROUNDDIGITS),

round(mean(InputTableMonth70sTrim$TempMax), digits=ROUNDDIGITS),
```

```
round(sum(InputTableMonth70sTrim$Precipitation),
digits=ROUNDDIGITS)))
    result_totals<-rbind(result_totals, c(paste0(getName(m),
"_1980s"), round(mean(InputTableMonth80sTrim$TempMin),
digits=ROUNDDIGITS),

round(mean(InputTableMonth80sTrim$TempMax), digits=ROUNDDIGITS),

round(sum(InputTableMonth80sTrim$Precipitation),
digits=ROUNDDIGITS)))
    result_totals<-rbind(result_totals, c(paste0(getName(m),
"_1990s"), round(mean(InputTableMonth90sTrim$TempMin),
digits=ROUNDDIGITS),

round(mean(InputTableMonth90sTrim$TempMax), digits=ROUNDDIGITS),

round(sum(InputTableMonth90sTrim$Precipitation),
digits=ROUNDDIGITS)))
    result_totals<-rbind(result_totals, c(paste0(getName(m),
"_2000s"), round(mean(InputTableMonth00sTrim$TempMin),
digits=ROUNDDIGITS),

round(mean(InputTableMonth00sTrim$TempMax), digits=ROUNDDIGITS),

round(sum(InputTableMonth00sTrim$Precipitation),
digits=ROUNDDIGITS)))
    result_totals<-rbind(result_totals, c(paste0(getName(m),
"_baseline"), round(mean(InputTableMonthTrim$TempMin),
digits=ROUNDDIGITS),

round(mean(InputTableMonthTrim$TempMax), digits=ROUNDDIGITS),

round(sum(InputTableMonthTrim$Precipitation),
digits=ROUNDDIGITS)))
  }
  colnames(result_totals)[1:4]<-c("Period","AvgTempMin",
"AvgTempMax", "SumPrecipitation")
  return (result_totals)
}

# Call calculation for each input station
for(file_name in file_list) {
  setwd(base_path)
  in_csv_path<-paste0(base_path, "input/", file_name,".csv")


  print(paste0("Processing ",in_csv_path))
  InputTable <- read.csv(in_csv_path)
  first_year<-as.numeric(format(as.Date(InputTable[1,4],"%Y-%m-
%d"),format="%Y"))
  last_year<-
as.numeric(format(as.Date(InputTable[nrow(InputTable),4],"%Y-%m-
```

```
%d"),format="%Y"))
 print(paste0("First year ", first_year, ", last year ",
last_year))


 out_csv_dir<-paste0(base_path,"/extreme weather/")
 dir.create(out_csv_dir, showWarnings=FALSE)

 result <-calculateRX1(InputTable)
 result <- merge(result, sort=FALSE, calculateRX5(InputTable),
by="Period")
 result <- merge(result, sort=FALSE, calculateCDD(InputTable),
by="Period")
 result <- merge(result, sort=FALSE, calculateR10(InputTable),
by="Period")
 result <- merge(result, sort=FALSE, calculateSDII(InputTable),
by="Period")
 result <- merge(result, sort=FALSE,
calculateExtremeTemps(InputTable), by="Period")
 result <- merge(result, sort=FALSE, calculateDTR(InputTable),
by="Period")
 result <- merge(result, sort=FALSE, calculateGSL(InputTable,
first_year, last_year), by="Period")
 result <- merge(result, sort=FALSE, calculateTotals(InputTable,
first_year, last_year), by="Period")

 out_csv_path <- paste0(out_csv_dir, file_name, ".csv")
 write.csv(result,out_csv_path,row.names=FALSE)
}
```

3.2. Percentile extreme weather event indices calculation and bootstrapping

```
#This script calculates the number of days in a year that fall
#into 10-th and 90-th temperature precentiles and number of days
#in 95-th precipitation percentile for the period 1961-2010, for
each representitive weather station. It uses 1961-1990 as a base
period for defining historic percentiles. For years that are
within the base period this script uses a bootstrapping
#procedure to avoid bias in calculation.

file_list <- c('CHALKRIVER', 'CORNWALL', 'HARTINGTON',
 'KINGSTON', 'KEMPTVILLE','LYNDHURST', 'OTTAWACDA', 'ARNPRIOR',
 'RUSSELL', 'STALBERT', 'STANICET')

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

# Defining quantile algorithm
qtype <- 8
# Defining percentiles:
# Lower percentile for temperature
lower_temp_percentile <- 10
# Upper percentile for temperature
upper_temp_percentile <- 90
# Upper percentile for precipitation
precip_percentile <- 95

# Converting percentile to fractions
lwtpv <- lower_temp_percentile / 100
uptpv <- upper_temp_percentile / 100
pppv <- precip_percentile / 100

# First and last year of bootstrapped period
first_year <- 1961
last_year <- 1990
# First and last year of the research period where bootstrapping
 is not needed (1991 - 2010)
outbase_first_year <- last_year + 1
outbase_last_year <- 2010

Year <- 1:12
PlantingSeason <- 4:5
GrowingSeason <- 5:9
HarvestingSeason <- 9:11

separateMonths <- 1:12
periods <- list(Year, PlantingSeason, GrowingSeason,
 HarvestingSeason)
```

```
getName <- function(period) {
  if (length(period) == 1) {
    return (monthNames[period])
  } else if (period == PlantingSeason) {
    return ("PS")
  } else if (period == GrowingSeason) {
    return ("GS")
  } else if (period == HarvestingSeason) {
    return ("HS")
  } else if (period == Year) {
    return ("Year")
  }
  return ("ERROR - PERIOD")
}

base_path <- "~/Documents/Rproj/MSc indices calculation/"
setwd(base_path)
out_csv_dir <- paste0(base_path,"/percentiles bootstrapped
 original/")
dir.create(out_csv_dir, showWarnings = FALSE)

# list of dates - Jan 1 of each year from 1961 to 1990
yearStarts <- c()

prepareYearStarts <- function(first_year, last_year) {
  for (y in first_year:last_year) {
    yearStart <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d")
    yearStarts <- c(yearStarts, yearStart)
  }
  return(yearStarts)
}

calculateExceedance <- function(InputTable, historicPercentiles,
 RRwn95, start_year, end_year, p) {
    result <- data.frame()
    InputTablePeriodTrim <-
      InputTable[as.numeric(format(as.Date(InputTable$Date,"%Y-
 %m-%d"),format =
                                    "%m")) %in% p,]
    for (y in start_year:end_year) {
      InputTableYearTrim <-
        InputTablePeriodTrim[as.numeric(format(as.Date(
          InputTablePeriodTrim$Date,"%Y-%m-%d"
        ),format = "%Y")) == y,]

      tn10p <- 0
      tn90p <- 0
      tx10p <- 0
      tx90p <- 0
      r95pTOT <- 0
      yearStart <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d")
      for (d in 0:365) {
```

```
        day <- yearStart + d
        # Check if day is still in the same year (for non-leap
years, day 95). If non-leap year - break
        if (d == 365 &
            as.numeric(format(as.Date(day,"%Y-%m-%d"),format =
"%Y")) > y)
          break
        tableLine <-
          InputTableYearTrim[as.Date(InputTableYearTrim$Date,"%Y-
%m-%d") == day,]
        # for seasonal calculations, not all days of the year
fall within those periods, so skip those days
        if (nrow(tableLine) == 0)
          next
        if (tableLine$TempMin <= historicPercentiles[d + 1,
"TN10p"]) {
          tn10p <- tn10p + 1
        } else if (tableLine$TempMin >= historicPercentiles[d +
1, "TN90p"]) {
          tn90p <- tn90p + 1
        }

        if (tableLine$TempMax <= historicPercentiles[d + 1,
"TX10p"]) {
          tx10p <- tx10p + 1
        } else if (tableLine$TempMax >= historicPercentiles[d +
1, "TX90p"]) {
          tx90p <- tx90p + 1
        }

        if (tableLine$Precipitation >= RRwn95) {
          r95pTOT <- r95pTOT + tableLine$Precipitation
        }
      }
      result <-
        rbind(result, c(paste0(y, " ", getName(p)), tn10p, tn90p,
tx10p, tx90p, r95pTOT))
    }
    colnames(result) <-
      c("Period", "TN10p", "TN90p", "TX10p", "TX90p", "R95pTOT")
    return (result)
  }

yearStarts <- prepareYearStarts(first_year, last_year)

calculateHistoricPercentiles <- function(InputTable) {
  historicPercentiles <- data.frame()
  # for each year from 1961 to 1990 calculate
  for (d in 0:365) {
    fiveDayWindow <- c()
    for (delta in-2:2) {
      fiveDayWindow <- c(fiveDayWindow, (yearStarts + (d +
```

```
delta)))
    }
    InputTableTrim <-
      InputTable[as.Date(InputTable$Date,"%Y-%m-%d") %in%
fiveDayWindow,]
    tn <-
      round(quantile(
        InputTableTrim$TempMin,c(lwtpv, uptpv), type = qtype,
na.rm = TRUE
      ),1)
    tx <-
      round(quantile(
        InputTableTrim$TempMax,c(lwtpv, uptpv), type = qtype,
na.rm = TRUE
      ),1)
    historicPercentiles <-
      rbind(historicPercentiles, c(d, unname(tn), unname(tx)))
  }
  BaselineTrim <-
    InputTable[as.numeric(format(as.Date(InputTable$Date,"%Y-%m-
%d"),format ="%Y")) >= first_year &
as.numeric(format(as.Date(InputTable$Date,"%Y-%m-%d"),format =
"%Y")) <= last_year,]
  RRwn95 <-
    unname(round(
      quantile(
        BaselineTrim$Precipitation,c(pppv), type = qtype, na.rm =
TRUE
      ),1
    ))
  colnames(historicPercentiles) <-
    c("DOY", "TN10p", "TN90p", "TX10p", "TX90p")
  return (list(historicPercentiles, RRwn95))
}

# Call calculation for each input station
for (file_name in file_list) {
  setwd(base_path)
  in_csv_path <- paste0(base_path, "full input/",
file_name,".CSV")

  print(paste0("Processing ",in_csv_path))
  InputTable <- read.csv(in_csv_path)
  # Bootstraping:
  # Perpare result tables
  result <- data.frame()
  result_ps <- data.frame()
  result_gs <- data.frame()
  result_hs <- data.frame()
  # For each year in the bootstrapped period (now called
outbase_year)
  # Replace it 29 times with each other year from the
```

```
bootstrapped period one by one (duplicated_year) and calculate
historic percentiles, using this modified 30-year period
(InputTableCopy).
 # Calculate exceedance for outbase_year using these modified
percentiles (29 times).
 # Then find mean between these 29 calculations, and that will
#be the boostrapped result for the outbase_year.

 for (outbase_year in first_year:last_year) {
   result_y <- NA
   print (paste0("Bootstraping year ", outbase_year))
   tn10pAcc <- c()
   tn90pAcc <- c()
   tx10pAcc <- c()
   tx90pAcc <- c()
   r95TotAcc <- c()

   tn10pAcc_ps <- c()
   tn90pAcc_ps <- c()
   tx10pAcc_ps <- c()
   tx90pAcc_ps <- c()
   r95TotAcc_ps <- c()

   tn10pAcc_gs <- c()
   tn90pAcc_gs <- c()
   tx10pAcc_gs <- c()
   tx90pAcc_gs <- c()
   r95TotAcc_gs <- c()

   tn10pAcc_hs <- c()
   tn90pAcc_hs <- c()
   tx10pAcc_hs <- c()
   tx90pAcc_hs <- c()
   r95TotAcc_hs <- c()

   for (duplicated_year in first_year:last_year) {
     if (duplicated_year == outbase_year)
       next
     InputTableCopy <-
       InputTable[as.numeric(format(as.Date(InputTable$Date,"%Y-
%m-%d"),format ="%Y")) >= first_year - 1 &

as.numeric(format(as.Date(InputTable$Date,"%Y-%m-%d"),format
="%Y")) <= last_year + 1,]
     outbaseYearStart <-
       as.Date(paste0(outbase_year, "-1-1"), "%Y-%m-%d")
     duplicatedYearStart <-
       as.Date(paste0(duplicated_year, "-1-1"), "%Y-%m-%d")
     # Copy 365 days
     for (d in 0:364) {
       InputTableCopy[as.Date(InputTableCopy$Date,"%Y-%m-%d") ==
(outbaseYearStart + d), c("TempMin", "TempMax",
```

```
"Precipitation")] =
          InputTableCopy[as.Date(InputTable$Date,"%Y-%m-%d") ==
(duplicatedYearStart + d), c("TempMin", "TempMax",
"Precipitation")]
      }
      # Fix for leap outbase_year
      if ((outbase_year %% 4 == 0) &
          (duplicated_year %% 4 == 0)) {
        # outbase leap year and duplicated leap year then fix
366th day of the copied year
        InputTableCopy[as.Date(InputTableCopy$Date,"%Y-%m-%d") ==
(outbaseYearStart + 365), c("TempMin", "TempMax",
"Precipitation")] = InputTableCopy[as.Date(InputTable$Date,"%Y-
%m-%d") == (duplicatedYearStart + 365), c("TempMin", "TempMax",
"Precipitation")]
      } else if ((outbase_year %% 4 == 0) &
                 (duplicated_year %% 4 != 0)) {
        # if outbase is a leap year and duplicated year is not a
leap year then fix 366 day of the copy, by duplicating its 365th
day
        InputTableCopy[as.Date(InputTableCopy$Date,"%Y-%m-%d") ==
(outbaseYearStart + 365), c("TempMin", "TempMax",
"Precipitation")] = InputTableCopy[as.Date(InputTable$Date,"%Y-
%m-%d") == (duplicatedYearStart +364), c("TempMin", "TempMax",
"Precipitation")]
      }

      for (p in periods) {
        historicPercentilesData <-
calculateHistoricPercentiles(InputTableCopy)
        result_y <- calculateExceedance(InputTable,
historicPercentilesData[[1]], historicPercentilesData[[2]],
outbase_year, outbase_year, p)
        if (p == Year) {
          tn10pAcc <- c(tn10pAcc, as.numeric(result_y[1,
"TN10p"]))
          tn90pAcc <- c(tn90pAcc, as.numeric(result_y[1,
"TN90p"]))
          tx10pAcc <- c(tx10pAcc, as.numeric(result_y[1,
"TX10p"]))
          tx90pAcc <- c(tx90pAcc, as.numeric(result_y[1,
"TX90p"]))
          r95TotAcc <-
            c(r95TotAcc, as.numeric(result_y[1, "R95pTOT"]))
        } else if (p == PlantingSeason) {
          tn10pAcc_ps <- c(tn10pAcc_ps, as.numeric(result_y[1,
"TN10p"]))
          tn90pAcc_ps <-
            c(tn90pAcc_ps, as.numeric(result_y[1, "TN90p"]))
          tx10pAcc_ps <-
            c(tx10pAcc_ps, as.numeric(result_y[1, "TX10p"]))
          tx90pAcc_ps <-
```

```
            c(tx90pAcc_ps, as.numeric(result_y[1, "TX90p"]))
          r95TotAcc_ps <-
            c(r95TotAcc_ps, as.numeric(result_y[1, "R95pTOT"]))
        } else if (p == GrowingSeason) {
          tn10pAcc_gs <- c(tn10pAcc_gs, as.numeric(result_y[1,
"TN10p"]))
          tn90pAcc_gs <-
            c(tn90pAcc_gs, as.numeric(result_y[1, "TN90p"]))
          tx10pAcc_gs <-
            c(tx10pAcc_gs, as.numeric(result_y[1, "TX10p"]))
          tx90pAcc_gs <-
            c(tx90pAcc_gs, as.numeric(result_y[1, "TX90p"]))
          r95TotAcc_gs <-
            c(r95TotAcc_gs, as.numeric(result_y[1, "R95pTOT"]))
        } else if (p == HarvestingSeason) {
          tn10pAcc_hs <- c(tn10pAcc_hs, as.numeric(result_y[1,
"TN10p"]))
          tn90pAcc_hs <-
            c(tn90pAcc_hs, as.numeric(result_y[1, "TN90p"]))
          tx10pAcc_hs <-
            c(tx10pAcc_hs, as.numeric(result_y[1, "TX10p"]))
          tx90pAcc_hs <-
            c(tx90pAcc_hs, as.numeric(result_y[1, "TX90p"]))
          r95TotAcc_hs <-
            c(r95TotAcc_hs, as.numeric(result_y[1, "R95pTOT"]))
        }
      }
    }
    result <- rbind(result, c(
      paste0(outbase_year, " Year"),
      round(mean(tn10pAcc), digits = 0),
      round(mean(tn90pAcc), digits = 0),
      round(mean(tx10pAcc), digits = 0),
      round(mean(tx90pAcc), digits = 0),
      round(mean(r95TotAcc), digits = 1)
    ))
    result_ps <- rbind(result_ps, c(
      paste0(outbase_year, " PS"),
      round(mean(tn10pAcc_ps), digits = 0),
      round(mean(tn90pAcc_ps), digits = 0),
      round(mean(tx10pAcc_ps), digits = 0),
      round(mean(tx90pAcc_ps), digits = 0),
      round(mean(r95TotAcc_ps), digits = 1)
    ))
    result_gs <- rbind(result_gs, c(
      paste0(outbase_year, " GS"),
      round(mean(tn10pAcc_gs), digits = 0),
      round(mean(tn90pAcc_gs), digits = 0),
      round(mean(tx10pAcc_gs), digits = 0),
      round(mean(tx90pAcc_gs), digits = 0),
      round(mean(r95TotAcc_gs), digits = 1)
    ))
```

```
    result_hs <- rbind(result_hs, c(
      paste0(outbase_year, " HS"),
      round(mean(tn10pAcc_hs), digits = 0),
      round(mean(tn90pAcc_hs), digits = 0),
      round(mean(tx10pAcc_hs), digits = 0),
      round(mean(tx90pAcc_hs), digits = 0),
      round(mean(r95TotAcc_hs), digits = 1)
    ))
  }

  colnames(result) <-
    c("Period", "TN10p", "TN90p", "TX10p", "TX90p", "R95pTOT")
  colnames(result_gs) <-
    c("Period", "TN10p", "TN90p", "TX10p", "TX90p", "R95pTOT")
  colnames(result_ps) <-
    c("Period", "TN10p", "TN90p", "TX10p", "TX90p", "R95pTOT")
  colnames(result_hs) <-
    c("Period", "TN10p", "TN90p", "TX10p", "TX90p", "R95pTOT")
  # End of bootstrapped calculation

  # Calculating out of base years 1991 - 2010
  historicPercentilesData <-
calculateHistoricPercentiles(InputTable)

  for (p in periods) {
    if (p == PlantingSeason) {
      result <- rbind(result, result_ps)
    } else if (p == GrowingSeason) {
      result <- rbind(result, result_gs)
    } else if (p == HarvestingSeason) {
      result <- rbind(result, result_hs)
    }

    result_out_base <-
      calculateExceedance(
        InputTable, historicPercentilesData[[1]],
historicPercentilesData[[2]], outbase_first_year,
outbase_last_year, p
      )
    result <- rbind(result, result_out_base)
  }

  out_csv_path <- paste0(out_csv_dir, file_name, ".csv")
  write.csv(result,out_csv_path,row.names = FALSE)
}
```

3.3. Converting days into percentiles

```
 # This script converts the number of exceedance days calculated
 # for percentile indices to percentiles.
file_list<-c('CHALKRIVER', 'CORNWALL', 'HARTINGTON', 'KINGSTON',
 'KEMPTVILLE', 'LYNDHURST', 'OTTAWACDA', 'ARNPRIOR',
 'RUSSELL','STALBERT', 'STANICET')

first_year <- 1961
last_year <- 2010
ROUNDDIGITS <- 5

base_path<-"~/Documents/Rproj/MSc indices calculation/percentiles
 bootstrapped original/"
setwd(base_path)

out_csv_dir<-paste0(base_path,"../percentiles bootstrapped/")

for(file_name in file_list) {
  setwd(base_path)
  in_csv_path<-paste0(base_path, file_name,".csv")

  print(paste0("Processing ",in_csv_path))
  InputTable <- read.csv(in_csv_path)

  dir.create(out_csv_dir, showWarnings=FALSE)
  InputIndicesTable <- read.csv(in_csv_path)
  result <- data.frame()

  InputIndicesTableTrim <- InputIndicesTable[c(1:50),]
  #Fix annual indices
  i <- 1
  while (i <= 50) {
    if (i %% 4 == 0)
      daysInYear <- 366
    else
      daysInYear <- 365
    fixed_row <- InputIndicesTable[i, ]

    fixed_row$TN10p <-  round(fixed_row$TN10p/ daysInYear, digits
 = ROUNDDIGITS) * 100
    fixed_row$TN90p <-  round(fixed_row$TN90p/ daysInYear, digits
 = ROUNDDIGITS) *  100
    fixed_row$TX10p <-  round(fixed_row$TX10p / daysInYear,
 digits = ROUNDDIGITS) * 100
    fixed_row$TX90p <-  round(fixed_row$TX90p / daysInYear,
 digits = ROUNDDIGITS) * 100

    result <- rbind(result, fixed_row)
    i <- i + 1
  }
```

```
  InputIndicesTablePS <- InputIndicesTable[c(51:100),]
  i <- 1
  daysInPS <- 61
  while (i <= 50) {

    fixed_row <- InputIndicesTablePS[i, ]

    fixed_row$TN10p <-  round(fixed_row$TN10p / daysInPS, digits
= ROUNDDIGITS) * 100
    fixed_row$TN90p <-  round(fixed_row$TN90p / daysInPS, digits
= ROUNDDIGITS) * 100
    fixed_row$TX10p <-  round(fixed_row$TX10p / daysInPS, digits
= ROUNDDIGITS) * 100
    fixed_row$TX90p <-  round(fixed_row$TX90p / daysInPS, digits
= ROUNDDIGITS) * 100

    result <- rbind(result, fixed_row)
    i <- i + 1
  }

  InputIndicesTableGS <- InputIndicesTable[c(101:150),]
  i <- 1
  daysInGS <- 151
  while (i <= 50) {
    fixed_row <- InputIndicesTableGS[i, ]
    fixed_row$TN10p <-  round(fixed_row$TN10p / daysInGS, digits
= ROUNDDIGITS) * 100
    fixed_row$TN90p <-  round(fixed_row$TN90p / daysInGS, digits
= ROUNDDIGITS) * 100
    fixed_row$TX10p <-  round(fixed_row$TX10p / daysInGS, digits
= ROUNDDIGITS) * 100
    fixed_row$TX90p <-  round(fixed_row$TX90p / daysInGS, digits
= ROUNDDIGITS) * 100

    result <- rbind(result, fixed_row)
    i <- i + 1
  }

  InputIndicesTableHS <- InputIndicesTable[c(151:200),]
  i <- 1
  daysInHS <- 91
  while (i <= 50) {
    fixed_row <- InputIndicesTableHS[i, ]
    fixed_row$TN10p <-  round(fixed_row$TN10p / daysInHS, digits
= ROUNDDIGITS) * 100
    fixed_row$TN90p <-  round(fixed_row$TN90p / daysInHS, digits
= ROUNDDIGITS) * 100
    fixed_row$TX10p <-  round(fixed_row$TX10p / daysInHS, digits
= ROUNDDIGITS) * 100
    fixed_row$TX90p <-  round(fixed_row$TX90p / daysInHS, digits
= ROUNDDIGITS) * 100
```

```
  result <- rbind(result, fixed_row)
  i <- i + 1
}

View(result)
out_csv_path <- paste0(out_csv_dir, file_name, ".csv")
write.csv(result,out_csv_path,row.names=FALSE)
```

3.4. Calculating trends for extreme weather event indices

```
# This script calculates trends for extreme weather event
 #inidices for each representative weather station. Trends are
 #calculated for annual and seasonal data (PS, GS and HS).

file_list<-c('CHALKRIVER', 'CORNWALL', 'HARTINGTON', 'KINGSTON',
 'KEMPTVILLE','LYNDHURST', 'OTTAWACDA', 'ARNPRIOR',
 'RUSSELL','STALBERT', 'STANICET')
base_path<-"~/Documents/Rproj/MSc indices calculation/"
setwd(base_path)
library(zyp)
out_result <-NA

for(file_name in file_list) {
  in_csv_path<-paste0(base_path, "extreme weather/",
 file_name,".csv")
  print(paste0("Processing ",in_csv_path))
  InputIndicesTable <- read.csv(in_csv_path)
  result <- data.frame()
  datarows <- ncol(InputIndicesTable)

  InputIndicesTableTrim <- InputIndicesTable[c(1:50),]
  InputIndicesTableTrim <-
 t(InputIndicesTableTrim)[c(2:datarows), ]
  trends <- zyp.trend.dataframe(InputIndicesTableTrim, 0,
 method=c("zhang"), conf.intervals=TRUE,
 preserve.range.for.sig.test=TRUE)
  trends[, "sig"] = round(trends[, "sig"], digits = 5)

  InputIndicesTablePS <- InputIndicesTable[c(51:100),]
  InputIndicesTableTrimPS <-
 t(InputIndicesTablePS)[c(2:datarows), ]
  trendsPS <- zyp.trend.dataframe(InputIndicesTableTrimPS, 0,
 method=c("zhang"), conf.intervals=TRUE,
 preserve.range.for.sig.test=TRUE)
  trendsPS[, "sig"] = round(trendsPS[, "sig"], digits = 5)

  InputIndicesTableGS <- InputIndicesTable[c(101:150),]
  InputIndicesTableTrimGS <-
 t(InputIndicesTableGS)[c(2:datarows), ]
  trendsGS <- zyp.trend.dataframe(InputIndicesTableTrimGS, 0,
 method=c("zhang"), conf.intervals=TRUE,
 preserve.range.for.sig.test=TRUE)
  trendsGS[, "sig"] = round(trendsGS[, "sig"], digits = 5)

  InputIndicesTableHS <- InputIndicesTable[c(151:200),]
  InputIndicesTableTrimHS <-
 t(InputIndicesTableHS)[c(2:datarows), ]
  trendsHS <- zyp.trend.dataframe(InputIndicesTableTrimHS, 0,
 method=c("zhang"), conf.intervals=TRUE,
```

```
preserve.range.for.sig.test=TRUE)
 trendsHS[, "sig"] = round(trendsHS[, "sig"], digits = 5)

 for (i in 1:nrow(trends)) {
   result_row <- trends[i, c("trend", "sig")]
   row.names(result_row) <- c(paste0(row.names(trends[i,]), "
annually"))
   result <- rbind(result, result_row)

   result_row <- trendsPS[i, c("trend", "sig")]
   row.names(result_row) <- c(paste0(row.names(trends[i,]), "
PS"))
   result <- rbind(result, result_row)

   result_row <- trendsGS[i, c("trend", "sig")]
   row.names(result_row) <- c(paste0(row.names(trends[i,]), "
GS"))
   result <- rbind(result, result_row)

   result_row <- trendsHS[i, c("trend", "sig")]
   row.names(result_row) <- c(paste0(row.names(trends[i,]), "
HS"))
   result <- rbind(result, result_row)
 }
 in_csv_path<-paste0(base_path, "percentiles bootstrapped/",
file_name,".csv")
 print(paste0("Processing ",in_csv_path))
 InputIndicesTable <- read.csv(in_csv_path)
 datarows <- ncol(InputIndicesTable)

 InputIndicesTableTrim <- InputIndicesTable[c(1:50),]
 InputIndicesTableTrim <-
t(InputIndicesTableTrim)[c(2:datarows), ]
 trends <- zyp.trend.dataframe(InputIndicesTableTrim, 0,
method=c("zhang"), conf.intervals=TRUE,
preserve.range.for.sig.test=TRUE)
 trends[, "sig"] = round(trends[, "sig"], digits = 5)

 InputIndicesTablePS <- InputIndicesTable[c(51:100),]
 InputIndicesTableTrimPS <-
t(InputIndicesTablePS)[c(2:datarows), ]
 trendsPS <- zyp.trend.dataframe(InputIndicesTableTrimPS, 0,
method=c("zhang"), conf.intervals=TRUE,
preserve.range.for.sig.test=TRUE)
 trendsPS[, "sig"] = round(trendsPS[, "sig"], digits = 5)

 InputIndicesTableGS <- InputIndicesTable[c(101:150),]
 InputIndicesTableTrimGS <-
t(InputIndicesTableGS)[c(2:datarows), ]
 trendsGS <- zyp.trend.dataframe(InputIndicesTableTrimGS, 0,
method=c("zhang"), conf.intervals=TRUE,
preserve.range.for.sig.test=TRUE)
```

```
  trendsGS[, "sig"] = round(trendsGS[, "sig"], digits = 5)

  InputIndicesTableHS <- InputIndicesTable[c(151:200),]
  InputIndicesTableTrimHS <-
t(InputIndicesTableHS)[c(2:datarows), ]
  trendsHS <- zyp.trend.dataframe(InputIndicesTableTrimHS, 0,
method=c("zhang"), conf.intervals=TRUE,
preserve.range.for.sig.test=TRUE)
  trendsHS[, "sig"] = round(trendsHS[, "sig"], digits = 5)

  for (i in 1:nrow(trends)) {
    result_row <- trends[i, c("trend", "sig")]
    row.names(result_row) <- c(paste0(row.names(trends[i,]), "
annually"))
    result <- rbind(result, result_row)

    result_row <- trendsPS[i, c("trend", "sig")]
    row.names(result_row) <- c(paste0(row.names(trends[i,]), "
PS"))
    result <- rbind(result, result_row)

    result_row <- trendsGS[i, c("trend", "sig")]
    row.names(result_row) <- c(paste0(row.names(trends[i,]), "
GS"))
    result <- rbind(result, result_row)

    result_row <- trendsHS[i, c("trend", "sig")]
    row.names(result_row) <- c(paste0(row.names(trends[i,]), "
HS"))
    result <- rbind(result, result_row)
  }
  colnames(result) <- c(paste0(file_name, ".trend"),
paste0(file_name, ".sig"))

  if (is.na(out_result))
    out_result <- result
  else {
    out_result <- cbind(out_result, result)
  }
}
out_csv_path <- paste0(base_path, "ALL_TRENDS.csv")
write.csv(out_result,out_csv_path,row.names = TRUE)
```

3.5. Calculating extreme weather event and percentile indices averages for eastern Ontario

```
# This script averages extreme weather and percentile
# indices for all representative stations, generating
# data for the whole eastern Ontario region

file_list<-c('CHALKRIVER', 'CORNWALL', 'HARTINGTON', 'KINGSTON',
 'KEMPTVILLE','LYNDHURST', 'OTTAWACDA', 'ARNPRIOR',
 'RUSSELL','STALBERT', 'STANICET')
base_path<-"~/Documents/Rproj/MSc indices calculation/"
setwd(base_path)
ROUNDDIGITS=1
library(plyr)
result <- NA
all_results <- NA
for(file_name in file_list) {
  in_csv_path<-paste0(base_path, "extreme weather/",
 file_name,".csv")
  print(paste0("Processing ",in_csv_path))
  EWTable <- read.csv(in_csv_path)
  in_csv_path<-paste0(base_path, "percentiles bootstrapped/",
 file_name,".csv")
  print(paste0("Processing ",in_csv_path))
  PercentilesTable <- read.csv(in_csv_path)
  EWTable <- EWTable[1:200,]
  PercentilesTable[,"Period"] <- EWTable[, "Period"]
  InputIndicesTable <- merge(EWTable, PercentilesTable,
 sort=FALSE, by="Period")

  InputTable <- cbind( data.frame( DataSet = rep(file_name,
 nrow(InputIndicesTable))), InputIndicesTable)
  if (is.na(all_results))
    all_results <- InputTable
  else
    all_results <- rbind(all_results, InputTable)
}
d1mean <- function(x) {
  return(round(mean(x), digits = ROUNDDIGITS))
}
out_result <- ddply(all_results, .(Period), colwise(d1mean,
 .(RX1, RX5, CDD,    R10,    SDII,   HWE,    CWE,DTR,    GSL,
    AvgTempMin, AvgTempMax, SumPrecipitation, TN10p, TN90p,
 TX10p, TX90p, R95pTOT)))
out_csv_path <- paste0(base_path, "ALL_STATIONS_MEAN.csv")
write.csv(out_result,out_csv_path,row.names = FALSE)
```

3.6. Generating density plots for extreme weather event and percentile indices

```
 # This script generates density plots for annual, PS, GS and HS
 #periods

file_list<-c('CHALKRIVER', 'CORNWALL', 'HARTINGTON', 'KINGSTON',
 'KEMPTVILLE','LYNDHURST', 'OTTAWACDA', 'ARNPRIOR',
 'RUSSELL','STALBERT', 'STANICET'
)

library(grid)

base_path<-"~/Documents/Rproj/MSc indices calculation/"
setwd(base_path)

LINEWIDTH=4
COLOURS_LIST <- c("black", "black")
STYLE_LIST <- c(1, 3)


indices <- c("RX1", "RX5", "CDD",   "R10",  "SDII", "HWE",
    "CWE",  "DTR",  "GSL",  "AvgTempMin",   "AvgTempMax",
    "SumPrecipitation", "TN10p", "TN90p", "TX10p", "TX90p",
 "R95pTOT")
indice_names <- c("RX1day", "RX5day", "CDD",    "R10",  "SDII",
    "HWE",  "CWE",
 "DTR",  "GSL",  "Year", "Year", "PRCPTOT", "TN10p", "TN90p",
 "TX10p", "TX90p", "R95p")
indice_units <- c("mm", "mm", "days",   "days", "mm/day",
    "days", "days", "°C",   "days", "°C",   "°C",   "mm", "%
 days", "% days", "% days", "% days", "mm")


all_results <- NA
for(file_name in file_list) {
  in_csv_path<-paste0(base_path, "extreme weather/",
 file_name,".csv")
  print(paste0("Reading ",in_csv_path))
  EWTable <- read.csv(in_csv_path)
  in_csv_path<-paste0(base_path, "percentiles bootstrapped/",
 file_name,".csv")
  print(paste0("Reading ",in_csv_path))
  PercentilesTable <- read.csv(in_csv_path)

  EWTable <- EWTable[1:200,]
  PercentilesTable[,"Period"] <- EWTable[, "Period"]
  InputIndicesTable <- merge(EWTable, PercentilesTable,
 sort=FALSE, by="Period")

  InputTable <- cbind( data.frame( DataSet = rep(file_name,
 nrow(InputIndicesTable))), InputIndicesTable)
```

```
  if (is.na(all_results))
    all_results <- InputTable
  else
    all_results <- rbind(all_results, InputTable)
}

InputTable <- all_result

for (period in c("PS", "HS", "GS")) {
  out_plot_dir <- paste0(base_path, "/plots/", period, "/")
  dir.create(out_plot_dir, showWarnings=FALSE)
  setwd(out_plot_dir)
  j <- 1
  for(i in indices) {
      if (period == "")
        period_suffixed <- ""
      else
        period_suffixed <- paste0(period, "_")

      if (i == "AvgTempMin" | i == "AvgTempMax" | i ==
"SumPrecipitation") {
        if (period == "PS") {
          indice_names[j] <- "Planting season"
        } else if (period == "GS") {
          indice_names[j] <- "Growing season"
        } else if (period == "HS") {
          indice_names[j] <- "Harvesting season"
        }
      }
      InputTable <- all_results[all_results$Period %in%
paste0(period_suffixed, c(1961:2010)),]
      InputTable6185sTrim<-InputTable[InputTable$Period %in%
paste0(period_suffixed, c(1961:1985)),]
      InputTable8610sTrim<-InputTable[InputTable$Period %in%
paste0(period_suffixed, c(1986:2010)),]

      xdrange <- function(g) {
        return (density(g)$x)
      }

      ydrange <- function(g) {
        return (density(g)$y)
      }

      xDensityRange = range(xdrange(InputTable6185sTrim[,i]),
xdrange(InputTable8610sTrim[,i]))
      yDensityRange = range(ydrange(InputTable6185sTrim[,i]),
ydrange(InputTable8610sTrim[,i]))
      jpeg(filename=paste0(i, ".jpg"), width = 6, height = 6,
units = 'in', res = 600)
      # breaks parameter controls bin size
      hist(InputTable[, i] ,breaks=(nrow(InputTable)/10),
```

```
inlude.lowest = TRUE, prob=TRUE,  col = "white", border =
"white",
            xlab=indice_units[j], main=indice_names[j],
xlim=xDensityRange, ylim=yDensityRange, freq = FALSE
           )

      plotLine <- function(g, gcol, glty) {
        lines(density(g), col=gcol, lwd=LINEWIDTH, lty = glty)
      }
      plotLine(InputTable6185sTrim[,i], gcol=COLOURS_LIST[1],
glty = STYLE_LIST[1])
      plotLine(InputTable8610sTrim[,i], gcol=COLOURS_LIST[2],
glty = STYLE_LIST[2])

      legend('topright', c("1961-1985", "1986-2010"),
lty=STYLE_LIST, lwd=LINEWIDTH, col=COLOURS_LIST, bty='n',
cex=.75)
      box(which = "plot", lty = "solid")

      dev.off()
      j <- j + 1
  }
}
```

3.7. Combining density plots for annual indices

```
# This script combines density plots for
# annual extreme weather and percentile indices
# into one multiplot

library(jpeg)

base_path<-"~/Documents/Rproj/MSc indices calculation/plots/"
setwd(base_path)

igraphs <- c("HWE", "CWE", "DTR", "GSL", "TN10p", "TX10p",
 "TN90p", "TX90p", "RX1", "RX5", "SDII", "R10", "CDD", "R95pTOT",
 "SumPrecipitation")

jpeg(filename="multiplot_annual.jpg", width = 12, height = 20,
 units = 'in', res = 600, quality = 100)

op <- par(mfrow=c(5, 3), mar = c(0, 0, 0, 0))
for (i in igraphs) {
  img <- readJPEG(paste0(i, ".jpg"), native = TRUE)
  plot(1:2, type="n", axes=F, xlab="", ylab="")
  rasterImage(img, 1, 1, 2, 2)
}

par(op)
dev.off()
```

3.8. Combining density plots for planting, growing and harvesting season indices

```
# This script combines extreme weather and percentile
# indices density plots for PS, GS and HS
# into corresponding multiplots

library(jpeg)

base_path<-"~/Documents/Rproj/MSc indices calculation/plots/"

LINEWIDTH=4

indice_graphs <- c("DTR", "TN10p", "TX10p", "TN90p", "TX90p",
 "RX1", "RX5", "SDII", "R10", "CDD", "R95pTOT",
 "SumPrecipitation")
periods<- c("PS", "GS", "HS")

for (period in periods)  {
  setwd(base_path)
  jpeg(filename=paste0(base_path, "multiplot_", period, ".jpg"),
 width = 12, height = 16, units = 'in', res = 600, quality = 100)

  setwd(paste0(base_path, period))
  op <- par(mfrow=c(4, 3), mar = c(0, 0, 0, 0))
  for (igraph in indice_graphs) {
    img <- readJPEG(paste0(igraph, ".jpg"), native = TRUE)
    plot(1:2, type="n", axes=F, xlab="", ylab="")
    rasterImage(img, 1, 1, 2, 2)
  }

  par(op)
  dev.off()
}
```

3.9. Combining Tmin density plots for planting, growing and harvesting season indices

```
# This script combines TempMin density plots
# for planting, growing and harvesting seasons

library(jpeg)

base_path<-"~/Documents/Rproj/MSc indices calculation/plots/"
indice_graphs <- c("PS/AvgTempMin", "GS/AvgTempMin",
 "HS/AvgTempMin")
setwd(base_path)
jpeg(filename=paste0(base_path,
 "multiplot_tempmin_PS_GS_HS.jpg"), width = 12, height = 4, units
 = 'in', res = 600, quality = 100)
op <- par(mfrow=c(1, 3), mar = c(0, 0, 0, 0))
for (igraph in indice_graphs) {
  img <- readJPEG(paste0(base_path, igraph, ".jpg"), native =
 TRUE)
  plot(1:2, type="n", axes=F, xlab="", ylab="")
  rasterImage(img, 1, 1, 2, 2)
}
par(op)
dev.off()
```

3.10. Combining Tmax density plots for planting, growing and harvesting season indices

```
# This script combines TempMax density plots
# for planting, growing and harvesting seasons
library(jpeg)

base_path<-"~/Documents/Rproj/MSc indices calculation/plots/"
indice_graphs <- c("PS/AvgTempMax", "GS/AvgTempMax",
 "HS/AvgTempMax")
setwd(base_path)
jpeg(filename=paste0(base_path,
 "multiplot_tempmax_PS_GS_HS.jpg"), width = 12, height = 4, units
 = 'in', res = 600, quality = 100)
op <- par(mfrow=c(1, 3), mar = c(0, 0, 0, 0))
for (igraph in indice_graphs) {
  img <- readJPEG(paste0(base_path, igraph, ".jpg"), native =
 TRUE)
  plot(1:2, type="n", axes=F, xlab="", ylab="")
  rasterImage(img, 1, 1, 2, 2)
}
par(op)
dev.off()
```

3.11. Combining PRCPTOT density plots for planting, growing and harvesting season indices

```
# This script combines Precipitation density plots
# for planting, growing and harvesting seasons
library(jpeg)

base_path<-"~/Documents/Rproj/MSc indices calculation/plots/"
indice_graphs <- c("PS/SumPrecipitation",
 "GS/SumPrecipitation","HS/SumPrecipitation")
setwd(base_path)
jpeg(filename=paste0(base_path,
 "multiplot_sumprecipitation_PS_GS_HS.jpg"), width = 12, height =
 4, units = 'in', res = 600, quality = 100)
op <- par(mfrow=c(1, 3), mar = c(0, 0, 0, 0))
for (igraph in indice_graphs) {
  img <- readJPEG(paste0(base_path, igraph, ".jpg"), native =
 TRUE)
  plot(1:2, type="n", axes=F, xlab="", ylab="")
  rasterImage(img, 1, 1, 2, 2)
}
par(op)
dev.off()
```

3.12. Calculating agroclimatic and corn-specific extreme event indices

```
 # This script calculates agroclimatic and corn-specific extreme
 # event indices
file_list<-c('CHALKRIVER', 'CORNWALL', 'HARTINGTON', 'KINGSTON',
 'KEMPTVILLE','LYNDHURST', 'OTTAWACDA', 'ARNPRIOR',
 'RUSSELL','STALBERT', 'STANICET')
base_path<-"~/Documents/Rproj/MSc indices calculation/"
out_csv_dir<-paste0(base_path,"/corn indices/")

options(stringsAsFactors = FALSE)

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

new.hashtable <- function() {
  e <- new.env()
  list(set = function(key, value) assign(as.character(key),
 value, e),
       get = function(key) get(as.character(key), e),
       rm = function(key) rm(as.character(key), e))
}
# hashtable: week -> mean weekly precipitation
meanPrecip <- new.hashtable()
# hashtable: year -> list of CHU start/end dates
CHUMap <- new.hashtable()

setwd(base_path)

# Define function for calculating Mean Weekly Precipitation

prepareMeanPrecip <- function(InputTable, first_year, last_year)
 {
  print("Prepare mean weekly precipitation")
  meanPrecip <- new.hashtable()
  for (week in 14:26) {
    startDay <- week *7
    weeklyData <- c()
    for (y in first_year:last_year) {
      firstDate <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d") +
 startDay
      WeeklyTableTrim<-InputTable[as.Date(InputTable$Date,"%Y-%m-
 %d")>= firstDate & as.Date(InputTable$Date,"%Y-%m-%d")<=
 (firstDate + 6),]
      weeklyData <- c(weeklyData,
 sum(WeeklyTableTrim$Precipitation, na.rm = TRUE))
    }
    meanPrecip$set(week, mean(weeklyData))
  }
  return (meanPrecip)
```

```
}

# Define function for calculating Corn Seeding Date

calculateCornSeedingDate <- function(InputTable, first_year,
 last_year) {
  # Find seeding date for each year
  # and fill hashtable: year -> seeding date
  print("Prepare corn seeding dates")
  seedingDates <- new.hashtable()
  for (y in first_year:last_year) {
    firstDate <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d")
    MayFirst <- as.Date(paste0(y, "-5-1"), "%Y-%m-%d")

    ySeedingDate <- NA
    for (week in 17:20) {
      prevWeekTableTrim<-InputTable[as.Date(InputTable$Date,"%Y-
%m-%d")>= (firstDate + (week-1)*7) &
                                      as.Date(InputTable$Date,"%Y-
%m-%d")<= (firstDate + (week-1)*7 + 6),]

      prevWeekPrecipitation <-
sum(prevWeekTableTrim$Precipitation, na.rm = TRUE)
      if (prevWeekPrecipitation < meanPrecip$get(week - 1) *1.3)
{
        ySeedingDate <- firstDate + week*7
        break
      }
    }
    if (is.na(ySeedingDate)) {
      print(paste0("Corn seeding date not found for year ", y));
    } else {
      if (ySeedingDate < MayFirst)
        ySeedingDate <- MayFirst
    }
    seedingDates$set(y, ySeedingDate)
  }
  return (seedingDates)
}

# Calculate Poor Seeding Conditions

calculatePSC <- function(InputTable, first_year, last_year) {
  print("PSC")

  PSCdf<-data.frame()
  for (y in first_year:last_year) {
    firstDayOfYear <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d")
    april22ThisYear <- as.Date(paste0(y, "-4-23"), "%Y-%m-%d")
    may20ThisYear <- as.Date(paste0(y, "-5-20"), "%Y-%m-%d")
    if (y %% 4 == 0) {
      # Leap year
```

```
      april22ThisYear <- april22ThisYear - 1
      may20ThisYear <- may20ThisYear - 1
    }
    day <- april22ThisYear
    rainyWeeks <- 0
    while (day <= may20ThisYear) {
      week <- as.integer((day - firstDayOfYear) / 7)
      WeeklyTableTrim<-InputTable[as.Date(InputTable$Date,"%Y-%m-
%d")>= day &
                                    as.Date(InputTable$Date,"%Y-
%m-%d")<= (day + 6),]
      weeklyPrecip <- sum(WeeklyTableTrim$Precipitation, na.rm =
TRUE)
      if (weeklyPrecip >= (meanPrecip$get(week) *1.3)) {
        rainyWeeks <- rainyWeeks + 1
      }
      day <- day + 7
    }
    PSCdf <- rbind(PSCdf, c(y, rainyWeeks))
  }
  colnames(PSCdf)[1:2]<-c("Period", "PSC")
  return (PSCdf)
}

# Define function for calculating CHUs based on seeding date

prepareCHU <- function(InputTable, seedingDates, first_year,
 last_year) {

  print("Prepare CHU")

  #Initialize index i with first_year
  i<-first_year
  # And iterate year-by-year
  CHUMap <- new.hashtable()

  while(i<=last_year) {
    # Create data frame for year 'i'
    InputTableTrim<-
InputTable[as.numeric(format(as.Date(InputTable$Date,"%Y-%m-
%d"),format="%Y"))==i,]
    firstDayOfYear <- as.Date(paste0(i, "-1-1"), "%Y-%m-%d")
    seedingDateThisYear <- seedingDates$get(i)
    if (is.na(seedingDateThisYear)) {
      CHUMap$set(i, NA)
      i <- i + 1
      next
    }
    # Trimming to start CHU calculation on seeding date
    InputTableTrim<-InputTableTrim[InputTableTrim$Date >=
seedingDateThisYear,]
    dayDelta <- seedingDateThisYear - firstDayOfYear
```

```
CHU<-0.0
j<-1
chu_list <- new.env()
chu_list$seeding <- seedingDateThisYear

while(j<=nrow(InputTableTrim)) {
  tmin<-InputTableTrim[j,"TempMin"]
  if (is.na(tmin)) {
    j <-j+1
    next
  }
  tmax<-InputTableTrim[j,"TempMax"]
  if (is.na(tmax)){
    j <-j+1
    next
  }
  tmax_10<-(tmax-10.0)
  YMax<-(3.33 * tmax_10) - (0.084 * tmax_10 * tmax_10)
  if (YMax < 0)
    YMax<-0
  YMin<-1.8*(tmin-4.4)
  if (YMin <0)
    YMin<-0

  CHU_step <- (YMin+YMax)/2

  if (CHU < 780 & CHU + CHU_step >= 780) {
    chu_list$EF_end <- j + dayDelta
  }
  if (CHU < 1301 & CHU + CHU_step >= 1301) {
    chu_list$PD_start <- j + dayDelta
  }
  if (CHU < 1600 & CHU + CHU_step >= 1600) {
    chu_list$PD_end <- j + dayDelta
  }
  if (CHU < 1601 & CHU + CHU_step >= 1601) {
    chu_list$R2D_start <- j + dayDelta
  }
  if (CHU < 1825 & CHU + CHU_step >= 1825) {
    chu_list$R2D_end <- j + dayDelta
  }
  if (CHU < 1826 & CHU + CHU_step >= 1826) {
    chu_list$R3D_start <- j + dayDelta
  }
  if (CHU < 2000 & CHU + CHU_step >= 2000) {
    chu_list$R3D_end <- j + dayDelta
  }
  if (CHU < 2001 & CHU + CHU_step >= 2001) {
    chu_list$R4D_start <- j + dayDelta
  }
  if (CHU < 2165 & CHU + CHU_step >= 2165) {
```

```
        chu_list$R4D_end <- j + dayDelta
      }
      if (CHU < 2166 & CHU + CHU_step >= 2166) {
        chu_list$EKF_start <- j + dayDelta
      }
      if (CHU < 2475 & CHU + CHU_step >= 2475) {
        chu_list$EKF_end <- j + dayDelta
      }
      if (CHU < 2476 & CHU + CHU_step >= 2476) {
        chu_list$FKF_start <- j + dayDelta
      }
      if (CHU < 2600 & CHU + CHU_step >= 2600) {
        chu_list$FKF_end <- j + dayDelta
        break;
      }
      CHU <-CHU + CHU_step
      j<-j+1
    }

    CHUMap$set(i, chu_list)
    i<-i+1
  }
  return(CHUMap)
}

# Calculate Early Flooding

calculateEF <- function(InputTable, CHUMap, first_year,
 last_year) {
  print("EF")

  EFdf<-data.frame()
  for (y in first_year:last_year) {
    if (is.na(CHUMap$get(y))) {
      EFdf <- rbind(EFdf, c(y, NA))
      next
    }

    firstDayOfYear <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d")
    EF_START <- (CHUMap$get(y))$seeding
    EF_END <- firstDayOfYear +  (CHUMap$get(y))$EF_end

    day <- EF_START
    rainyWeeks <- 0
    while (day <= EF_END) {
      week <- as.integer((day - firstDayOfYear) / 7)
      WeeklyTableTrim<-InputTable[as.Date(InputTable$Date,"%Y-%m-
 %d")>= day &
                                    as.Date(InputTable$Date,"%Y-
 %m-%d")<= (day + 6),]
      weeklyPrecip <- sum(WeeklyTableTrim$Precipitation, na.rm =
 TRUE)
```

```
      if (weeklyPrecip >= (meanPrecip$get(week) *1.3)) {
        rainyWeeks <- rainyWeeks + 1
      }
      day <- day + 7
    }
    EFdf <- rbind(EFdf, c(y, rainyWeeks))
  }
  colnames(EFdf)[1:2]<-c("Period", "EF")
  return (EFdf)
}

# Calculate Pollination Drought

calculatePD <- function(InputTable, CHUMap, first_year,
 last_year) {
  print("PD")
  PDdf<-data.frame()
  for (y in first_year:last_year) {
    if (is.na(CHUMap$get(y))) {
      PDdf <- rbind(PDdf, c(y, NA))
      next
    }
    firstDayPD <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d") +
 (CHUMap$get(y))$PD_start
    lastDayPD <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d") +
 (CHUMap$get(y))$PD_end
    InputTableTrim <- InputTable[as.Date(InputTable$Date,"%Y-%m-
 %d") >= firstDayPD &
                                 as.Date(InputTable$Date,"%Y-%m-
 %d") <= lastDayPD,]
    cdd <- 0
    pd_value <- 'no'
    d<-1
    while (d <= nrow(InputTableTrim)) {
      if (InputTableTrim[d, "Precipitation"] < 1)
        cdd <- cdd + 1
      else
        cdd <- 0
      if (cdd >= 10)
        pd_value <- 'yes'
      d <- d + 1
    }
    PDdf <- rbind(PDdf, c(y, pd_value))
  }
  colnames(PDdf)<-c("Period", "PD")
  return (PDdf)
}
```

```
# Calculate R2 Drought

calculateR2D <- function(InputTable, CHUMap, first_year,
 last_year) {
  print("R2D")
  R2Ddf<-data.frame()
  for (y in first_year:last_year) {
    if (is.na(CHUMap$get(y))) {
      R2Ddf <- rbind(R2Ddf, c(y, NA))
      next
    }
    firstDayR2D <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d") +
 (CHUMap$get(y))$R2D_start
    lastDayR2D <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d") +
 (CHUMap$get(y))$R2D_end
    InputTableTrim <- InputTable[as.Date(InputTable$Date,"%Y-%m-
 %d") >= firstDayR2D &
                                      as.Date(InputTable$Date,"%Y-
 %m-%d") <= lastDayR2D,]
    R2precipitation <- sum(InputTableTrim$Precipitation)
    if (R2precipitation < 8)
      R2D_value <- 'yes'
    else
      R2D_value <- 'no'
    R2Ddf <- rbind(R2Ddf, c(y, R2D_value))
  }
  colnames(R2Ddf)<-c("Period", "R2D")
  return (R2Ddf)
}

# Calculate R3 Drought

calculateR3D <- function(InputTable, CHUMap, first_year,
 last_year) {
  print("R3D")
  R3Ddf<-data.frame()
  for (y in first_year:last_year) {
    if (is.na(CHUMap$get(y))) {
      R3Ddf <- rbind(R3Ddf, c(y, NA))
      next
    }
    firstDayR3D <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d") +
 (CHUMap$get(y))$R3D_start
    lastDayR3D <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d") +
 (CHUMap$get(y))$R3D_end
    InputTableTrim <- InputTable[as.Date(InputTable$Date,"%Y-%m-
 %d") >= firstDayR3D &
                                      as.Date(InputTable$Date,"%Y-
 %m-%d") <= lastDayR3D,]
    R3precipitation <- sum(InputTableTrim$Precipitation)
    if (R3precipitation < 45)
      R3D_value <- 'yes'
```

```
    else
      R3D_value <- 'no'
    R3Ddf <- rbind(R3Ddf, c(y, R3D_value))
  }
  colnames(R3Ddf)<-c("Period", "R3D")
  return (R3Ddf)
}

# Calculate Early Killing Frost

calculateEKF <- function(InputTable, CHUMap, first_year,
 last_year) {
  print("EKF")
  EKFdf<-data.frame()
  for (y in first_year:last_year) {
    if (is.na(CHUMap$get(y))) {
      EKFdf <- rbind(EKFdf, c(y, NA))
      next
    }
    firstDayEKF <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d") +
 (CHUMap$get(y))$EKF_start
    lastDayEKF <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d") +
 (CHUMap$get(y))$EKF_end
    InputTableTrim <- InputTable[as.Date(InputTable$Date,"%Y-%m-
 %d") >= firstDayEKF &
                                      as.Date(InputTable$Date,"%Y-
 %m-%d") <= lastDayEKF,]
    EKF_value <- 0
    for (i in 1:nrow(InputTableTrim)) {
      if(InputTableTrim[i, "TempMin"] <= -2) {
        EKF_value <- EKF_value + 1
      }
    }
    EKFdf <- rbind(EKFdf, c(y, EKF_value))
  }
  colnames(EKFdf)<-c("Period", "EKF")
  return (EKFdf)
}

# Calculate R4 Drought

calculateR4D <- function(InputTable, CHUMap, first_year,
 last_year) {
  print("R4D")
  R4Ddf<-data.frame()
  for (y in first_year:last_year) {
    if (is.na(CHUMap$get(y))) {
      R4Ddf <- rbind(R4Ddf, c(y, NA))
      next
    }
    firstDayR4D <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d") +
 (CHUMap$get(y))$R4D_start
```

```
    lastDayR4D <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d") +
 (CHUMap$get(y))$R4D_end
    InputTableTrim <- InputTable[as.Date(InputTable$Date,"%Y-%m-
 %d") >= firstDayR4D &
                                     as.Date(InputTable$Date,"%Y-
 %m-%d") <= lastDayR4D,]
    R3precipitation <- sum(InputTableTrim$Precipitation)
    if (R3precipitation < 45)
      R4D_value <- 'yes'
    else
      R4D_value <- 'no'
    R4Ddf <- rbind(R4Ddf, c(y, R4D_value))
  }
  colnames(R4Ddf)<-c("Period", "R4D")
  return (R4Ddf)
}

# Calculate Fall Killing Frost

calculateFKF <- function(InputTable, CHUMap, first_year,
 last_year) {
  print("FKF")
  FKFdf<-data.frame()
  for (y in first_year:last_year) {
    if (is.na(CHUMap$get(y))) {
      FKFdf <- rbind(FKFdf, c(y, NA))
      next
    }
    firstDayFKF <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d") +
 (CHUMap$get(y))$FKF_start
    lastDayFKF <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d") +
 (CHUMap$get(y))$FKF_end
    InputTableTrim <- InputTable[as.Date(InputTable$Date,"%Y-%m-
 %d") >= firstDayFKF &
                                     as.Date(InputTable$Date,"%Y-
 %m-%d") <= lastDayFKF,]
    FKF_value <- 0
    for (i in 1:nrow(InputTableTrim)) {
      if(InputTableTrim[i, "TempMin"] <= -2) {
        FKF_value <- FKF_value + 1
      }
    }
    FKFdf <- rbind(FKFdf, c(y, FKF_value))
  }
  colnames(FKFdf)<-c("Period", "FKF")
  return (FKFdf)

}

# Corn seeding date output

outputCornSeedingDate <- function(cornSeedingDates, first_year,
```

```
last_year) {
  print("Corn seeding date")
  CSDdf<-data.frame()
  for (y in first_year:last_year) {
    firstDayOfYear <- as.Date(paste0(y, "-1-1"), format="%Y-%m-
%d")
    if (is.na(cornSeedingDates$get(y))) {
      value <- NA
      value_doy <- NA
    } else {
      value <- format(cornSeedingDates$get(y), format="%Y-%m-%d")
      value_doy <- cornSeedingDates$get(y) + 1 - firstDayOfYear
    }
    targetSeedingDate <- 121
    if (y %% 4 == 0) {
      # Leap year
      targetSeedingDate <- 122
    }
    CSDdf <- rbind(CSDdf, c(y, value, value_doy, value_doy -
targetSeedingDate))
  }
  colnames(CSDdf)<-c("Period", "Corn seeding date", "Corn seeding
doy", "SDELAY")
  return (CSDdf)
}

# Growing Season Length

calculateGrowingSeasonLength <- function(InputTable, first_year,
last_year) {

  print("GSL")
  #Create result table
  result_gsl<-data.frame()

  #Initialize index i with first_year
  i<-first_year
  # And iterate year-by-year

  while(i<=last_year) {
    # Create data frame for year 'i' and cdd  == 1
    InputTableTrim<-
InputTable[as.numeric(format(as.Date(InputTable$Date,"%Y-%m-
%d"),format="%Y"))==i,]
    result_gsl_i<-InputTableTrim[,3:4]
    result_gsl_i<-
cbind(result_gsl_i,apply(InputTableTrim[,c("TempMin","TempMax")]
,1,mean))
    result_gsl_i<-cbind(result_gsl_i, rep(0,nrow(result_gsl_i)))
    # We assume Growing Season can't start before April 1st
    j<-91
    if (i %% 4 == 0) {
```

```
      #leap year fix
      j <- 92
    }
    countNA<-0

    gslStartDate <- NA
    gslEndDate <- NA
    while(j<=nrow(result_gsl_i)) {
      if (!is.na(result_gsl_i[j,3]) & !is.na(result_gsl_i[j-1,3])
&
          !is.na(result_gsl_i[j-2,3]) & !is.na(result_gsl_i[j-
3,3]) &
          !is.na(result_gsl_i[j-4,3]) & !is.na(result_gsl_i[j-
5,3])) {
        if (((result_gsl_i[j-1,4] > 0) |
             ((result_gsl_i[j,3] > 5) & (result_gsl_i[j-1,3] > 5)
&
              (result_gsl_i[j-2,3] > 5) & (result_gsl_i[j-3,3] >
5) &
              (result_gsl_i[j-4,3] > 5) & (result_gsl_i[j-5,3] >
5)))&
            !((result_gsl_i[j,3]<5) & (result_gsl_i[j-1,3]<5) &
              (result_gsl_i[j-2,3]<5) & (result_gsl_i[j-3,3]<5) &
              (result_gsl_i[j-4,3]<5) & (result_gsl_i[j-5,3]<5) &
j >= 183)) {
          result_gsl_i[j,4]<-1
          if (is.na(gslStartDate)) {
            gslStartDate <- InputTableTrim[j, "Date"]
            gslStartDateDOY <- j
          }
        }
      } else {
        countNA <- countNA + 1
        result_gsl_i[j,4]<-result_gsl_i[j-1,4]
      }
      if (result_gsl_i[j, 4] == 1) {
        gslEndDate <- InputTableTrim[j, "Date"]
        gslEndDateDOY <- j
      }
      j <- j + 1
    }
    if (countNA > 0) {
      print(paste0("Year ", i, " has ", countNA, " days for which
NAs affected calculation"))
    }
    result_gsl<-rbind(result_gsl,c(i, sum(result_gsl_i[,4], na.rm
= NARM), gslStartDate, gslEndDate, gslStartDateDOY,
gslEndDateDOY))
    i<-i+1
  }

  colnames(result_gsl)<-c("Period","GSL", "start GS", "end GS",
```

```
"GS_START", "GS_END")
  return (result_gsl)
}

# Calculate CHU (as an agroclimatic indicator)

calculateCHU <- function(InputTable, first_year, last_year) {

  print("CHU")
  result_chu <- data.frame()
  i <- first_year
  while(i<=last_year) {
    # Create data frame for year 'i'
    InputTableTrim<-
InputTable[as.numeric(format(as.Date(InputTable$Date,"%Y-%m-
%d"),format="%Y"))==i,]
    # Trimming to start on May 1st
    InputTableTrim<-
InputTableTrim[as.numeric(format(as.Date(InputTableTrim$Date,"%Y
-%m-%d"),format="%m")) %in% c(5:12),]
    firstDayOfYear <- as.Date(paste0(i, "-1-1"), "%Y-%m-%d")
    CHU<-0.0
    j<-1
    while(j<=nrow(InputTableTrim)) {
      tmin<-InputTableTrim[j,"TempMin"]
      if (is.na(tmin)) {
        j <-j+1
        next
      }

      if (j > 92 & tmin <= -2) {
        break
      }

      tmax<-InputTableTrim[j,"TempMax"]
      if (is.na(tmax)){
        j <-j+1
        next
      }
      tmax_10<-(tmax-10.0)
      YMax<-(3.33 * tmax_10) - (0.084 * tmax_10 * tmax_10)
      if (YMax < 0)
        YMax<-0
      YMin<-1.8*(tmin-4.4)
      if (YMin <0)
        YMin<-0

      CHU_step <- (YMin+YMax)/2
      CHU <-CHU + CHU_step
      j<-j+1
    }
    result_chu <- rbind(result_chu, c(i, round(CHU, digits = 0)))
```

```
    i<-i+1
  }

  colnames(result_chu)[1:2]<-c("Period","CHU")
  return (result_chu)
}

for(file_name in file_list) {
  setwd(base_path)
  in_csv_path<-paste0(base_path, "input/", file_name,".csv")

  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"))

  # Calculate mean precipitation for weeks 14 - 26 and base
period 1961 - 1990
  meanPrecip <- prepareMeanPrecip(InputTable, 1961, 1990)
  # Based on mean precipitation calculate seeding date for each
year
  cornSeedingDates <- calculateCornSeedingDate(InputTable,
first_year, last_year)
  # Based on corn seeding date calculate CHU periods for each of
the indices
  CHUMap <- prepareCHU(InputTable, cornSeedingDates, first_year,
last_year)

  dir.create(out_csv_dir, showWarnings=FALSE)

  result <-calculatePSC(InputTable, first_year, last_year)
  result <- merge(result, sort=FALSE, calculateEF(InputTable,
CHUMap, first_year, last_year), by="Period")
  result <- merge(result, sort=FALSE, calculatePD(InputTable,
CHUMap, first_year, last_year), by="Period")
  result <- merge(result, sort=FALSE, calculateR2D(InputTable,
CHUMap, first_year, last_year), by="Period")
  result <- merge(result, sort=FALSE, calculateR3D(InputTable,
CHUMap, first_year, last_year), by="Period")
  result <- merge(result, sort=FALSE, calculateEKF(InputTable,
CHUMap, first_year, last_year), by="Period")
  result <- merge(result, sort=FALSE, calculateR4D(InputTable,
CHUMap, first_year, last_year), by="Period")
  result <- merge(result, sort=FALSE, calculateFKF(InputTable,
CHUMap, first_year, last_year), by="Period")
  result <- merge(result, sort=FALSE,
calculateGrowingSeasonLength(InputTable, first_year, last_year),
by="Period")
  result <- merge(result, sort=FALSE,
```

```
outputCornSeedingDate(cornSeedingDates, first_year, last_year),
by="Period")
  result <- merge(result, sort=FALSE, calculateCHU(InputTable,
first_year, last_year), by="Period")

  out_csv_path <- paste0(out_csv_dir, file_name, ".csv")
  write.csv(result,out_csv_path,row.names=FALSE)
}
```

3.13. Calculating soybean-specific extreme event indices

```
# This script calculates soybean-specific extreme event indices

file_list<-c('CHALKRIVER', 'CORNWALL', 'HARTINGTON', 'KINGSTON',
 'KEMPTVILLE', 'LYNDHURST', 'OTTAWACDA', 'ARNPRIOR',
 'RUSSELL','STALBERT', 'STANICET')

options(stringsAsFactors = FALSE)

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


base_path<-"~/Documents/Rproj/MSc indices calculation/"
out_csv_dir<-paste0(base_path,"/soy indices/")
setwd(base_path)

new.hashtable <- function() {
  e <- new.env()
  list(set = function(key, value) assign(as.character(key),
 value, e),
       get = function(key) get(as.character(key), e),
       rm = function(key) rm(as.character(key), e))
}
# hashtable: week -> mean weekly precipitation
meanPrecip <- new.hashtable()

# Define function for calculating mean weekly precipitation

prepareMeanPrecip <- function(InputTable, first_year, last_year)
 {
  print("Prepare mean weekly precipitation")
  meanPrecip <- new.hashtable()
  for (week in 14:26) {
    startDay <- week *7
    weeklyData <- c()
    for (y in first_year:last_year) {
      firstDate <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d") +
 startDay
      WeeklyTableTrim<-InputTable[as.Date(InputTable$Date,"%Y-%m-
 %d")>= firstDate & as.Date(InputTable$Date,"%Y-%m-%d")<=
 (firstDate + 6),]
      weeklyData <- c(weeklyData,
 sum(WeeklyTableTrim$Precipitation, na.rm = TRUE))
    }
    meanPrecip$set(week, mean(weeklyData))
  }
  return (meanPrecip)
}
```

```
# Define function for calculating soybean seeding date

calculateSoySeedingDates <- function(InputTable, first_year,
 last_year) {
  print("Prepare soy seeding dates")
  seedingDates <- new.hashtable()
  for (y in first_year:last_year) {
    firstDate <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d")
    ySeedingDate <- NA
    for (week in 19:24) {
      prevWeekTableTrim<-InputTable[as.Date(InputTable$Date,"%Y-
%m-%d")>= (firstDate + (week-1)*7) &
                                      as.Date(InputTable$Date,"%Y-
%m-%d")<= (firstDate + week*7 -1),]

      prevWeekPrecipitation <-
sum(prevWeekTableTrim$Precipitation, na.rm = TRUE)
      if (prevWeekPrecipitation < meanPrecip$get(week - 1) *1.3)
{
        ySeedingDate <- firstDate + week*7
        break
      }
    }
    if (is.na(ySeedingDate)) {
      print(paste0("Soy seeding date not found for year ", y));
    } else {

    }
    seedingDates$set(y, ySeedingDate)
  }
  return (seedingDates)
}

# Calculate Poor Seeding Conditions

calculatePSC <- function(InputTable, first_year, last_year) {
  print("PSC")

  PSC<-data.frame()
  for (y in first_year:last_year) {
    firstDayOfYear <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d")
    may7ThisYear <- as.Date(paste0(y, "-5-7"), "%Y-%m-%d")
    june10ThisYear <- as.Date(paste0(y, "-6-10"), "%Y-%m-%d")
    if (y %% 4 == 0) {
      # Leap year
      may7ThisYear <- may7ThisYear - 1
      june10ThisYear <- june10ThisYear - 1
    }

    day <- may7ThisYear
    rainyWeeks <- 0
```

```
    while (day <= june10ThisYear) {
      week <- as.integer((day - firstDayOfYear) / 7)
      WeeklyTableTrim<-InputTable[as.Date(InputTable$Date,"%Y-%m-
%d")>= day &
                                    as.Date(InputTable$Date,"%Y-
%m-%d")<= (day + 6),]
      weeklyPrecip <- sum(WeeklyTableTrim$Precipitation, na.rm =
TRUE)
      if (weeklyPrecip >= (meanPrecip$get(week) *1.3)) {
        rainyWeeks <- rainyWeeks + 1
      }
      day <- day + 7
    }
    PSC <- rbind(PSC, c(y, rainyWeeks))
  }
  colnames(PSC)[1:2]<-c("Period", "PSC")
  return (PSC)
}

# Calculate Spring Killing Frost

calculateSKF <- function(InputTable, soySeedingDays, first_year,
last_year) {
  print("SKF")
  SKF<-data.frame()
  for (y in first_year:last_year) {
    if(is.na(soySeedingDays$get(y))) {
      SKF <- rbind(SKF, c(y, NA))
      next;
    }

    firstDayOfYear <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d")
    seedingDay <- soySeedingDays$get(y)
    startOfThePeriod <- seedingDay + 26
    endOfThePeriod <- seedingDay + 50
    InputTableTrim <- InputTable[as.Date(InputTable$Date,"%Y-%m-
%d") >= startOfThePeriod &
                                  as.Date(InputTable$Date,"%Y-
%m-%d") <= startOfThePeriod,]
    freezingDays <- 0
    for (j in 1:nrow(InputTableTrim)) {
      if (InputTableTrim[j, "TempMin"] < 0)
        freezingDays <- freezingDays + 1
    }
    SKF <- rbind(SKF, c(y, freezingDays))
  }
  colnames(SKF)[1:2]<-c("Period", "SKF")
  return (SKF)
}

#Calculate Early Flooding
```

```
calculateEF <- function(InputTable, soySeedingDays, first_year,
 last_year) {
  print("EF")
  EFdf<-data.frame()
  for (y in first_year:last_year) {
    if(is.na(soySeedingDays$get(y))) {
      EFdf <- rbind(EFdf, c(y, NA))
      next;
    }

    firstDayOfYear <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d")
    seedingDay <- soySeedingDays$get(y)
    startOfThePeriod <- seedingDay + 25
    endOfThePeriod <- seedingDay + 45
    InputTableTrim <- InputTable[as.Date(InputTable$Date,"%Y-%m-
 %d") >= startOfThePeriod &
                                      as.Date(InputTable$Date,"%Y-
 %m-%d") <= startOfThePeriod,]
    freezingDays <- 0
    for (j in 1:nrow(InputTableTrim)) {
      if (InputTableTrim[j, "TempMin"] < 0)
        freezingDays <- freezingDays + 1
    }
    EFdf <- rbind(EFdf, c(y, freezingDays))
  }
  colnames(EFdf)[1:2]<-c("Period", "EF")
  return (EFdf)
}

# Calculate Cool Nigths

calculateCoolNights <- function(InputTable, soySeedingDays,
 first_year, last_year) {
  print("CN")
  CNdf<-data.frame()
  for (y in first_year:last_year) {
    if(is.na(soySeedingDays$get(y))) {
      df <- rbind(CNdf, c(y, NA))
      next;
    }

    firstDayOfYear <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d")
    seedingDay <- soySeedingDays$get(y)
    startOfThePeriod <- seedingDay + 45
    endOfThePeriod <- seedingDay + 55
    InputTableTrim <- InputTable[as.Date(InputTable$Date,"%Y-%m-
 %d") >= startOfThePeriod &
                                      as.Date(InputTable$Date,"%Y-
 %m-%d") <= startOfThePeriod,]
    coolNights <- 0
    for (j in 1:nrow(InputTableTrim)) {
      if (InputTableTrim[j, "TempMin"] < 10)
```

```
        coolNights <- coolNights + 1
    }
    if (coolNights >= 5)
      cNValue <- 'yes'
    else
      cNValue <- 'no'
    CNdf <- rbind(CNdf, c(y, cNValue))
  }
  colnames(CNdf)[1:2]<-c("Period", "CN")
  return (CNdf)
}
```

```
# Calculate Warm Nights

calculateWarmNights <- function(InputTable, soySeedingDays,
 first_year, last_year) {
  print("WN")
  WNdf<-data.frame()
  for (y in first_year:last_year) {
    if(is.na(soySeedingDays$get(y))) {
      df <- rbind(WNdf, c(y, NA))
      next;
    }

    firstDayOfYear <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d")
    seedingDay <- soySeedingDays$get(y)
    startOfThePeriod <- seedingDay + 55
    endOfThePeriod <- seedingDay + 100

    InputTableTrim <- InputTable[as.Date(InputTable$Date,"%Y-%m-
 %d") >= startOfThePeriod &
                                    as.Date(InputTable$Date,"%Y-
 %m-%d") <= startOfThePeriod,]
    warmNights <- 0
    for (j in 1:nrow(InputTableTrim)) {
      if (InputTableTrim[j, "TempMin"] >= 24)
        warmNights <- warmNights + 1
    }
    WNdf <- rbind(WNdf, c(y, warmNights))
  }
  colnames(WNdf)[1:2]<-c("Period", "WN")
  return (WNdf)
}

# Calculate Mid-Season Flooding

calculateMidSeasonFlooding <- function(InputTable,
 soySeedingDays, first_year, last_year) {
  print("MSF")
  MSFdf<-data.frame()
  for (y in first_year:last_year) {
    if(is.na(soySeedingDays$get(y))) {
      df <- rbind(MSFdf, c(y, NA))
      next;
    }

    firstDayOfYear <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d")
    seedingDay <- soySeedingDays$get(y)
    startOfThePeriod <- seedingDay + 60
    endOfThePeriod <- seedingDay + 80

    InputTableTrim <- InputTable[as.Date(InputTable$Date,"%Y-%m-
 %d") >= startOfThePeriod &
                                    as.Date(InputTable$Date,"%Y-
```

```
%m-%d") <= startOfThePeriod,]
    sumPrecip <- sum(InputTableTrim$Precipitation)
    if (sumPrecip > 90)
      MSFValue <- 'yes'
    else
      MSFValue <- 'no'
    MSFdf <- rbind(MSFdf, c(y, MSFValue))
  }
  colnames(MSFdf)[1:2]<-c("Period", "MSF")
  return (MSFdf)
}

# Calculate Pod Filling Drought

calculatePodFillingDrought <- function(InputTable,
 soySeedingDays, first_year, last_year) {
  print("PD")
  PDdf<-data.frame()
  for (y in first_year:last_year) {
    if(is.na(soySeedingDays$get(y))) {
      df <- rbind(PDdf, c(y, NA))
      next;
    }

    firstDayOfYear <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d")
    seedingDay <- soySeedingDays$get(y)
    startOfThePeriod <- seedingDay + 81
    endOfThePeriod <- seedingDay + 95

    InputTableTrim <- InputTable[as.Date(InputTable$Date,"%Y-%m-
%d") >= startOfThePeriod &
                                    as.Date(InputTable$Date,"%Y-
%m-%d") <= startOfThePeriod,]
    sumPrecip <- sum(InputTableTrim$Precipitation)
    if (sumPrecip < 10)
      pDValue <- 'yes'
    else
      pDValue <- 'no'
    PDdf <- rbind(PDdf, c(y, pDValue))
  }
  colnames(PDdf)[1:2]<-c("Period", "PD")
  return (PDdf)
}

# Calculate Early Killing Frost

calculateEarlyKillingFrost <- function(InputTable,
 soySeedingDays, first_year, last_year) {
  print("EKF")
  EKFdf<-data.frame()
  for (y in first_year:last_year) {
    if(is.na(soySeedingDays$get(y))) {
```

```
      df <- rbind(EKFdf, c(y, NA))
      next;
    }

    firstDayOfYear <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d")
    seedingDay <- soySeedingDays$get(y)
    startOfThePeriod <- seedingDay + 90
    endOfThePeriod <- seedingDay + 100

    InputTableTrim <- InputTable[as.Date(InputTable$Date,"%Y-%m-
%d") >= startOfThePeriod &
                                 as.Date(InputTable$Date,"%Y-
%m-%d") <= startOfThePeriod,]
    EKFValue <- 0
    for (j in 1:nrow(InputTableTrim)) {
      if (InputTableTrim[j, "TempMin"] < -1)
        EKFValue <- EKFValue + 1
    }
    EKFdf <- rbind(EKFdf, c(y, EKFValue))
  }
  colnames(EKFdf)[1:2]<-c("Period", "EKF")
  return (EKFdf)
}

# Calculate Extreme Heat

calculateExtremeHeat <- function(InputTable, soySeedingDays,
first_year, last_year) {
  print("EXH")
  EXHdf<-data.frame()
  for (y in first_year:last_year) {
    if(is.na(soySeedingDays$get(y))) {
      df <- rbind(EXHdf, c(y, NA))
      next;
    }

    firstDayOfYear <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d")
    seedingDay <- soySeedingDays$get(y)
    startOfThePeriod <- seedingDay + 90
    endOfThePeriod <- seedingDay + 100

    InputTableTrim <- InputTable[as.Date(InputTable$Date,"%Y-%m-
%d") >= startOfThePeriod &
                                 as.Date(InputTable$Date,"%Y-
%m-%d") <= startOfThePeriod,]
    EXHValue <- 0
    for (j in 1:nrow(InputTableTrim)) {
      if (InputTableTrim[j, "TempMin"] < -1)
        EXHValue <- EXHValue + 1
    }
    EXHdf <- rbind(EXHdf, c(y, EXHValue))
  }
```

```
  colnames(EXHdf)[1:2]<-c("Period", "EXH")
  return (EXHdf)
}

# Calculate Fall Killing Frost
calculateFallKillingFrost <- function(InputTable, soySeedingDays,
 first_year, last_year) {
  print("FKF")
  FKFdf<-data.frame()
  for (y in first_year:last_year) {
    if(is.na(soySeedingDays$get(y))) {
      df <- rbind(FKFdf, c(y, NA))
      next;
    }

    firstDayOfYear <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d")
    seedingDay <- soySeedingDays$get(y)
    startOfThePeriod <- seedingDay + 101
    endOfThePeriod <- seedingDay + 110

    InputTableTrim <- InputTable[as.Date(InputTable$Date,"%Y-%m-
 %d") >= startOfThePeriod &
                                      as.Date(InputTable$Date,"%Y-
 %m-%d") <= startOfThePeriod,]
    FKFValue <- 0
    for (j in 1:nrow(InputTableTrim)) {
      if (InputTableTrim[j, "TempMin"] < -1)
        FKFValue <- FKFValue + 1
    }
    FKFdf <- rbind(FKFdf, c(y, FKFValue))
  }
  colnames(FKFdf)[1:2]<-c("Period", "FKF")
  return (FKFdf)
}

# Calculate Seed Development Drought

calculateSeedDevelopmentDrought <- function(InputTable,
 soySeedingDays, first_year, last_year) {
  print("SDD")
  SDDdf<-data.frame()
  for (y in first_year:last_year) {
    if(is.na(soySeedingDays$get(y))) {
      df <- rbind(SDDdf, c(y, NA))
      next;
    }

    firstDayOfYear <- as.Date(paste0(y, "-1-1"), "%Y-%m-%d")
    seedingDay <- soySeedingDays$get(y)
    startOfThePeriod <- seedingDay + 96
    endOfThePeriod <- seedingDay + 115
    InputTableTrim <- InputTable[as.Date(InputTable$Date,"%Y-%m-
```

```
%d") >= startOfThePeriod &
                                        as.Date(InputTable$Date,"%Y-
%m-%d") <= startOfThePeriod,]
    sumPrecip <- sum(InputTableTrim$Precipitation)
    if (sumPrecip < 5)
      SDDValue <- 'yes'
    else
      SDDValue <- 'no'
    SDDdf <- rbind(SDDdf, c(y, SDDValue))
  }
  colnames(SDDdf)[1:2]<-c("Period", "SDD")
  return (SDDdf)
}

# Calculate soy seeding date

outputSoySeedingDate <- function(soySeedingDates, first_year,
last_year) {
  print("Soy seeding date")
  SSDdf<-data.frame()
  for (y in first_year:last_year) {
    firstDayOfYear <- as.Date(paste0(y, "-1-1"), format="%Y-%m-
%d")
    if (is.na(soySeedingDates$get(y))) {
      value <- NA
      value_doy <- NA
    } else {
      value <- format(soySeedingDates$get(y), format="%Y-%m-%d")
      value_doy <- soySeedingDates$get(y) + 1 - firstDayOfYear
    }
    targetSeedingDate <- 130
    if (y %% 4 == 0) {
      # Leap year
      targetSeedingDate <- 131
    }
    SSDdf <- rbind(SSDdf, c(y, value, value_doy, value_doy -
targetSeedingDate))
  }
  colnames(SSDdf)<-c("Period", "Soy seeding date", "Soy seeding
doy", "SDELAY")
  return (SSDdf)
}
for(file_name in file_list) {
  setwd(base_path)
  in_csv_path<-paste0(base_path, "input/", file_name,".csv")

  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"))

  # Calculate mean precipitation for weeks 14 - 26 and base
period 1961 - 1990
  meanPrecip <- prepareMeanPrecip(InputTable, 1961, 1990)
  # Calculate seeding date for each year based on mean
precipitation
  soySeedingDates <- calculateSoySeedingDates(InputTable,
first_year, last_year)

  dir.create(out_csv_dir, showWarnings=FALSE)

  result <-calculatePSC(InputTable, first_year, last_year)
  result <- merge(result, sort=FALSE, calculateSKF(InputTable,
soySeedingDates, first_year, last_year), by="Period")
  result <- merge(result, sort=FALSE, calculateEF(InputTable,
soySeedingDates, first_year, last_year), by="Period")
  result <- merge(result, sort=FALSE,
calculateCoolNights(InputTable, soySeedingDates, first_year,
last_year), by="Period")
  result <- merge(result, sort=FALSE,
calculateWarmNights(InputTable, soySeedingDates, first_year,
last_year), by="Period")
  result <- merge(result, sort=FALSE,
calculateMidSeasonFlooding(InputTable, soySeedingDates,
first_year, last_year), by="Period")
  result <- merge(result, sort=FALSE,
calculatePodFillingDrought(InputTable, soySeedingDates,
first_year, last_year), by="Period")
  result <- merge(result, sort=FALSE,
calculateEarlyKillingFrost(InputTable, soySeedingDates,
first_year, last_year), by="Period")
  result <- merge(result, sort=FALSE,
calculateExtremeHeat(InputTable, soySeedingDates, first_year,
last_year), by="Period")
  result <- merge(result, sort=FALSE,
calculateFallKillingFrost(InputTable, soySeedingDates,
first_year, last_year), by="Period")
  result <- merge(result, sort=FALSE,
calculateSeedDevelopmentDrought(InputTable, soySeedingDates,
first_year, last_year), by="Period")
  result <- merge(result, sort=FALSE,
outputSoySeedingDate(soySeedingDates, first_year, last_year),
by="Period")

  out_csv_path <- paste0(out_csv_dir, file_name, ".csv")
  write.csv(result,out_csv_path,row.names=FALSE)
}
```

3.14. Calculating trends for agroclimatic indices

```
 # This script caclulates GSL, GSS, GSE and CHU trends and their
```

```
#significance

file_list<-c('CHALKRIVER', 'CORNWALL', 'HARTINGTON', 'KINGSTON',
 'KEMPTVILLE','LYNDHURST', 'OTTAWACDA', 'ARNPRIOR',
 'RUSSELL','STALBERT', 'STANICET')

base_path<-"~/Documents/Rproj/MSc indices calculation/"
setwd(base_path)
library(zyp)
out_result <-NA

for(file_name in file_list) {
  in_csv_path<-paste0(base_path, "corn indices/",
 file_name,".csv")
  print(paste0("Processing ",in_csv_path))
  InputIndicesTable <- read.csv(in_csv_path)
  InputIndicesTable <- InputIndicesTable[, c("GSL", "GS_START",
 "GS_END", "CHU")]
  result <- data.frame()
  datarows <- ncol(InputIndicesTable)
  InputIndicesTableTrim <- InputIndicesTable[c(1:50),]
  InputIndicesTableTrim <-
 t(InputIndicesTableTrim)[c(1:datarows), ]
  trends <- zyp.trend.dataframe(InputIndicesTableTrim, 0,
 method=c("zhang"), conf.intervals=TRUE,
 preserve.range.for.sig.test=TRUE)
  trends[, "sig"] = round(trends[, "sig"], digits = 5)

  for (i in 1:nrow(trends)) {
    result_row <- trends[i, c("trend", "sig")]
    row.names(result_row) <- row.names(trends[i,])
    result <- rbind(result, result_row)
  }
  colnames(result) <- c(paste0(file_name, ".trend"),
 paste0(file_name, ".sig"))

  if (is.na(out_result))
    out_result <- result
  else {
    out_result <- cbind(out_result, result)
  }
}
out_csv_path <- paste0(base_path, "ALL_TRENDS_AGROCLIMATIC.csv")
write.csv(out_result,out_csv_path,row.names = TRUE)
```

3.15. Calculating mean and standard deviation for agroclimatic, corn and soybean extreme event indices

```
# This script calculates mean and standard deviation
# for agroclimatic indices
file_list<-c('CHALKRIVER', 'CORNWALL', 'HARTINGTON', 'KINGSTON',
 'KEMPTVILLE','LYNDHURST', 'OTTAWACDA', 'ARNPRIOR',
 'RUSSELL','STALBERT', 'STANICET'
)
options(stringsAsFactors = FALSE)
base_path<-"~/Documents/Rproj/MSc indices calculation/"
setwd(base_path)
library(plyr)

ROUNDDIGITS <- 0

all_input <- NA
for(file_name in file_list) {
  in_csv_path<-paste0(base_path, "corn indices/",
 file_name,".csv")
  print(paste0("Processing ",in_csv_path))
  InputIndicesTable <- read.csv(in_csv_path)

  InputTable <- cbind( data.frame( DataSet = rep(file_name,
 nrow(InputIndicesTable))), InputIndicesTable)
  if (is.na(all_input))
    all_input <- InputTable
  else
    all_input <- rbind(all_input, InputTable)
}
# mean wrapper
myMEAN <- function(x) {
  return (round(mean(x, na.rm = TRUE), digits = ROUNDDIGITS))
}
# standard diviation wrapper
mySD <- function(x) {
  return (round(sd(x, na.rm = TRUE), digits = 2))
}
all_input6185 <- all_input[all_input$Period %in% 1961:1985,]
all_input8610 <- all_input[all_input$Period %in% 1986:2010,]

int_result <- ddply(all_input6185, .(DataSet), colwise(myMEAN,
 .(GSL)))
int_result <- join(int_result,  ddply(all_input8610, .(DataSet),
 colwise(myMEAN, .(GSL))), by="DataSet")
int_result <- join(int_result,  ddply(all_input6185, .(DataSet),
 colwise(mySD, .(GSL))), type="left", by="DataSet")
int_result <- join(int_result,  ddply(all_input8610, .(DataSet),
 colwise(mySD, .(GSL))), type="left", by="DataSet")

int_result <- join(int_result,  ddply(all_input6185, .(DataSet),
```

```
 colwise(myMEAN, .(CHU))), type="left", by="DataSet")
int_result <- join(int_result,  ddply(all_input8610, .(DataSet),
 colwise(myMEAN, .(CHU))), type="left", by="DataSet")
int_result <- join(int_result,  ddply(all_input6185, .(DataSet),
 colwise(mySD, .(CHU))), type="left", by="DataSet")
int_result <- join(int_result,  ddply(all_input8610, .(DataSet),
 colwise(mySD, .(CHU))), type="left", by="DataSet")

int_result <- join(int_result,  ddply(all_input6185, .(DataSet),
 colwise(myMEAN, .(GS_START))), type="left", by="DataSet")
int_result <- join(int_result,  ddply(all_input8610, .(DataSet),
 colwise(myMEAN, .(GS_START))), type="left", by="DataSet")
int_result <- join(int_result,  ddply(all_input6185, .(DataSet),
 colwise(mySD, .(GS_START))), type="left", by="DataSet")
int_result <- join(int_result,  ddply(all_input8610, .(DataSet),
 colwise(mySD, .(GS_START))), type="left", by="DataSet")

int_result <- join(int_result,  ddply(all_input6185, .(DataSet),
 colwise(myMEAN, .(GS_END))), type="left", by="DataSet")
int_result <- join(int_result,  ddply(all_input8610, .(DataSet),
 colwise(myMEAN, .(GS_END))), type="left", by="DataSet")
int_result <- join(int_result,  ddply(all_input6185, .(DataSet),
 colwise(mySD, .(GS_END))), type="left", by="DataSet")
int_result <- join(int_result,  ddply(all_input8610, .(DataSet),
 colwise(mySD, .(GS_END))), type="left", by="DataSet")

colnames(int_result) <- c("Station", "GSL 1961-1985", "GSL 1986-
 2010", "GSL SD 1961-1985", "GSL SD 1986-2010", "CHU 1961-1985",
 "CHU 1986-2010", "CHU SD 1961-1985", "CHU SD 1986-2010",
 "GS_START 1961-1985", "GS_START 1986-2010", "GS_START SD 1961-
 1985", "GS_START SD 1986-2010","GS_END 1961-1985", "GS_END 1986-
 2010", "GS_END SD 1961-1985", "GS_END SD 1986-2010")

out_csv_path <- paste0(base_path, "ALL_GSL_AND_CHU.csv")
write.csv(int_result,out_csv_path,row.names = FALSE)
```

3.16. Calculating regional mean and standard deviation for agroclimatic, corn and soybean extreme event indices

```
 #This script calculates regional mean and standard deviation for
 #all ecodistricts for GSL, GSS, GSE and CHU agroclimatic
 #indices, for corn PSC and EF and for soy PSC

file_list<-c('CHALKRIVER', 'CORNWALL', 'HARTINGTON',
 'KEMPTVILLE', 'KINGSTON','LYNDHURST', 'OTTAWACDA', 'ARNPRIOR',
 'RUSSELL', 'STALBERT', 'STANICET')

base_path<-"~/Documents/Rproj/MSc indices calculation/"
setwd(base_path)
out_csv_path <- paste0(base_path, "REGIONAL_MEANs_AND_SDs.csv")

options(stringsAsFactors = FALSE)
ROUNDDIGITS <- 2

indices <- c("GS_START", "GS_END", "GSL",   "CHU", "PSC", "EF",
 "PSC")
indices_dirs <- c("corn indices/", "corn indices/", "corn
 indices/","corn indices/", "corn indices/", "corn indices/",
 "soy indices/")
indices_out_names <- c("GSS", "GSE", "GSL", "CHU", "PSC_corn",
 "EF", "PSC_soy")

result_summary <- data.frame()
# For all indices:
for (i in c(1:7)) {
  index <- indices[i]
  index_dir <- indices_dirs[i]
  index_out_name <- indices_out_names[i]
  index_df6185 <- data.frame()
  index_df8610 <- data.frame()
  # Read index data for the index
  for(file_name in file_list) {
    in_csv_path<-paste0(base_path, index_dir, file_name,".csv")
    print(paste0("Reading ",in_csv_path))
    InputIndicesTable <- read.csv(in_csv_path)

    index_df6185 <- rbind(index_df6185,
 InputIndicesTable[c(1:25),index])
    index_df8610 <- rbind(index_df8610,
 InputIndicesTable[c(26:50),index])
  }
  result_summary <- rbind(result_summary, c(index_out_name,
 round(mean(rowMeans(index_df6185), na.rm = TRUE), digits =
 ROUNDDIGITS),

 round(sd(rowMeans(index_df6185), na.rm = TRUE), digits =
 ROUNDDIGITS),
```

```
 round(mean(rowMeans(index_df8610), na.rm = TRUE), digits =
 ROUNDDIGITS),

 round(sd(rowMeans(index_df8610), na.rm = TRUE), digits =
 ROUNDDIGITS)))
}
colnames(result_summary)[1:5]<-c("Index", "MEAN 1961-1985", "SD
 1961-1985", "MEAN 1986-2010", "SD 1986-2010")
print(paste0(out_csv_path, " done"))
write.csv(result_summary,out_csv_path,row.names=FALSE)
```

3.17. Plotting agroclimatic and corn-specific extreme event indices

```
 #This script generates boxplots for GSL, GSS, GSE and CHU
 #agroclimatic indices and for PSC and EF corn indices for all
 #ecodistricts

library(ggplot2)
options(stringsAsFactors = FALSE)
file_list<-c('CHALKRIVER', 'CORNWALL', 'HARTINGTON',
 'KEMPTVILLE', 'KINGSTON','LYNDHURST', 'OTTAWACDA', 'ARNPRIOR',
 'RUSSELL', 'STALBERT', 'STANICET')

ecodistrict_names<-c('AN', 'GP', 'AS', 'SFP', 'NPE', 'F', 'OVP',
 'ML', 'RPP', 'NGWP', 'USLP')

library(grid)

base_path<-"~/Documents/Rproj/MSc indices calculation/"
setwd(base_path)
out_plot_dir <- paste0(base_path, "/boxplots/")
dir.create(out_plot_dir, showWarnings=FALSE)

indices <- c("GS_START", "GS_END", "GSL",   "CHU", "PSC", "EF")
indices_names <- c("GSS", "GSE", "GSL", "CHU", "PSC_corn", "EF")
indices_units <- c("Day of Year", "Day of Year", "Days",    "Crop
 Heat Units", "Weeks", "Weeks")

# For all indices:
for (i in c(1:6)) {
  index <- indices[i]
  out_file_name <- indices_names[i]
  index_units <- indices_units[i]
  index_data6185 <- c()
  index_data8610 <- c()
  # Read index data for the index
  for(file_name in file_list) {
    in_csv_path<-paste0(base_path, "corn indices/",
 file_name,".csv")
    print(paste0("Reading ",in_csv_path))
    InputIndicesTable <- read.csv(in_csv_path)

    index_data6185 <-c(index_data6185,
 InputIndicesTable[c(1:25),index], recursive=TRUE)
    index_data8610 <-c(index_data8610,
 InputIndicesTable[c(26:50),index], recursive=TRUE)
  }
  # Box-plot index for 61-85 period
  InputTable6185 <- data.frame(Ecodistrict =
 factor(rep(ecodistrict_names, each=25), levels =
 ecodistrict_names), indexdata = index_data6185)
  print(paste0("Plotting ", out_file_name, " 1961-1985"))
```

```
  if (index == "PSC")
    plot_title <- "a. PSC 1961-1985"
  else
    plot_title <- paste0("a. ", out_file_name, " 1961-1985")
  ggplot(InputTable6185, aes(x=Ecodistrict, y=indexdata))  +
stat_boxplot(geom = "errorbar", width = 0.5) +
    geom_boxplot() + ylab(index_units) + ggtitle(plot_title)
  ggsave(filename=paste0(out_plot_dir, out_file_name, "_1961-
1985", ".jpg"), width = 6, height = 6, dpi = 600)

  # Box-plot index for 86-10 period
  InputTable8610 <- data.frame(Ecodistrict =
factor(rep(ecodistrict_names, each=25), levels =
ecodistrict_names), indexdata = index_data8610)
  print(paste0("Plotting ", out_file_name, " 1986-2010"))
  if (index == "PSC")
    plot_title <- "b. PSC 1986-2010"
  else
    plot_title <- paste0("b. ", out_file_name, " 1986-2010")
  ggplot(InputTable8610, aes(x=Ecodistrict, y=indexdata)) +
stat_boxplot(geom = "errorbar", width = 0.5) +
    geom_boxplot() + ylab(index_units) + ggtitle(plot_title)
  ggsave(filename=paste0(out_plot_dir, out_file_name, "_1986-
2010", ".jpg"), width = 6, height = 6, dpi = 600)
}
```

3.18. Plotting soybean-specific extreme event indices

```
 # This script generates boxplots for PSC soy index for all
 #ecodistricts

library(ggplot2)
options(stringsAsFactors = FALSE)
file_list<-c('CHALKRIVER', 'CORNWALL', 'HARTINGTON',
 'KEMPTVILLE', 'KINGSTONCLIMATE','LYNDHURST', 'OTTAWACDA',
 'ARNPRIOR', 'RUSSELL', 'STALBERT', 'STANICET')

ecodistrict_names<-c('AN', 'GP', 'AS', 'SFP', 'NPE', 'F', 'OVP',
 'ML', 'RPP', 'NGWP', 'USLP')

library(grid)

base_path<-"~/Documents/Rproj/MSc indices calculation/"
setwd(base_path)
out_plot_dir <- paste0(base_path, "/boxplots/")
dir.create(out_plot_dir, showWarnings=FALSE)

index <- "PSC"
out_file_name <- "PSC_soy"
index_units <- "Weeks"
index_data6185 <- c()
index_data8610 <- c()
# Read index data for the index
for(file_name in file_list) {
  in_csv_path<-paste0(base_path, "soy indices/",
 file_name,".csv")
  print(paste0("Reading ",in_csv_path))
  InputIndicesTable <- read.csv(in_csv_path)

  index_data6185 <-c(index_data6185,
 InputIndicesTable[c(1:25),index], recursive=TRUE)
  index_data8610 <-c(index_data8610,
 InputIndicesTable[c(26:50),index], recursive=TRUE)
}
# Box-plot index for 61-85 period
InputTable6185 <- data.frame(Ecodistrict =
 factor(rep(ecodistrict_names, each=25), levels =
 ecodistrict_names), index = index_data6185)
print(paste0("Plotting ", out_file_name, " 1961-1985"))
ggplot(InputTable6185, aes(x=Ecodistrict, y=index)) +
 stat_boxplot(geom = "errorbar", width = 0.5) +
  geom_boxplot() + ylab(index_units) +
  ggtitle("a. PSC 1961-1985")
ggsave(filename=paste0(out_plot_dir, out_file_name, "_1961-1985",
 ".jpg"), width = 6, height = 6, dpi = 600)
# Box-plot index for 86-10 period
InputTable8610 <- data.frame(Ecodistrict =
```

```
 factor(rep(ecodistrict_names, each=25), levels =
 ecodistrict_names), index = index_data8610)
print(paste0("Plotting ", out_file_name, " 1986-2010"))
ggplot(InputTable8610, aes(x=Ecodistrict, y=index)) +
 stat_boxplot(geom = "errorbar", width = 0.5) +
  geom_boxplot() + ylab(index_units) + ggtitle("b. PSC 1986-
 2010")
ggsave(filename=paste0(out_plot_dir, out_file_name, "_1986-2010",
 ".jpg"), width = 6, height = 6, dpi = 600)
```

Appendix 4: Trend magnitudes and p-values for extreme event indices

Table 1: Trend magnitudes and p-values for extreme event indices in eastern Ontario ecodistricts

Indicator	Algonquin North		Glengarry Plain		Algonquin South		Napanee - Prince Edward		Smith Falls Plain		Frontenac		Ottawa Valley Plain		Muskrat Lake		Russell and Prescott Plains		North Gower - Winchester Plains		Upper St. Lawrence Plain	
	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value
RX1day	0.23958333	0.04123	0.22857143	0.16232	0.03860749	0.72378	0.07531254	0.5871	0.14545455	0.15739	0.12380952	0.34453	0.16191675	0.18152	0.26153846	0.01873	0.22424242	0.04739	0.2875	0.01265	0.29861954	0.06894
RX5day	0.20652174	0.16751	0.34651163	0.12998	0.21251298	0.23764	0.1387962	0.33867	0.37419355	0.00306	0.375	0.01181	0.49	0.00253	0.21363636	0.11196	0.33333333	0.10108	0.38518519	0.02239	0.37894737	0.01791
CDD	0	0.58976	-0.0357143	0.33354	0	0.57694	0	0.64386	0	0.91968	0	0.60202	0	0.85336	0	0.46836	0	0.61963	0	0.74222	-0.0555556	0.09213
R10	0	0.75628	0.06076967	0.37918	0.07142857	0.09292	0.02439024	0.50684	0.02857143	0.49088	0.09677419	0.08827	0.05410685	0.16778	0.01266601	0.85633	0.15141354	0.01336	0.18488693	0.00082	0	0.63224
SDII	-0.0079912	0.48502	-0.0030303	0.59123	-0.0054358	0.38868	-0.0076923	0.19924	0.00588235	0.37869	0.00294118	0.669	0.015	0.01965	-0.0194873	0.02793	0.00950349	0.3173	0	0.94651	-0.0137933	0.12705
HWE	0.03809357	0.69169	0.14285714	0.04521	0.15384615	0.11725	0	0.83297	0	0.86026	0.1	0.10881	0.05555556	0.48633	0.05263158	0.50237	0.02439024	0.63267	0.07692308	0.31051	0.03846154	0.54058
CWE	-0.2752319	0.00151	-0.2238775	0.00241	-0.1890597	0.011	-0.1212121	0.03531	-0.2759338	0.00248	-0.072587	0.45849	-0.2591252	0.00038	-0.3888271	0.00029	-0.1264945	0.20511	-0.0952381	0.26863	-0.1666667	0.05498
DTR	-0.0080087	0.01153	-0.0041938	0.67894	-0.0004414	0.95188	-0.0041261	0.7173	-0.0026524	0.72374	0	0.77905	0	0.5392	-0.0080072	0.19895	0	0.51419	0.0027027	0.07288	-0.0185026	0.00469
GSL	0.33333333	0.02827	0.35714286	0.03084	0.25	0.12354	0.30798709	0.09968	-0.0588235	0.63923	0.14285714	0.37501	0.1	0.41186	0.1975004	0.24455	0.28561536	0.06384	0.12195122	0.41189	0.27272727	0.06082
AvgTempMin	0.03710333	0	0.04027057	0	0.03363319	0.00017	0.02911352	0.00228	0.0282018	9.00E-04	0.02058824	0.01979	0.03603502	0	0.03921487	1.00E-05	0.03568111	0	0.02287828	0.00221	0.04077002	0
AvgTempMax	0.0291057	0.00023	0.03707157	0	0.02584491	4.00E-05	0.02212168	0.00241	0.02283063	5.00E-04	0.02492035	0.00088	0.03201098	4.00E-05	0.02879563	0.00028	0.03216984	1.00E-05	0.02913908	4.00E-05	0.02612974	0.00612
PRCPTOT	1.31717634	0.3132	3.625	0.01209	2.90473535	0.01273	0.95555556	0.46167	0.9523918	0.47433	2.65063058	0.01543	2.58455072	0.05245	2.49000695	0.00596	4.21636878	0.00138	5.635234	0	3.26570795	0.02674
TN10p	-0.1880359	0	-0.1900062	0	-0.1561671	0.00028	-0.1520167	0.00119	-0.1443878	1.00E-05	-0.1164399	0.00045	-0.166971	0	-0.2652705	0	-0.1411649	2.00E-05	-0.1395813	0.00596	-0.1648859	0
TN90p	0.0888	0.00432	0.0995	0.00258	0.09278038	0.00399	0.07328571	0.07745	0.05074074	0.10782	0.08633333	0.05123	0.09932	0.00201	0.02277778	0.61553	0.12968077	0.00367	0.04566667	0.19744	0.16036042	0
TX10p	-0.1119121	2.00E-05	-0.1599716	0	-0.0994286	7.00E-04	-0.1267684	1.00E-05	-0.109323	3.00E-04	-0.0913333	0.01041	-0.1416226	0	-0.1014815	0.00259	-0.1337353	0	-0.1297056	0	-0.1206764	0.00013
TX90p	0.07899943	0.04106	0.11984327	0.00773	0.13359305	0.00367	0.06799708	0.24455	0.06077254	0.1652	0.10687762	0.01777	0.09301118	0.01402	0.06066884	0.11271	0.08991011	0.03325	0.08344801	0.0292	0.08010358	0.05678
R95p	0.60967742	0.54699	3.5	0.00534	2	0.03157	0.94444444	0.34883	2.18451735	0.08317	2.22439024	0.03361	2.825	0.00423	0.96969697	0.22838	2.84427826	0.00509	3.56071429	0.0036	1.42692308	0.23491

Table 2: Trend magnitudes and p-values for extreme event indices in eastern Ontario ecodistricts during the planting season

Indicator	Algonquin North		Glengarry Plain		Algonquin South		Napanee - Prince Edward		Smith Falls Plain		Frontenac		Ottawa Valley Plain		Muskrat Lake		Russell and Prescott Plains		North Gower - Winchester Plains		Upper St. Lawrence Plain	
	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value
RX1day	0.09831795	0.33867	0.13888889	0.07206	-0.1	0.36173	-0.0666667	0.62754	0.17272727	0.0863	0.02481827	0.85635	0.13571429	0.07339	0.06579974	0.38397	0.11226615	0.23764	0.1	0.29552	0.18616154	0.01046
RX5day	-0.0030303	0.68742	0.0175	0.41088	0.01428571	0.40559	-0.0091033	0.72376	0	0.99332	-0.04	0.0527	0.00740741	0.66336	-0.0272727	0.26409	-0.0285714	0.25415	-0.0483068	0.12284	0.04666667	0.04382
CDD	-0.0155695	0.74972	0	0.73618	0	0.98653	0.03225806	0.24839	-0.0052699	0.84275	0.02173913	0.32734	-0.0310719	0.44796	-0.0205421	0.63538	0	0.90627	-0.0555547	0.30493	-0.0555556	0.15488
R10	0.02941176	0.11077	0	0.35321	0	0.34955	0	0.92582	0	0.65107	0	0.80582	0	0.31785	0	0.56992	0.03125	0.07778	0.04761905	0.01549	0	0.38902
SDII	-0.0076641	0.52919	0.01363636	0.38854	-0.0157731	0.33004	-0.0292683	0.10978	0.0137931	0.33973	0.00833333	0.66939	0.00555556	0.71259	-0.00625	0.62113	0.01290323	0.37492	0.00454545	0.7759	0.00322581	0.80165
HWE	0	0.76834	0	0.5204	0	0.73756	0	0.9405	0	0.72341	0	0.85035	0	0.54543	0.00805546	0.27248	0	0.57695	0	0.3912	0	0.15851
DTR	-0.0089036	0.28127	0.00093891	0.9176	0.00034917	0.98624	-0.0076583	0.72373	0.00129829	0.92446	0	0.19492	-0.0047206	0.60501	0.00146055	0.96562	0	0.75332	0	0.13371	-0.0182448	0.13143
AvgTempMin	0.04443122	0.00814	0.03915997	0.00123	0.02529803	0.13816	0.01574903	0.44295	0.02463287	0.0305	0.02212994	0.12075	0.03099247	0.02136	0.03318426	0.01402	0.03076923	0.01617	0.01665449	0.19302	0.04449519	1.00E-05
AvgTempMax	0.02448715	0.12708	0.03470691	0.05245	0.02238412	0.12708	0.00621144	0.62929	0.01667765	0.26986	0.02024954	0.17871	0.02727552	0.12284	0.02180128	0.18152	0.03212291	0.05038	0.03040828	0.08015	0.02325177	0.16001
PRCPTOT	0.71111111	0.05648	0.61891892	0.34883	0.34166667	0.49804	0.10555556	0.82131	0.4	0.41712	0.43	0.41236	0.65454545	0.17272	0.395	0.31548	0.946875	0.0503	1.04848485	0.03961	0.91666667	0.10642
TN10p	-0.2178387	4.00E-05	-0.1993944	0.00293	-0.1365324	0.04094	-0.072965	0.50125	-0.1855284	0.00142	-0.2724509	0.00022	-0.1644313	7.00E-04	-0.2630631	0	-0.273773	2.00E-04	-0.2107607	0.00189	-0.2408109	0
TN90p	0.11621601	0.14994	0.12353885	0.10131	0.11843765	0.21761	0.04310964	0.69167	0.05549225	0.33851	0	0.76158	0.11308398	0.15234	-0.0104627	0.9176	0	0.47341	0	0.98624	0.21293887	0.01433
TX10p	-0.1024972	0.12697	-0.1359005	0.03934	-0.1078981	0.11656	-0.0997896	0.3007	-0.1423872	0.06892	-0.0381395	0.4047	-0.1515718	0.0147	-0.0847722	0.27353	-0.1344262	0.0218	-0.1381669	0.03251	-0.1561429	0.00889
TX90p	0.11291849	0.17042	0.17076838	0.03619	0.15864516	0.05454	0.0517994	0.48487	0.09646342	0.27738	0.16724258	0.02918	0.11709985	0.18713	0.10245313	0.23752	0.13022545	0.15739	0.14919466	0.14042	0.12574197	0.21435
R95p	0.30882353	0.31952	0.68333333	0.07342	-0.0764706	0.9134	-0.2552632	0.56942	0.56428571	0.25172	0.27647059	0.4565	0.49230769	0.14322	-0.1139243	0.7109	0.66	0.05435	0.68888889	0.02664	0.59166667	0.15478

Table 3: Trend magnitudes and p-values for extreme event indices in eastern Ontario ecodistricts during the growing season

Indicator	Algonquin North		Glengarry Plain		Algonquin South		Napanee - Prince Edward		Smith Falls Plain		Frontenac		Ottawa Valley Plain		Muskrat Lake		Russell and Prescott Plains		North Gower - Winchester Plains		Upper St. Lawrence Plain	
	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value
RX1day	0.14347826	0.24825	0.33142857	0.08484	-0.0025	0.97998	0.06	0.51408	-0.0054054	0.96663	0.16585366	0.28799	0.13432037	0.42276	0.29655172	0.02551	0.15769231	0.18347	0.28484848	0.03359	0.28235294	0.04122
RX5day	0.0221885	0.09955	0.01891892	0.04913	0.01491299	0.26971	0.01159499	0.28503	0	0.76926	0.01428571	0.31388	0.01	0.24301	0	0.8864	0.00588235	0.46986	0	0.73069	0.01666667	0.20177
CDD	0	0.62475	0	0.93967	0	0.35141	0	0.71153	0	0.6258	0	0.50656	0.04545455	0.26317	0.02295422	0.58698	0	0.49456	0	0.61953	0	0.52161
R10	0	0.68672	0.06578298	0.10317	0.05118223	0.25881	0	0.78031	0.03846154	0.27773	0.0756217	0.04185	0.04761905	0.10579	0	0.79393	0.09944188	0.0097	0.11385648	0.00215	0.04735663	0.2176
SDII	0.00344828	0.75665	0	0.89341	-0.0110178	0.48505	-0.0034483	0.78875	0.01891892	0.08453	0.01839532	0.20511	0.02083333	0.09229	-0.0098586	0.59902	0.01794872	0.27649	0.00714286	0.60944	0	0.97996
HWE	0.02985723	0.74322	0.13636364	0.04889	0.15151515	0.1253	0	0.83297	0	0.84056	0.1	0.11066	0.05555556	0.50799	0.05263158	0.53505	0.02272727	0.69355	0.07317073	0.3565	0.03571429	0.59164
DTR	-0.0153846	0.00244	-0.0086598	0.36082	-0.0125	0.46901	-0.0202492	0.28123	-0.0075019	0.27738	0	0.37898	-0.005	0.2676	-0.0125079	0.08626	-0.0057143	0.09811	0	0.23438	-0.0212138	0.00302
AvgTempMin	0.04153891	0	0.03973501	0	0.02869397	0.01618	0.03879272	0.0147	0.02545276	0.00068	0.016	0.025	0.03241527	0	0.03306317	2.00E-05	0.03456812	0	0.01176471	0.0261	0.03935056	0
AvgTempMax	0.02432432	0.00384	0.03246734	1.00E-05	0.015	0.14253	0.00666667	0.40142	0.00909091	0.27214	0.01428571	0.11319	0.02142857	0.00362	0.01707317	0.05068	0.02162162	0.00404	0.01875	0.01433	0.01315789	0.12289
PRCPTOT	0.81111111	0.40288	2.2553665	0.00735	1.83722026	0.08628	1.02	0.15259	1.2	0.08948	1.71295339	0.05245	1.75	0.02191	1.66896552	0.00801	2.4027027	0.00434	2.885	0.00124	2.61989118	0.00482
TN10p	-0.236196	0	-0.2321962	0	-0.1586093	0.03251	-0.2682448	0.00482	-0.1654735	2.00E-05	-0.1586878	1.00E-05	-0.2246129	6.00E-05	-0.3165877	0	-0.2100457	0	-0.1500561	0.01694	-0.2237637	0
TN90p	0.14434961	0.00105	0.11937874	0.01304	0.11791775	0.05348	0.12335954	0.00901	0.0255	0.54024	0.08278072	0.11266	0.09134483	0.028	-0.0572991	0.38394	0.08903671	0.06506	-0.0391406	0.46372	0.14656628	0.00255
TX10p	-0.1471852	5.00E-05	-0.1811644	0	-0.082775	0.01049	-0.1241875	0.00095	-0.1018607	0.00064	-0.1003636	0.01431	-0.1651331	0	-0.0848974	0.01497	-0.1524958	0	-0.1243695	1.00E-05	-0.1311006	0.00011
TX90p	0.03914309	0.55197	0.10737838	0.06042	0.04728571	0.47115	-0.0472857	0.51346	-0.0348684	0.45048	0.06027273	0.27233	0.01789189	0.69991	0	0.97325	0	0.98661	0	0.93317	0	0.84717
R95p	0.52045455	0.44156	1.3969697	0.03961	1.1016117	0.23086	0.5	0.43659	1.39473684	0.03504	1.03333333	0.16496	1.14615385	0.1387	0.81860465	0.2623	1.81443458	0.05906	1.80333333	0.03092	1.45294118	0.07079

Table 4: Trend magnitudes and p-values for extreme event indices in eastern Ontario ecodistricts during the harvesting season

Indicator	Algonquin North		Glengarry Plain		Algonquin South		Napanee - Prince Edward		Smith Falls Plain		Frontenac		Ottawa Valley Plain		Muskrat Lake		Russell and Prescott Plains		North Gower - Winchester Plains		Upper St. Lawrence Plain	
	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value	trend	p-value
RX1day	0.12934477	0.30907	0.25789474	0.07342	0.2131327	0.08317	0.14285714	0.22509	0.1047619	0.48746	0.27272727	0.09765	0.2	0.09585	0.10666667	0.25172	0.1	0.49804	0.2	0.1217	0.22692308	0.06949
RX5day	0.03125	0.0686	0	0.81437	0.01071429	0.50715	0	0.81414	0	0.98663	0.02272727	0.19073	0.00909091	0.63915	-0.0090909	0.42483	0.03243243	0.13595	0.008	0.63881	0.01111111	0.51847
CDD	0	0.61277	-0.0384615	0.14296	0	0.37417	0	0.59761	0	0.37561	0.01225158	0.82259	0	1	0	0.71725	0	0.48919	-0.0384615	0.1859	-0.025641	0.26888
R10	0	0.80042	0.0625	0.05274	0.01348261	0.40742	0	0.68528	0	0.97312	0	0.44667	0	0.57238	0	0.95951	0	0.3444	0	0.34824	0.06060606	0.02063
SDII	-0.0147497	0.41285	0.00625	0.66925	0.01290323	0.38868	0.00731707	0.5978	0.0097561	0.64523	0.02642924	0.18434	0.02307692	0.12768	-0.0305641	0.20203	0	0.90001	-0.0066667	0.60961	0	0.8276
HWE	0	0.57317	0	0.03908	0	0.01797	0	0.65336	0	0.81904	0	0.14915	0	0.21045	0	0.35585	0	0.04509	0	0.21059	0	0.03578
DTR	-0.0044444	0.48089	0.01098455	0.22093	0.01821397	0.08013	0.01837895	0.08164	0.00536638	0.5694	0	0.25666	0.01362491	0.11869	-0.0004454	0.97249	0	0.82406	0.00606061	0.01138	-0.0030912	0.66646
AvgTempMin	0.024	0.03712	0.02571429	0.03269	0.01970237	0.11079	0.00588235	0.55193	0.01034483	0.24736	0.00625	0.37903	0.01904762	0.08001	0.02857143	0.00217	0.021875	0.03461	0.00952381	0.5692	0.02727273	0.01443
AvgTempMax	0.02	0.12951	0.03802494	0.00294	0.02368421	0.04443	0.02	0.07042	0.012	0.20295	0.0175	0.19133	0.03138654	0.02236	0.016	0.20265	0.02093023	0.08292	0.01764706	0.20019	0.01981132	0.12493
PRCPTOT	0.56666667	0.34029	1.47058824	0.0523	1.57704571	0.02236	1.06363636	0.12377	0.3375	0.53592	1.38684211	0.0587	0.8	0.12377	0.4952381	0.31952	1.15	0.12173	1.77777778	0.0136	1.91212121	0.0026
TN10p	-0.13188	0.01425	-0.1465	0.01444	-0.0890762	0.13361	-0.033303	0.51801	-0.1252414	0.02135	-0.0686875	0.20194	-0.0803902	0.14175	-0.2544239	0	-0.1268186	0.03395	-0.1234703	0.12705	-0.1177143	0.02075
TN90p	0.05233333	0.24195	0.03434375	0.47002	0.07145424	0.28123	0	0.83345	0	0.97986	0	0.87303	0.05784211	0.28197	0	0.82664	0	0.8203	-0.056359	0.18873	0.06464706	0.16762
TX10p	-0.0915833	0.10181	-0.2098958	0.00051	-0.0814074	0.06336	-0.1114486	0.01655	-0.114964	0.02039	-0.1099	0.0536	-0.146232	0.00679	-0.0834748	0.09789	-0.114039	0.03251	-0.0999091	0.05892	-0.139506	0.04278
TX90p	0.03663333	0.42984	0.0407037	0.40086	0.11376164	0.08626	0	0.84026	0	0.95315	0.05495	0.32598	0	0.71207	0	1	0	0.62576	0	1	0.03529034	0.60498
R95p	0.14285714	0.83435	1.2	0.09598	1.47397726	0.02236	0.9	0.11387	0.81333333	0.2623	1.41399021	0.01777	0.9625	0.09106	0.32647059	0.56946	0.81041667	0.33189	0.8	0.18629	1.35652174	0.01329

Appendix 5: Boxplots showing the distribution of data in agroclimatic, corn, and soybean-specific extreme event indices in eastern Ontario ecodistricts in 1961-1985 and 1986-2010

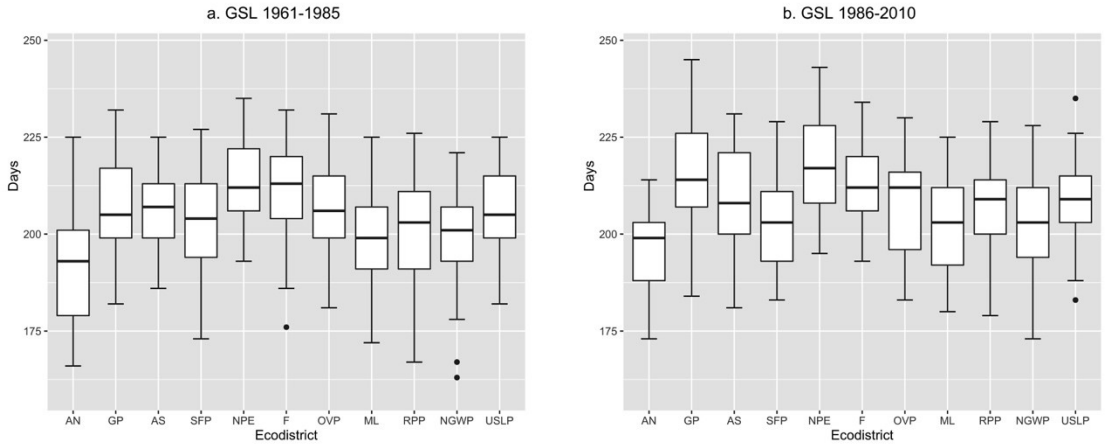

Figure 1: Data distribution in growing season length indicator in eastern Ontario ecodistricts in (a) 1961-1985 and (b) 1986-2010. Outliers are represented by dots and defined as values beyond 1.5*IQR of the hinge. Acronyms represent ecodistrict names as follows: AN – Algonquin North, GP – Glengarry Plain, AS – Algonquin South, SFP – Smith Falls Plain, NPE – Napanee-Prince Edward, F – Frontenac, OVP – Ottawa Valley Plain, ML – Muskrat Lake, RPP – Russell and Prescott Plains, NGWP – North Gower-Winchester Plains, USLP – Upper St. Lawrence Plain.

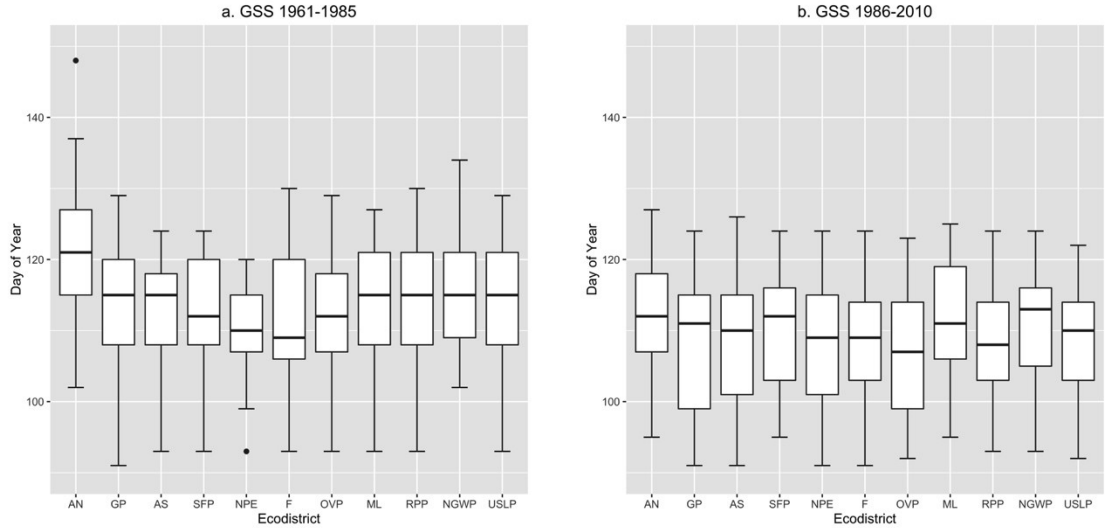

Figure 2: Data distribution in growing season start indicator in eastern Ontario ecodistricts in (a) 1961-1985 and (b) 1986-2010. Outliers are represented by dots and defined as values beyond 1.5*IQR of the hinge. Acronyms represent ecodistrict names as follows: AN – Algonquin North, GP – Glengarry Plain, AS – Algonquin South, SFP – Smith Falls Plain, NPE – Napanee-Prince Edward, F – Frontenac, OVP – Ottawa Valley Plain, ML – Muskrat Lake, RPP – Russell and Prescott Plains, NGWP – North Gower-Winchester Plains, USLP – Upper St. Lawrence Plain.

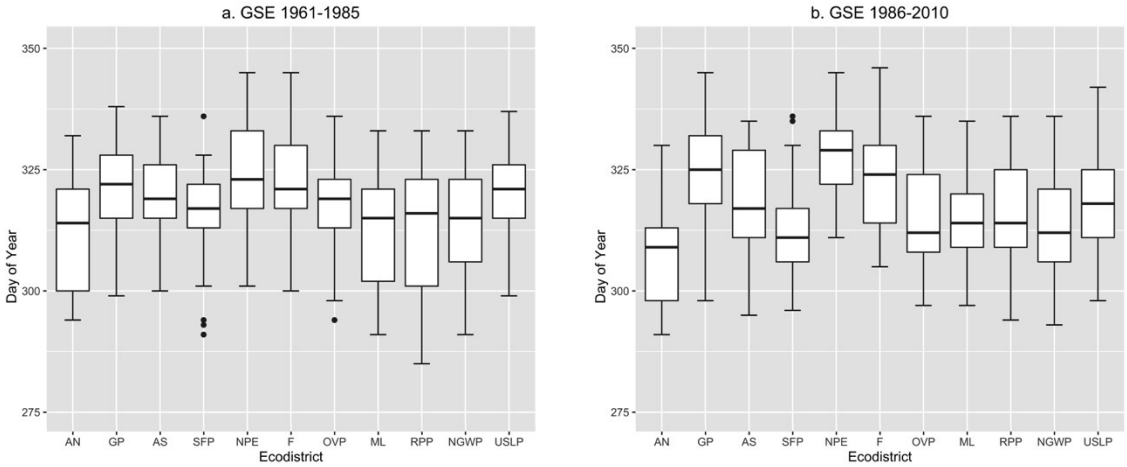

Figure 3: Data distribution in growing season end indicator in eastern Ontario ecodistricts in (a) 1961-1985 and (b) 1986-2010. Outliers are represented by dots and defined as values beyond 1.5*IQR of the hinge. Acronyms represent ecodistrict names as follows: AN – Algonquin North, GP – Glengarry Plain, AS – Algonquin South, SFP – Smith Falls Plain, NPE – Napanee-Prince Edward, F – Frontenac, OVP – Ottawa Valley Plain, ML – Muskrat Lake, RPP – Russell and Prescott Plains, NGWP – North Gower-Winchester Plains, USLP – Upper St. Lawrence Plain.

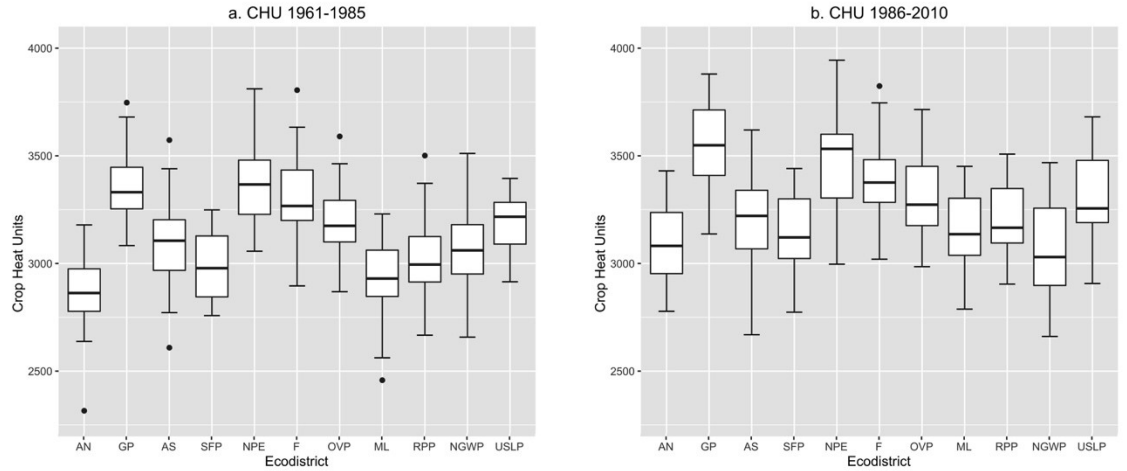

Figure 4: Data distribution in crop heat units indicator in eastern Ontario ecodistricts in (a) 1961-1985 and (b) 1986-2010. Outliers are represented by dots and defined as values beyond 1.5*IQR of the hinge. Acronyms represent ecodistrict names as follows: AN – Algonquin North, GP – Glengarry Plain, AS – Algonquin South, SFP – Smith Falls Plain, NPE – Napanee-Prince Edward, F – Frontenac, OVP – Ottawa Valley Plain, ML – Muskrat Lake, RPP – Russell and Prescott Plains, NGWP – North Gower-Winchester Plains, USLP – Upper St. Lawrence Plain.

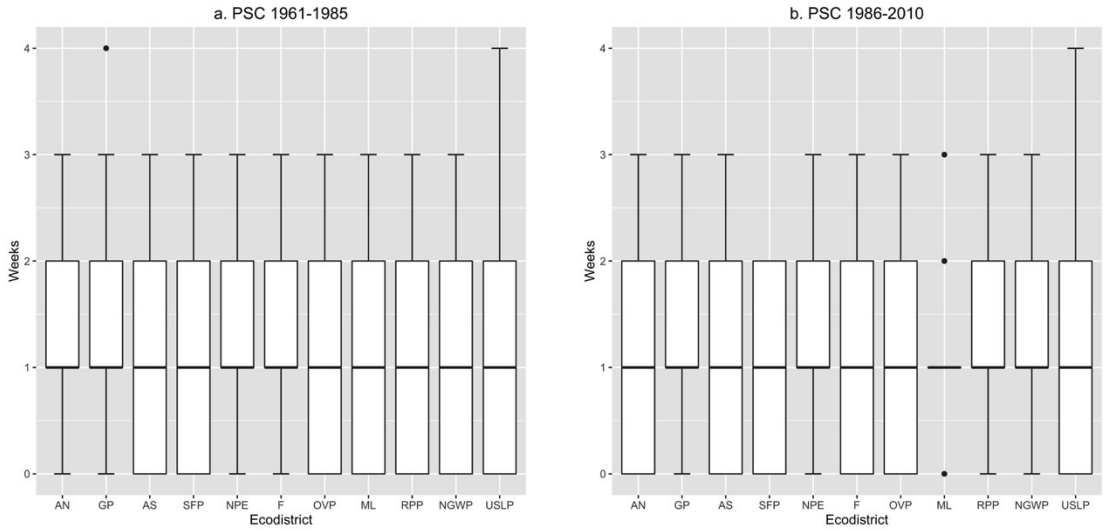

Figure 5: Data distribution in poor seeding conditions indicator for corn in eastern Ontario ecodistricts in (a) 1961-1985 and (b) 1986-2010. Outliers are represented by dots and defined as values beyond 1.5*IQR of the hinge. Acronyms represent ecodistrict names as follows: AN – Algonquin North, GP – Glengarry Plain, AS – Algonquin South, SFP – Smith Falls Plain, NPE – Napanee-Prince Edward, F – Frontenac, OVP – Ottawa Valley Plain, ML – Muskrat Lake, RPP – Russell and Prescott Plains, NGWP – North Gower-Winchester Plains, USLP – Upper St. Lawrence Plain.

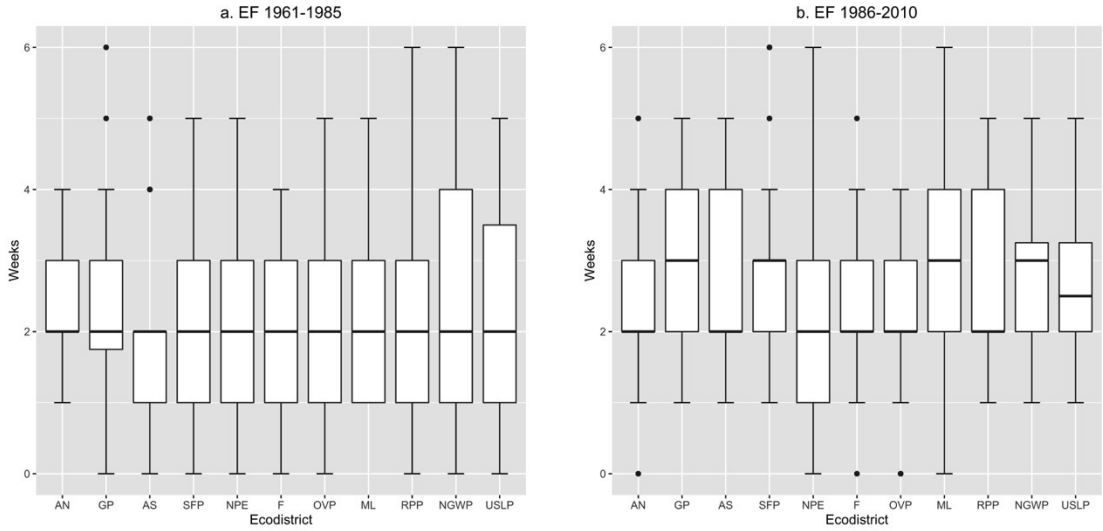

Figure 6: Data distribution in early flooding indicator for corn in eastern Ontario ecodistricts in (a) 1961-1985 and (b) 1986-2010. Outliers are represented by dots and defined as values beyond 1.5*IQR of the hinge. Acronyms represent ecodistrict names as follows: AN – Algonquin North, GP – Glengarry Plain, AS – Algonquin South, SFP – Smith Falls Plain, NPE – Napanee-Prince Edward, F – Frontenac, OVP – Ottawa Valley Plain, ML – Muskrat Lake, RPP – Russell and Prescott Plains, NGWP – North Gower-Winchester Plains, USLP – Upper St. Lawrence Plain.

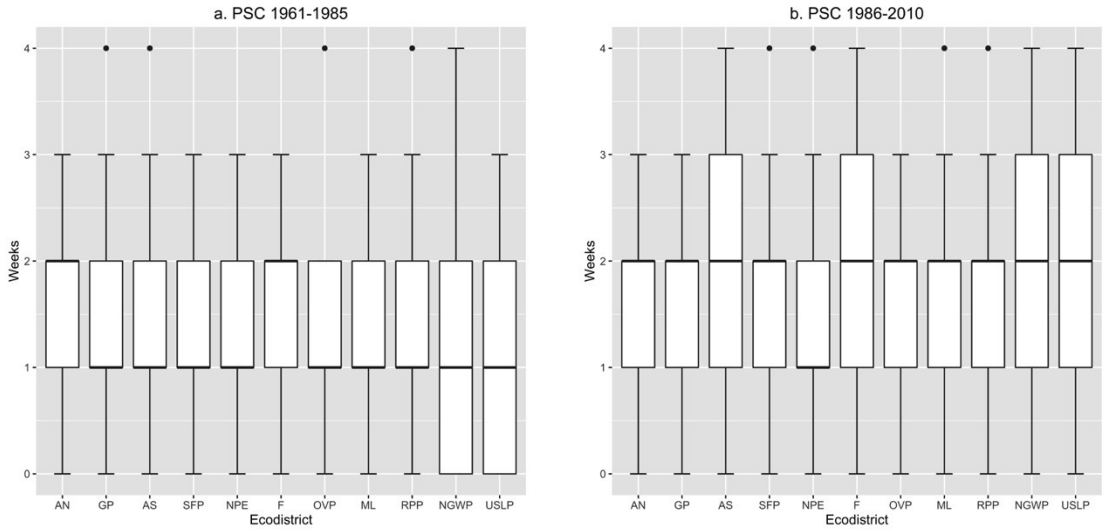

Figure 7: Data distribution in poor seeding conditions indicator for soybeans in eastern Ontario ecodistricts in (a) 1961-1985 and (b) 1986-2010. Outliers are represented by dots and defined as values beyond 1.5*IQR of the hinge. Acronyms represent ecodistrict names as follows: AN – Algonquin North, GP – Glengarry Plain, AS – Algonquin South, SFP – Smith Falls Plain, NPE – Napanee-Prince Edward, F – Frontenac, OVP – Ottawa Valley Plain, ML – Muskrat Lake, RPP – Russell and Prescott Plains, NGWP – North Gower-Winchester Plains, USLP – Upper St. Lawrence Plain.