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Water Use in Ontario's Greenbelt: A Foundation for Understanding the Costs and Benefits of Adaptation Measures During Water Shortages

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Water Use in Ontario's Greenbelt: A Foundation for Understanding the Costs and Benefits of Adaptation Measures During Water Shortages

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1. Executive Summary

The goal of this project was to understand the role agricultural producers in the Greenbelt can play in adapting to water scarcity and droughts resulting from climate change and a growing population. The objectives for the project were to assess the influence of agricultural adaptation measures in the context of regional water supply and evaluate the costs and benefits of agricultural adaptation measures related to water management within Ontario's Greenbelt.

The project involved three main components, each with their own methodology:

1. Water use predictions – this component focused on estimating the water use for a range of sectoral water users within the Greenbelt region to provide the important water use context from a diverse cross-section of sectoral water users. Where possible, this water use context also explored the impact of drought conditions on water use (i.e. in the context of municipal / domestic water use). These water uses were also projected under future population and economic growth conditions.
2. Improving regional water supply – this component of the approach focused on implementing a crop model to explore the impact of agricultural adaptation practices on crop production and an overall crop water budget, including changes in ground water recharge. The outputs of the model explore the implications of crop water conditions and yields with and without the use of agricultural adaptation practices under several drought scenarios.
3. Cost-benefit analysis – this component of the project was an exploration of the costs and benefits associated with the modelled outcomes above. Changes in yield were processed and net benefits associated with the use of soil health practices were analyzed along with how they vary depending on drought conditions.

To evaluate the effects of climate and adaptation actions on crop yield, water use, and water supply, we constructed four drought scenarios and one adaptation scenario. These scenarios offer insight into the effects of drought and adaptation on water use and supply.

The study results can be summarized as follows:

- There is significant water use pressure within the Greenbelt region. The results indicate that during drought conditions the total water use increases. In addition, population growth translates into increased water use. The findings demonstrate that municipal water use will increase as populations grow within the study area, and if drought conditions become more frequent, water demand will put additional pressure on the water supply. The impact of increased water use is variable across the Greenbelt region.
- Since 94% of the agricultural lands (~345,000 ha) in the Greenbelt are composed of non-irrigated crops, these lands offer opportunity for water containment, groundwater recharge, and thus replenishment of the supply of water for other agriculture and non-agriculture uses.

- The crop modelling lays the foundation for more detailed future modelling work and demonstrates the implications of using adaptation measures to help adapt to drought conditions and improve contributions to ground water supply.
- The cost-benefit analysis results indicate that the use of soil health practices does not guarantee a cost-effective solution to adapting to drought conditions, but rather the effectiveness of these practices in relation to drought (both from a production and cost perspective) depends on location specific conditions. In some cases, it can be highly beneficial. For example, under the baseline (i.e. non-drought) conditions, there were 973 locations where soil health practices improved production for a total net benefit of $7.0 million. Under the lower drought scenarios, less locations exhibited a net benefit (358 and 370 locations with a net benefit of $3.0 and $3.1 million, respectively). Under the most severe drought modelled, a total of 1,703 locations exhibited a positive net benefit from the use of soil health practices, for a total net benefit of $3.2 million. Of the areas that exhibited a positive net benefit from the use of soil health practices, the average benefit was $8.41 per ha under baseline conditions, $3.75 per ha during a D0 drought, $3.77 per ha during a D1 drought, and $5.77 per ha during a D2 drought.

Given the wide number of actors and factors affecting water takings, the report includes several suggestions for future research related to water management in the Greenbelt.

2. Introduction

Climate change models predict less frequent and more intense rainfall events in Southern Ontario. These changes will adversely affect water flow rates in streams and rivers in the region and subsequently the quality (e.g., due to in-stream and overland erosion) and quantity (e.g., due to increasing severity of drought conditions) of water resources. The increasing fluctuations in rainfall events, in combination with population growth and increased water use, are likely to result in a rise in water scarcity. While the majority of the water withdrawals in the Greenbelt (including all the major municipalities and industries) come directly from the Great Lakes and are therefore less vulnerable to climate change impacts and drought (and hence excluded from this study), rural, agricultural and inland municipalities and industries are vulnerable to climate change impacts and water shortages. Indeed, recent indicators for Canada corroborate this trajectory and suggest that sub-drainage areas in Southern Ontario have medium to high levels of threat to water availability.[1]

Among sectors in the region using water, agricultural irrigation represents less than 1% of the volume of withdrawals but has the highest consumptive use coefficient (85% of the water withdrawn for agricultural irrigation is transpired and not returned to the system).[2] Inefficiencies in water use in one sector can reduce the availability of water for other sectors and competition for water use between sectors can ensue (e.g., residential versus industrial versus agricultural) when water resources are shared. It can be argued that agriculture is the most vulnerable sector, as the periods of greatest agricultural demand (i.e., July and August) coincide with high potential for drought conditions, which exacerbate the constraints, and therefore costs, imposed on all water users.

This project began to examine regional water use dynamics in Ontario's Greenbelt to better understand water use trade-offs during periods of drought in the region. Specifically, the project sought to understand the role agriculture producers can play from an adaptation perspective in the context of increasing droughts and water scarcity resulting from climate change and a growing population. The objectives for the project were to assess the influence of agricultural adaptation measures in the context of regional water supply and evaluate the costs and benefits of agricultural adaptation measures related to water management within Ontario's Greenbelt.

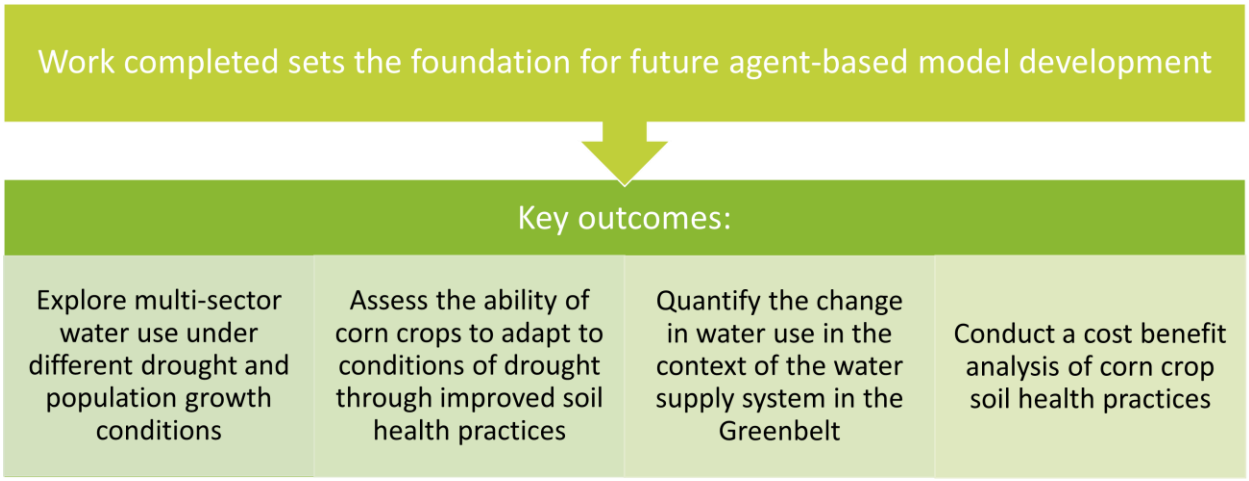
One of the major goals of the project was to set the foundation for developing an agent-based modelling framework – a framework that can be used to represent individual on-farm decision making and their collective impact on water resources across Southern Ontario. While multiple aspects of the work presented within this report will contribute to this framework, the critical developments involved the processing of permit to take water data and the implementation of a crop model. Future work can take these foundations

[1] https://www.canada.ca/en/environment-climate-change/services/environmental-indicators/water-availability.html

[2] http://waterbudget.ca/consumptiveuse

and build in heterogenous agricultural decision-making to investigate how individuals and regions differentially respond to water use constraints due to climate and policy outcomes. In addition to laying this foundation, key outcomes of this project are summarized in Figure 1.

Figure 1: Overview of key project outcomes

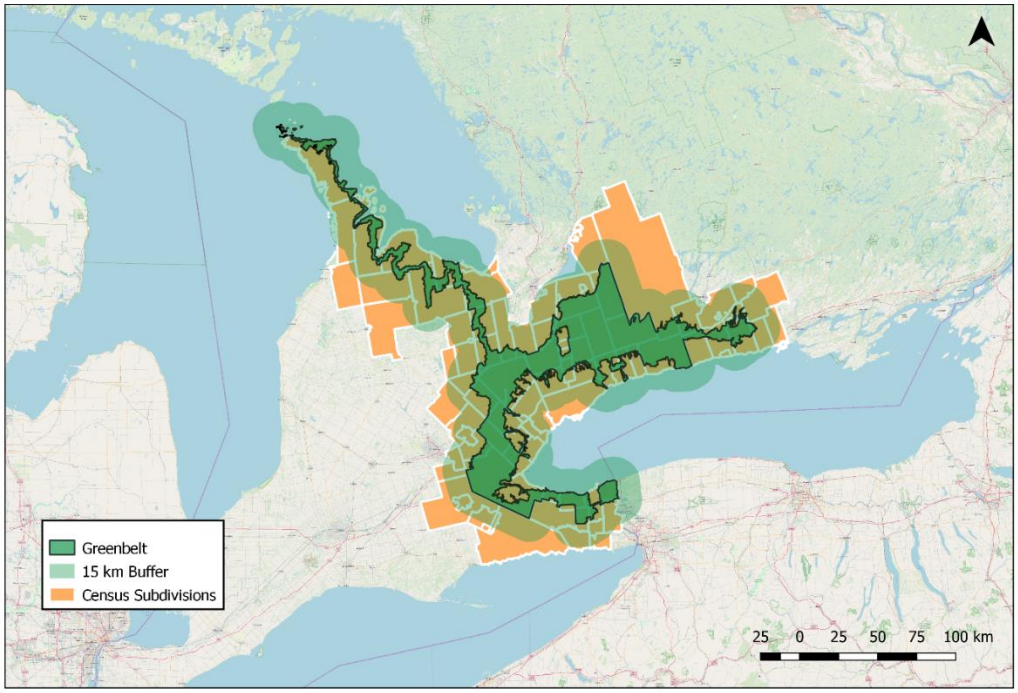


3. Study Area

The study area for this project is Ontario's Greenbelt, which is in the Greater Golden Horseshoe. The Greenbelt, and more broadly the Greater Golden Horseshoe, faces environmental challenges related to water quality and quantity. At the same time, the Greenbelt is located within one of the fastest growing regions in North America. The population of the Greater Golden Horseshoe is expected to grow by 4 million people by 2041, putting additional strain on water resources in the region and reducing water availability across all sectors. Currently, 9.2 million people live within 20 kilometres of the Greenbelt's boundaries. The Greenbelt itself is composed of 2 million acres (816,074 hectares) of permanently protected land. Approximately half of the Greenbelt is agricultural land, over one third is forests, wetlands, lakes and rivers, and the remainder is rural communities. The Greenbelt contains 25% of all irrigated farmland in Ontario (and 6% of the total farmed area).

To define the study area for this assessment, a 15km buffer was placed around the boundary of the Greenbelt. Because a number of the data source are organized by census boundaries, and there are significant edge effects from the influence of water supply and demand within and outside the Greenbelt boundary, the study area was defined as all census subdivisions (CSDs) intersecting the 15km buffered area. The study area thus encompasses the area of the Greenbelt as well as the area of the surrounding CSDs (Figure 2).

Figure 2: Location and extent of Ontario's Greenbelt and the defined study area



4. Approach

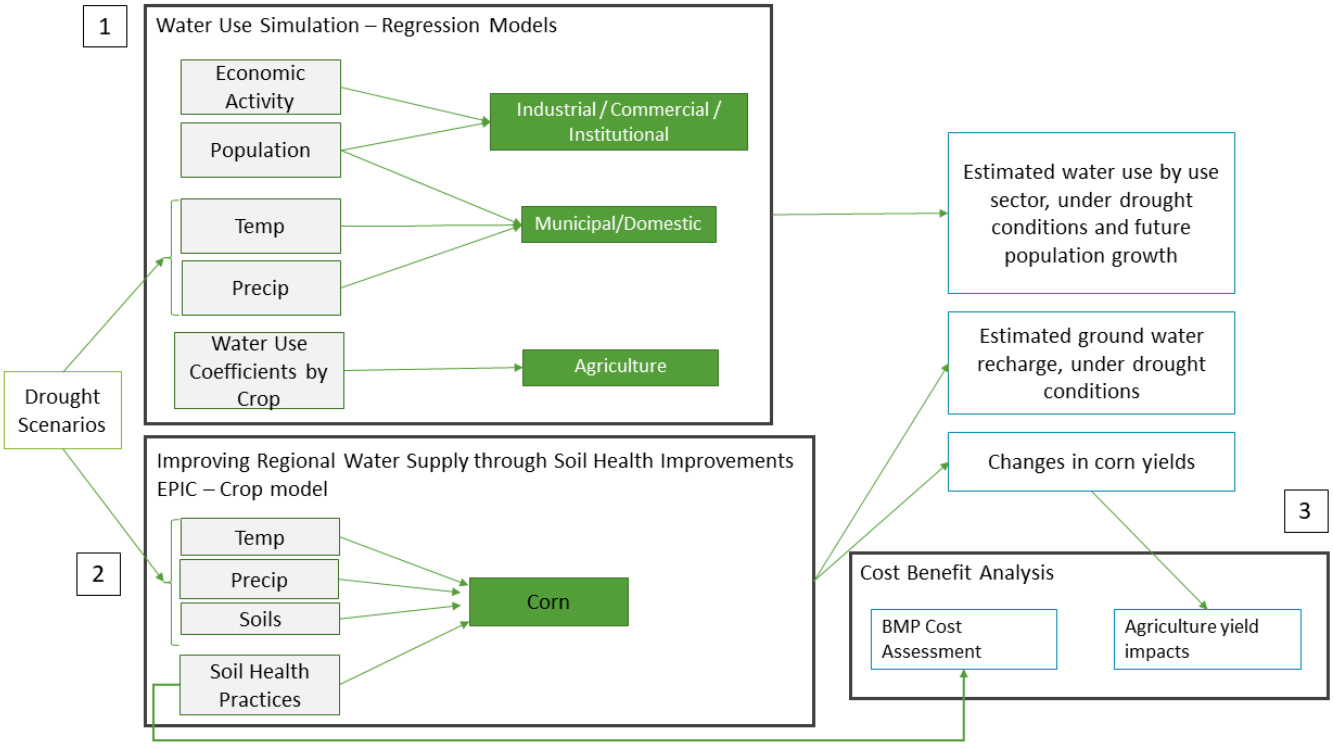
The complex nature of the hydrological system and human activities necessitated the use of several different methods to estimate water use and address the project objectives. To gain a better understanding of the role of different sectors on water demand under differing climate conditions, water use predictions were made by different sectors comprising industrial/commercial/institutional, municipal, and domestic use, and agricultural. To assess the benefits and trade-offs associated with soil health improvements to enhance the regional water supply, drought scenarios were applied in a crop model. This section of the report provides an overview of the methods, data, and scenarios employed to achieve the project objectives.

4.1 Approach Overview

The project involved three components: water use predictions, improving regional water supply, and cost-benefit analysis (Figure 3) as follows.

1. Water use predictions (Box 1 in Figure 3) – focuses on estimating the water use for a range of sectoral water users within the Greenbelt region. The objective of this component of the research was to provide the important water use context from a diverse cross-section of sectoral water users. Where possible, this water use context also explored the impact of drought conditions on water use (i.e. in the context of municipal / domestic water use). These water uses were also projected under future population and economic growth conditions.
2. Improving regional water supply (Box 2 in Figure 3) – focuses on implementing a crop model to explore the impact of agricultural adaptation practices on crop production and an overall crop water budget, including changes in ground water recharge. The outputs of the model explore the implications of crop water conditions and yields with and without the use of agricultural adaptation practices under several drought scenarios.
3. Cost-benefit analysis (Box 3 in Figure 3) – this component of the project was an exploration of the costs and benefits associated with the modelled outcomes determined from item #2 (above). Changes in yield were processed and net benefits associated with the use of soil health practices were analyzed along with how they vary depending on drought conditions.

Figure 3: Overview of the modelling framework



Part 1 of our modelling framework focused on the water demand side of the water budget, while Parts 2 and 3 focused on the water supply side of the water budget. While both sides of the water budget are addressed in some way, it is important to know they were not formally integrated in this project. However, the presented framework and completed work serves as an important foundation for future model developments that will continue to increase in complexity (see Section 5.2 for a more detailed discussion of future research objectives) and seek to integrate our representation of water supply and demand.

4.2 Data

The research used a variety of data, including soil data, climate data and land use and land cover data. Table 1 summarizes some of the key data that was collected and processed for this project. The following subsections provide additional details on specific data items.

Table 1: Summary of relevant data

Dataset	Source	Summary (within study area)
Water Taking Permit Locations	Ontario PTTW Database (https://www.javacoeapp.lrc.gov.on.ca/geonetwork/srv/en/metadata.show?id=13665)	**# of Permits** Municipal: 829 Commercial: 1998 Construction: 1131 Industrial: 506 Aggregates: 407 Agriculture: 319
2014 to 2017 Reported Actual Daily Water Taking	Data obtained through Conservation Authority partners	Water taking in litres for various water taking permit locations.
Weather Stations & Historical Data	Environment and Climate Change Canada (http://climate.weather.gc.ca)	An R Statistical Programming script was developed to identify weather stations in Ontario with consistent daily reporting between 2013 and 2017. A total of 27 applicable stations were identified. Using R, the daily weather data for each of these stations was extracted.
Dissemination Area (DA) Population	Statistics Canada – GeoSuite 2016 (http://geosuite.statcan.gc.ca/geosuite/en/)	**Complete DA only**[3] Count: 9,574 DAs 2016 Population count: 7,158,179 2016 Private Dwelling count: 2,747,036 **Complete DA + Allowance of Partial DAs**[4] Count: 10,071 DAs 2016 Population count: 7,516,462 2016 Private Dwelling count: 2,896,914
Census Subdivision (CSD) Population	Statistics Canada – GeoSuite 2016 (http://geosuite.statcan.gc.ca/geosuite/en/)	**Complete CSD only**[5] Count: 27 CSDs 2016 Population count: 2,782,340 2016 Dwelling count: 940,456 **Complete CSD + Allowance of Partial CSDs**[6] Count: 84 CSDs 2016 Population count: 8,306,440 2016 Private Dwelling count: 3,231,310
Gridded 10 km Canada Daily Temperature and Precipitation	Landscape analysis and application section (LAAS), Great Lakes Forestry Centre (GLFC), Canadian Forest	Resolution: Daily resolution at 10 km grid, 2012-2017

[3] For DAs where the entire DA is within the study area
[4] For DAs that intersect with the study area but have some area outside of it
[5] For CSDs where the entire CSD is within the study area
[6] For CSDs that intersect with the study area but have some area outside of it

Dataset, ANUSPLIN V4.5 Model	Service (CFS) and Natural Resources Canada (NRCAN)	Variables captured: min and max temperature, total precipitation, mean precipitation
Annual Crop Inventory Data (AAFC 2017)	https://open.canada.ca/data/en/dataset/ba2645d5-4458-414d-b196-6303ac06c1c9	Summarized in 5.1.3
Labour Force (2016)	Source: Statistics Canada Catalogue no. 98-316-X2016001.	In Labour Force Total: Aggregates: 4645 Commercial: 555,820 Construction: 223,675 Industrial: 224,720
Canada Drought Monitoring (CDM)	Agriculture and Agri-Food Canada https://open.canada.ca/data/en/dataset/292646cd-619f-4200-afb1-8b2c52f984a2	The CDM is a composite product developed from a wide assortment of information that identifies drought designated areas for Canada.
Detailed Soil Survey	Agriculture and Agri-Food Canada https://open.canada.ca/data/en/dataset/7ed13bbe-fbac-417c-a942-ea2b3add1748	A soil survey is an inventory of soils and their spatial distribution over a landscape. Soil survey reports contain two parts. The first part is a soil map or series of maps at a particular scale with coding for each soil. The second part is a suite of attributes that describe the soil characteristics in each mapped unit.

4.2.1 Permit to Take Water

In the province of Ontario, water taking permits (known as “permits to take water”, or “PTTW”) are required for any user who takes more than 50,000 litres of water per day. If this threshold is exceeded for even one single day over the course of the year, a permit is required. However, users who do not breach this threshold do not require a permit.

The permits reflect the maximum allowable amount of water that can be taken, which is potentially different from the actual amount of water taken on any given day (https://data.ontario.ca/dataset/permit-to-take-water). Users are required to report the amount of water they take from the system daily.

Water taking data is organized by water taking purpose and sub-purpose category, these are shown in Table 2.

Table 2: Permit to Take Water Categories

PTTW Purpose Category	PTTW Sub-purpose Category
Industrial*	Aggregate Washing Brewing and Soft Drinks Cooling Water Food Processing Manufacturing Other – Industrial Power Production
Water Supply	Campgrounds Communal Municipal Other – Water Supply
Commercial*	Aquaculture Bottled Water Golf Course Irrigation Mall/Business Other – Commercial Snowmaking
Dewatering	Pits and Quarries Other – Dewatering
Dewatering Construction	Construction
Miscellaneous	Dams and Reservoirs Heat Pumps Pumping Test Other – Miscellaneous
Recreational	Aesthetics Wetlands Other – Recreational
Remediation	Groundwater Other – Remediation
Construction	Road Building Other – Construction
Institutional	Schools
Agricultural	Field and Pasture Crops Fruit Orchards Market Gardens / Flowers Nursery Sod Farm Other – Agricultural
Remediation	Groundwater Other Remediation

*In some cases, industrial and commercial sources may be captured under municipal water supply

In Ontario, the PTTW database contains the permit, source and date of water taking. A separate file contains the spatial locations, categories, client names and other information related to the water taking. To perform calculations and divide these data into categories, these two sources of data were reconciled.

Actual 2017 water takings by purpose category (the categories used in granting water permits) in the study area is presented in Table 3. The majority of water taking is from the industrial sector (93.5%), followed by water supply and commercial purposes.

Table 3: Total Water Taking (m3) for 2017 within the Greenbelt study area by PTTW Categories

PTTW Purpose Category	Total Water Taking	Percent of Total
Agricultural	7,489,000	0.04
Commercial	55,564,000	0.30
Construction	340,000	0.00
Dewatering	53,398,000	0.29
Dewatering Construction	10,481,000	0.06
Industrial	17,346,029,000	93.51
Institutional	1,064,000	0.01
Miscellaneous	10,354,000	0.06
Recreational	2,009,000	0.01
Remediation	1,765,000	0.01
Water Supply	1,062,045,000	5.73

4.2.2 Weather Data

Weather data were gathered through multiple sources throughout this study. Weather station data was downloaded using the R libraries *weathercan* and *rclimateca* for the period 1990-2018. Weather stations allow for a longer historic record of weather conditions that can be used to calculate various indices related to drought and longer climatic indices. Initially, models were created for each water taking point based on the *nearest* weather station. Unfortunately, the weather station data had many inconsistencies, especially in 2014, which lead to erroneous relationships. Further, not all weather stations were consistent and some permits may have the same weather station despite being located in areas where local weather conditions would vary.

After exploring the discrepancies with the weather station data, a gridded 10 km dataset (described below) was chosen. This allowed us to extract more information for each CSD and permit location.

Gridded 10 km Canada Daily Temperature and Precipitation Dataset, ANUSPLIN V4.5 Model:

- Data source: Landscape analysis and application section (LAAS), Great Lakes Forestry Centre (GLFC), Canadian Forest Service (CFS) and Natural Resources Canada (NRCAN)
- Resolution: Daily resolution at 10 km grid, 2012-2017
    - Variables captured: min and max temperature, total precipitation, mean precipitation

The daily gridded weather is pre-processed, interpolated, and checked for data quality by NRCAN**.** This dataset was chosen to reduce the error and time that would be required to interpolate daily weather station data across the Greenbelt area.

4.3 Estimating Water Taking for the Greenbelt

The methods used for municipal, commercial, construction, industrial and aggregate, and agricultural water takings are described below.

To process the PTTW data into water taking for the Greenbelt, and actual water extractions from the system, the following data cleaning steps were taken:

- Source IDs that contained phrases like: “treatment plant”, “power” and “hydro” were removed
- Some Source IDs contained white spaces or new line characters, or other data entry/database errors and could not be joined to the water takings directly. An additional data processing step to remove all new line characters and spaces was used so that these could be joined correctly.
- There were duplicate points contained in the database with the same information, in these cases a point was randomly selected from the duplicates to be used in further analysis.
- In some cases, points could not be matched directly to the permit data due to inconsistency between the two datasets (e.g. missing “source number” in water taking points or no corresponding permit in the point data). In these cases, the water taking could not be matched to a specific point or location and was excluded. In other words, for these data, there was no way of determining if the water taking was within or outside the Greenbelt or where in Ontario the permit was granted.
- For each year within the study period, there was a lack of consistency in the database schema. This led to some difficulties in joining the PTTW to the actual water taking data. For instance, when SOURCE_NUMBER was introduced into the water taking data, this added complications to any calculation, since the SOURCE_NUMBER could not be properly allocated to water taking points. Therefore, any calculations with the same PERMIT ID and SOURCEID had to first have all SOURCE_NUMBERS summed and allocated to the single water taking

point. Additionally, the date formats used between years was not always consistent.

- The daily water taking data usually only contains values of water taking for the date in the database, rarely is there a “zero” value and an attributed date. For exploring daily relationships and/or models, all water taking permits were assigned a value of “zero” on days where no water taking was recorded.
- A spatial intersection of the study area (Greenbelt + 15km buffer) for all CSDs that intersected with the buffer was performed.

Once the above data cleaning and consistency check were completed, the data was divided into six water taking categories:

1. Municipal
2. Industrial
3. Construction
4. Aggregates
5. Commercial
6. Agriculture

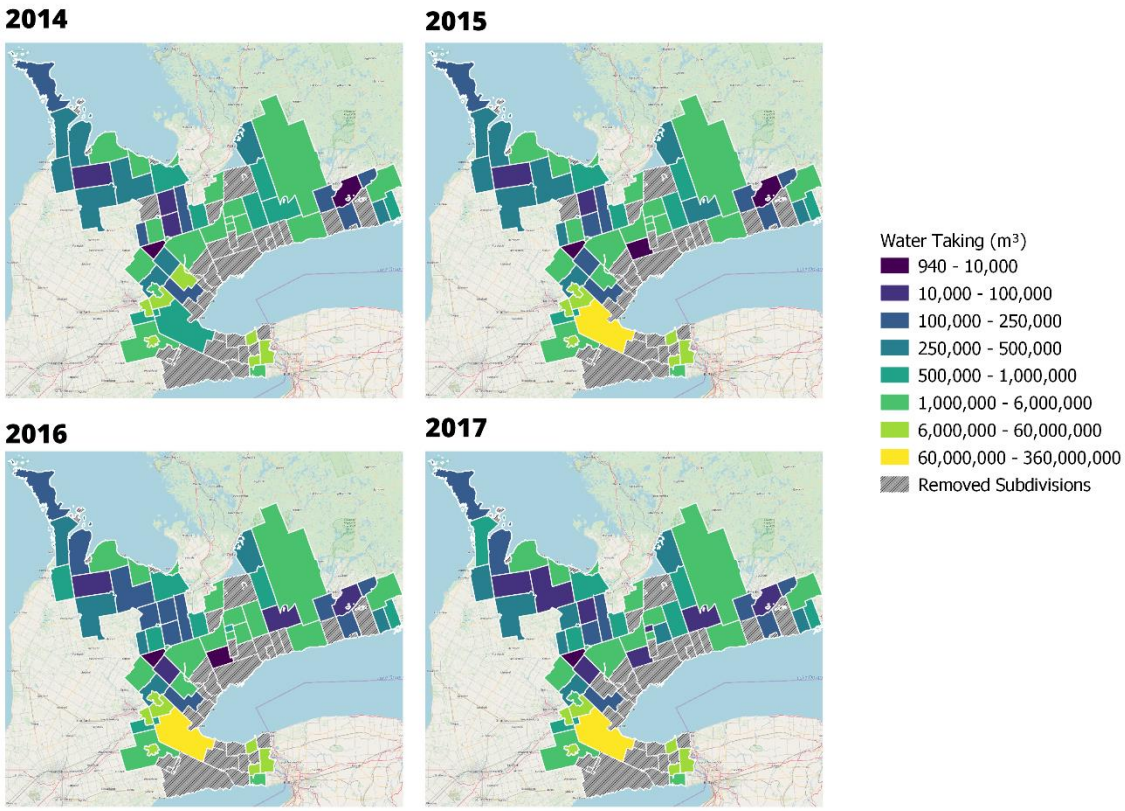
The categories were further divided into those relevant to the study, which included Aggregates, Agricultural, Commercial, Construction, Industrial and Municipal. For Aggregates, sub-categories including “aggregate washing”, “Pits and Quarries” and “Other – Dewatering” were included. Construction contains “Construction” and “Dewatering Construction.” Municipal includes “Water Supply” and sub purposes in “Municipal”. The rest of the study categories (Industrial, Commercial and Agriculture) followed the PTTW categories (including all their sub-categories). All other categories that did not fit these criteria were not included in this analysis.

4.3.1 Municipal Water Taking

The objective of this portion of the analysis was to develop regression equations that could be used in a modelling framework to predict how weather variables might influence municipal water taking within the study area.

Municipal water taking totals for the study period (Figure 4) based on the PTTW data varies by completeness and type of CSD. The data presented in Figure 4 was further reduced in our scenario analysis to remove CSDs that had 100% of their water derived from a lake source, however all available data is reported here. There are some CSDs that are missing data in some years of our study period. It is possible that the data cleaning process removed some of these permits, that reporting changed in a given year, or that one CSD may have its municipal water supplied by another adjacent CSD.

Figure 4: Municipal Water Taking totals for each CSD over the study period, note some subdivisions are missing data (shown in grey stripes) in 2014, 2015 (Melancthon) and 2017 (Halton Hills).



Using the cleaned PTTW data, time-series-based regression equations were developed for each CSD based on their monthly total water taking (i.e., the dependent variable). The goal of the regression analysis was to explore the role weather variables play in determining aggregate monthly water taking from 2014 to 2017 (the years for which actual water taking data was available). To that end, independent variables were defined as season, total precipitation, and maximum temperature. The regression can be represented as follows:

$$\textit{Water Taking} = \alpha + \beta_{1\ season} + \beta_{2\ Total\ Precipitation} + \beta_{3\ Maximum\ Temperature} + \varepsilon$$

Where:

- Water taking – total reported municipal water taking by month from January 2014 to December 2017[7]
- Season

[7] Total monthly water taking by CSD was determined by summing the daily reported water taking for all permits located with the CSD. The main caveat to this approach is that not all water taking locations within a CSD are accurate and these locations may not be where the water will be used/stored.

    - Winter: December, January, February
    - Spring: March, April, May
    - Summer: June, July, August
    - Fall: September, October, November
- Precipitation – total precipitation
- Maximum Temperature – highest reported temperature within a CSD

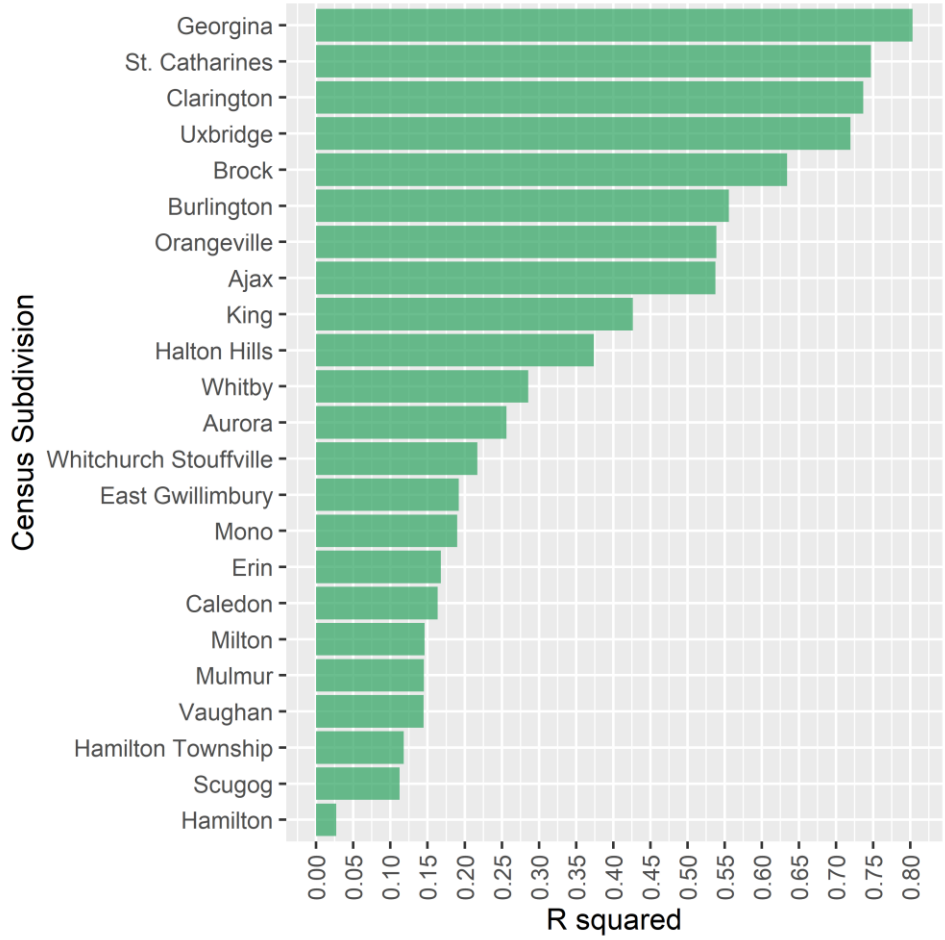
Daily gridded weather data was aggregated to a monthly scale and the entire CSD polygon was used to extract values such as: minimum temperature, maximum temperature, total precipitation, maximum precipitation, and average precipitation. Additional variables were explored as well (e.g. population). However, these variables did not contain enough variation over the 4-year period to improve the models.

To establish the relationship between water taking and climate variables, several modelling approaches were explored, specifically:

1. Linear regression
2. Fixed effects model
3. Random effects model
4. Pooling for random effects
5. Splm models
6. ARIMA Models
7. Classification Regression Trees
8. Individual regression models for each CSD area

The difficulty with some of these approaches is that there are limitations in terms of developing models for prediction and scenario analysis. For example, an ARIMA model may be better suited for time series data, but it cannot be used for prediction of scenarios in our case, as ARIMA models will predict into the future based on the data contained in the model. Through this model selection process, a “one size fits all” model was determined to be unreasonable. Instead, a nested modelling approach was used so that a regression model was fitted to each individual CSD. The benefit of this approach is that each CSD can be examined in detail using a simplistic model that can be built upon in the future. There are 94 CSDs that intersect the 15 km buffer. To scope the number of CSDs to a reasonable number for the regression analysis, only the CSDs with more than 50% of their area in the Greenbelt are discussed here. Results for all CSDs are contained in Appendix A – Model Coefficients and Significance by CSD. The regression models had varying degree of success capturing the water taking trends. This is demonstrated in Figure 5, which provides a summary of the R^2 results for the nested models.

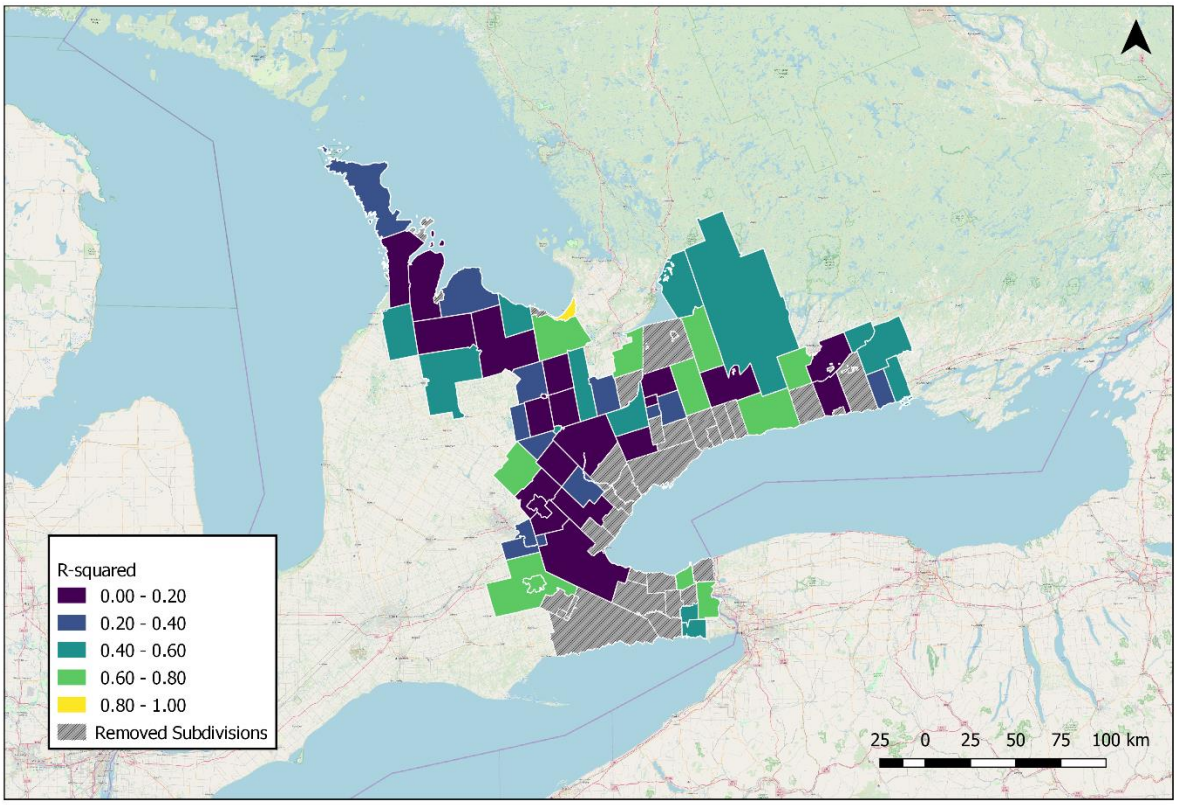
Figure 5: R squared for CSDs



R-squared values range from 0-1. They demonstrate the degree of model fit for any give CSD. A high R-squared value indicates that the chosen independent variables and regression model is a “good fit”. However, it is worth noting that R-squared values need to be interpreted in the context of other model diagnostics for a comprehensive assessment of model fit. A high R-squared value is simply one metric to be evaluated against. It has the potential to have exaggerated values, which indicate an “over-fit” model. Models that are over-fit may have high R-squared values but perform poorly when used for predictions.

The CSDs with high R-squared values are Georgina, St. Catharines, Clarington, Uxbridge and Brock (Figure 6 shows the spatial distribution of the CSDs). Brock and Uxbridge are adjacent communities and monthly water takings exhibit a similar shape and pattern. Clarington and Georgina are also adjacent to each other and exhibit a similar shape. St. Catharines has a larger monthly water taking than the other four CSDs. The subdivisions with high R-squared values also have significant climate variables.

Figure 6: Spatial distribution of the R squared by CSD



For the CSDs with lower R-squared values, there are a few potential contributing factors. For instance, in Hamilton, Scugog, Vaughan and Halton Hills there were data quality issues with one year of data having drastically different water taking values.

In Hamilton, the model performed markedly worse in the year 2014, which may be due to a potential data entry error or a change in permits for years after 2014. For instance, yearly totals of water taking increased markedly for three years after 2014. Additionally, the R-squared and adjusted-r-squared values are very low for Hamilton which indicates that this model is not appropriate for the data.

In Figure 7, the residuals represent the variation left unexplained by the model. If there is an underlying pattern with the residuals, it may indicate an inappropriate model. A good model will typically show a normal distribution around zero, any large deviation from zero indicates areas where the model may be mis-specified. For example, Ajax, Burlington, St. Catharines, Whitby and Hamilton show a large amount of variation.

Figure 7: Model Residuals for each CSD

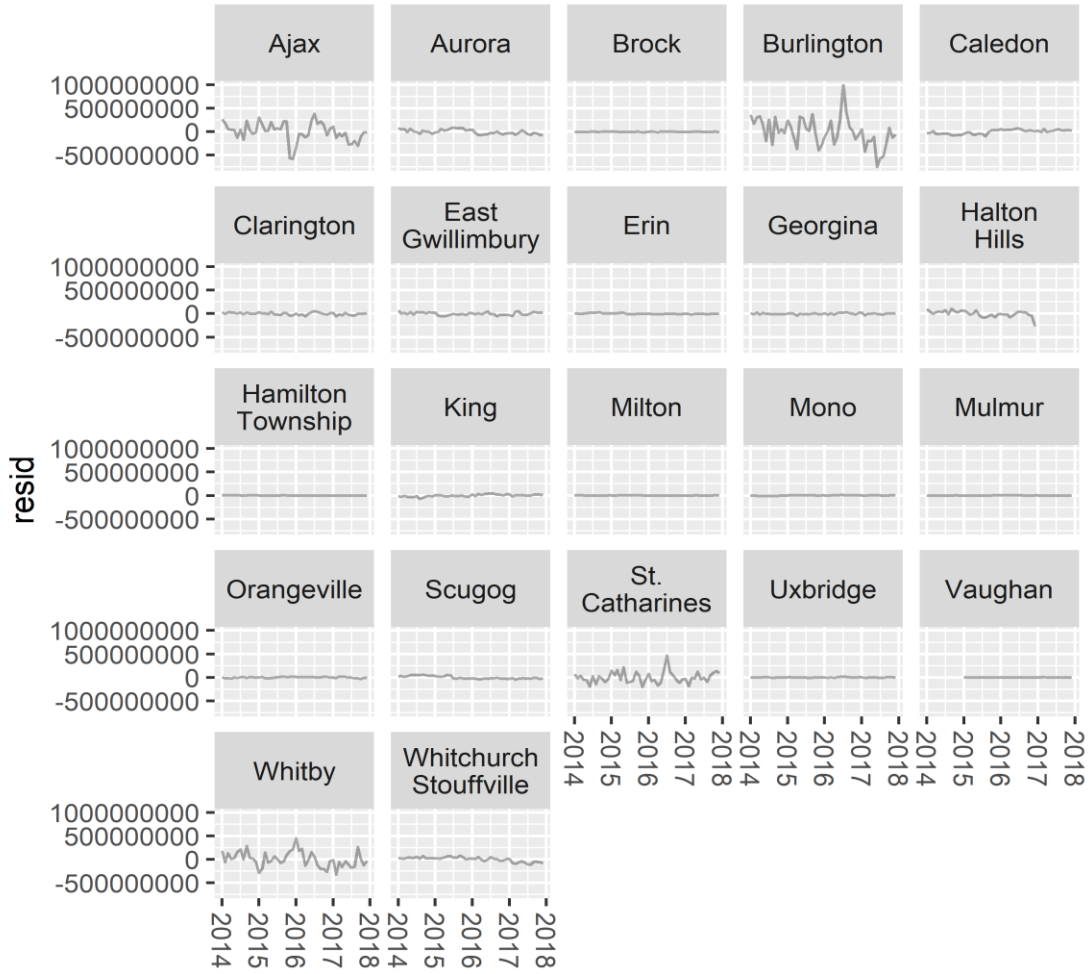
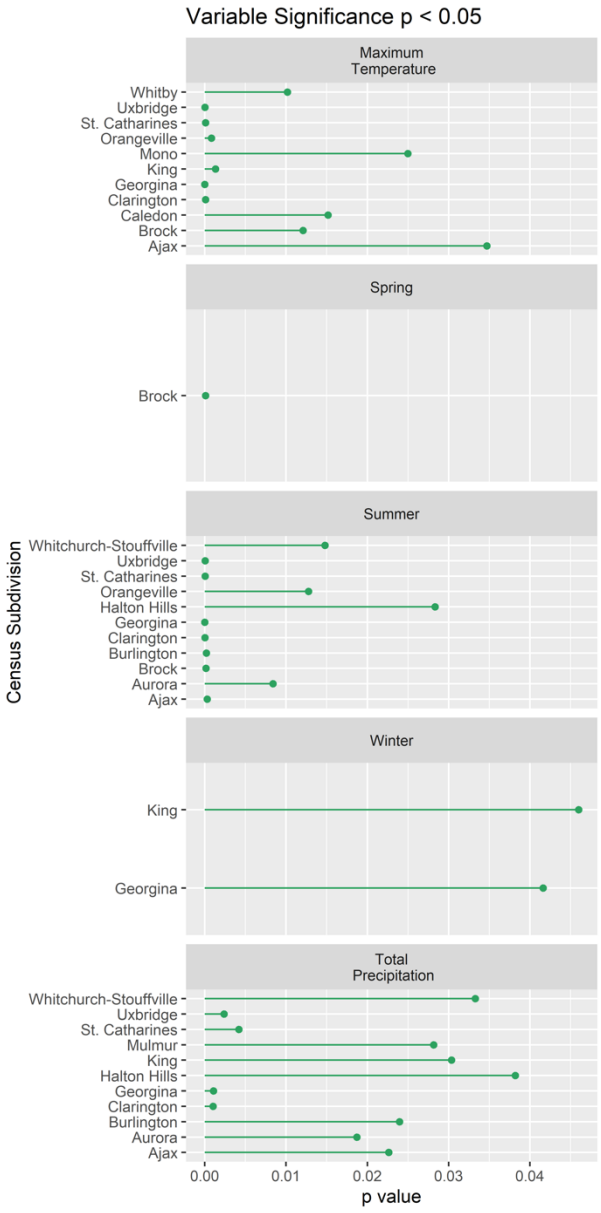


Figure 8 shows the results of variable significance for each CSD. For P-values less than 0.05, these variables are statistically significant predictors of water taking for that CSD. Smaller p-values (or smaller bars in Figure 8) indicate increased significance. For most CSDs, the summer season was significant. However, for Brock, spring was significant and for King[8] and Georgina[9], the winter was significant.

In some cases, smaller townships may have their water provided by a larger municipality. For example, “York Region supplies water to its nine local municipalities. They collect, treat, store and distribute water to the Towns of Aurora, East Gwillimbury, Georgina, Newmarket, Richmond Hill, Whitchurch-Stouffville, the Township of King and the Cities of Markham and Vaughan.”[10]

[8] For context: https://www.yorkregion.com/news-story/6251857-king-township-passes-new-water-wastewater-rates/
[9] For context: https://www.yorkregion.com/news-story/5532539-georgina-be-prepared-to-spend-more-on-water-sewer-service/
[10] https://www.yorkregion.com/news-story/5532539-georgina-be-prepared-to-spend-more-on-water-sewer-service/

Figure 8: Variable Significance at p < 0.05 for CSDs



Generally, municipal water taking increases in summer months (although not all CSDs exhibit an increase in water taking in the summer – e.g. Aurora, Scugog and Hamilton). In terms of model significance, the summer months are significant for 11 CSDs within the study area. Additionally, the climatic variables maximum temperature and total precipitation were also significant for 11 CSDs.

This modelling approach indicates that for a given CSD within the Greenbelt, some models fit the CSD reasonably well, while for others, there may be additional factors that contribute to municipal water use that are not captured in the regression models (e.g. lower thresholds of water use, water being transferred to different municipalities, and voluntarily water use restrictions).

4.3.2 Commercial, Construction, Industrial and Aggregate Water Taking

For non-agricultural sectors, an average water use intensity factor per employee for commercial, industrial, construction, and aggregate water was developed. These intensity factors were used to approximate how water taking might increase in response to economic and population growth.

Intensity factors were determined for each CSD by dividing the total water taking in each sector by the number of employees working in that sector as reported by North American Industrial Classification System (NAICS) code. To do this, Aggregates, Industrial, Construction and Commercial water taking categories were matched to their closest NAICS codes and grouped according to Table 4.

Table 4. Assumed linkage between water taking categories and NAICS sector

Water Taking Category	**NAICs**
Aggregates	21 Mining, quarrying, and oil and gas extraction
Construction	23 Construction
Industrial	31-33 Manufacturing
Commercial	41 Wholesale trade
	44-45 Retail trade

This approach was used as a starting point for incorporating these sectors into the model. Since CSD employment statistics report the number of employees by sector based on where they live, as opposed to where they work, these intensity factors will not be accurate reflections of the actual water use intensity per employee for sectoral activity within a given CSD. However, they do provide an initial basis for projecting economic and population growth to these sectors across the Greenbelt.

Future economic growth scenarios are addressed by assuming increased employment in each sector, which is based on the assumed population growth rates in each CSD. In other words, the population growth for the low and high growth scenarios were assumed to create employment growth proportionally to all existing NAICS sectors within the CSD.

4.3.3 Agricultural Water Taking

In the absence of self-reported estimates or measurements of water taking, as provided by the PTTW data, measurements of agricultural water use have been generalized and applied to other locations undergoing similar agricultural activities to estimate agricultural water taking. This approach, known as an inventory approach, has several benefits that are a function of its simplicity. The approach requires a small amount of data relative to other approaches (e.g., statistical and mechanistic); it is transparent and repeatable, which allows the approach to be easily communicated and implemented by others without specialized training; and it can be operationalized quickly, which reduces the amount of overhead required to derive a first estimate. Due in part to these benefits, the approach and its results may also be compared among different study regions and provide a

benchmark for comparison against other more complicated and dynamic approaches to estimating water use. The inventory approach is equivalent to the Tier 1 Intergovernmental Panel on Climate Change (IPCC) approach to carbon accounting when the water use coefficients are generalized beyond the location of study and Tier 2 when the coefficients are the result of locally collected data.

A number of examples of applications of the water use coefficient approach can be found in academic literature (e.g., Beaulieu et al. 2001, Kulshreshtha and Grant 2007). Within the province of Ontario, Canada, a lineage of research deriving agricultural water use coefficients began with Myslik (1991) and a report completed for the Ontario Ministry of Agriculture and Forestry by a consulting firm (Ecologistics 1993). The coefficients provided in the report were updated three times by Ivey (1998), De Loë et al. (2001), and De Loë (2005). The modifications were primarily done through qualitative meetings with farmers, crop specialists, and farming related organizations that provided expert and experiential opinions to validate water use coefficient modifications (De Loë et al. 2001).

The resultant coefficients are a product of a variety of factors that include: the number of irrigation applications and typical irrigation volume applied; the number of applications and volume of water used in herbicide, pesticide, and fungicide spraying; produce or equipment washing; on-farm processing; and other water uses. These data provide an annual representation of water use and are used to derive a water use coefficient for a specific crop, which is then applied against the total area of that crop. While spatial differences were represented by Ecologistics (1993), Ivey (1998), De Loë et al. (2001), and De Loë (2005), their applications were aggregated to the CSD spatial geographic unit provided by the Canadian Census of Agriculture. We acquired the coefficients used by De Loë (2005) and applied them to agricultural crops represented by Agriculture and Agri-Food Canada (AAFC) annual crop inventory data within the Greenbelt boundary.

4.4 Water Supply on Non-irrigated Agricultural Fields

This portion of the analysis examined the potential for improvements in soil health practices have the potential to increase water supply through improved ground water recharge on non-irrigated agricultural lands. Non-irrigated crops comprise the largest proportion of agricultural crop land (e.g., corn and soy account for 35% of the agricultural cover in the Greenbelt), which, when combined with other low water use agricultural activities (e.g., pasture and forage), comprise a substantial amount of land area. Recharge improvements on these lands are a direct gain in ground water supply.

To quantify the amount of precipitation used by non-irrigated crops and estimate the amount of ground water recharge, a dynamic growth vegetation model was used. Dynamic growth vegetation models (DGVMs) represent the processes of photosynthesis, respiration, nutrient and water uptake, evapotranspiration, and decay in concert with climate, soil, and topographic conditions that incorporate the water, carbon, and nitrogen cycles. In the context of water supply, a DGVM can be used to estimate the amount of water consumed by a crop under different climate conditions, the amount of irrigation

required for crop consumption to acquire yields reported in the Census of Agriculture, the amount of water intercepted by a crop, the amount of evapotranspiration, and among other processes, the amount of water percolating through the soil profile (i.e., ground water recharge). Furthermore, a dynamic crop growth model can be used to estimate changes in crop water use, ground water recharge, and crop yield under different temperature, precipitation, and growing season length scenarios as well as under different management activities. Therefore, we altered the proposed research to include the implementation of a DGVM to better understand the water requirements and use of water resources under different drought scenarios.

The Environmental Policy Integrated Climate (EPIC) model was chosen as the crop model to apply across the Greenbelt. The source code for the model was acquired from the development team at Texas A&M[11] and the model is widely used. A search of the academic database Scopus, using keywords “environmental policy integrated climate model EPIC” yielded 153 published articles. Among these published articles are applications of EPIC to the Canadian prairies (Lychuk et al. 2017), the Lake Erie region (Wang et al. 2018), and southern Alberta (Roloff et al. 1998).

The EPIC model dynamically grows crops under climate and soil conditions. The model operates vertically and has no representation of horizontal transfers of water or other materials, which is typical of most dynamic vegetation models (e.g., BIOME-BGC, LPJ-GUESS). The model operates at a daily time-step and utilizes a homogeneous land use unit, which acts much like hydrological response units in hydrological modelling (e.g., Kompanizare et al. 2018). The homogeneous land use (HLU) unit, was designed to represent the conditions of a single farm field (up to ~100ha) that comprises a relatively uniform distribution of soil and topographic characteristics that experience the same weather and have the same management activities applied (Gerik et al. 2015).

The EPIC model was run for each individual soil polygon residing within the CSDs intersecting the Greenbelt region (n = 31,933). Parameterization of the model involved first extracting the following 18 soil related variables from the Detailed Soil Survey using Safesoft’s FME software: soil polygon id, soil id, depth, bulk density, percent sand, percent silt, pH, organic carbon, sum of bases, cation exchange capacity (CEC), percent of soil in calcium carbonate (CACO3), hydrological conductivity at field capacity (K33), hydrological conductivity of soil at plant wilting point (KP1500), hydrological conductivity of soil at saturation (KSAT), hydrology soil group, the latitude and longitude of the centroid of the soil polygon, and area of the soil polygon.

Each soil polygon was included in a spatial search to obtain the weather station identification number from among the nearest 13 weather stations. Weather stations were chosen based on their proximity to the study site as well as their inclusion of data for each of the drought scenario years. Initially 35 stations were identified, however, if a station was missing climate data required for EPIC for a duration greater than 1 week, then the

[11] https://epicapex.tamu.edu/epic/, Last accessed Oct. 24, 2018.

station was excluded. In cases where temperature data were missing for one or more days, but less than 7, the average of the data prior and following the missing day were used. When precipitation data were missing a value of zero was given.

The EPIC model provides a dynamic growth representation of different crops that enables responses to changing management activities and climate. Each crop contains a set of 64 growth related variables. While the majority of these variables were determined to be adequately set using the EPIC defaults, the following variables were adjusted to represent corn growth in Ontario and generate output yield values comparable with those reported in the province: optimal temperature (23.5 °C), minimum temperature for plant growth (8 °C), maximum potential leaf area index (7.5), and a maximum plant height of 2.6 m.

The representation of nutrient cycling, vegetation growth, hydrology, and erosion, means that the EPIC model has the potential to generate a large number of outputs. Given our focus on water use and availability and the cost-benefit of adaptation actions, we reviewed the following annual model outputs: crop yield (YLD), evapotranspiration (ET), annual surface runoff (Q), lateral subsurface flow (SSF), percolation (PRK), crop available water (soil water at planting + growing season rainfall – runoff; CAW), growing season ET, water use efficiency (WUE), and water stress days (WS).

4.5 Scenarios

To evaluate the effects of climate and adaptation actions on crop yield, water use, and water supply, we constructed four drought scenarios and one adaptation scenario. While these scenarios do not provide comprehensive coverage of all potential futures, they offer insight into the effects of drought and adaptation on water use and supply. To situate these scenarios in a more realistic future context, we also include projections of population growth.

4.5.1 Incorporating Drought

Drought conditions are monitored across Canada by the Canadian Drought Monitor (CDM) program. The CDM combines data from regional, provincial, and federal sources to produce a drought classification comprising five classes: abnormally dry (D0), moderate drought (D1), severe drought (D2), extreme drought (D3), and exceptional drought (D4). Classification of conditions as no-drought or D0-D4 involves assimilating the following drought indicators: 30-day accumulated precipitation; precipitation percentile (since April 1); 30- and 90-day standard precipitation index; Palmer drought index; soil moisture as a percent of normal conditions, which is a modelled indicator; 30-day percent saturated surface soil moisture; evaporative stress index; Canadian Precipitation Analysis; VegDRI; and ESI.

Predicting or forecasting drought is a complicated, intensive process. According to Alberta's Water Portal Society: "Drought arises from a highly complicated set of interactions between the earth's surface and the atmosphere, making the accurate

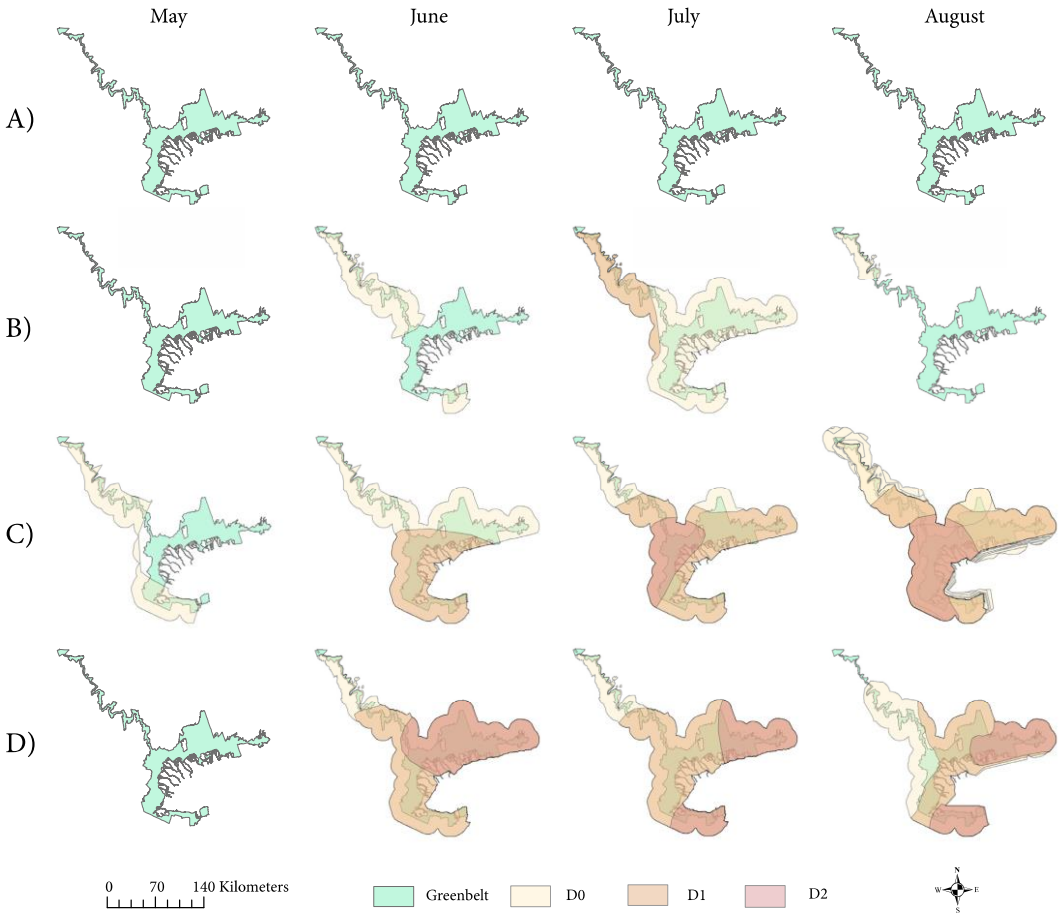
prediction of future occurrences of drought challenging. Some of the major scientific challenges for forecasting drought with a high degree of accuracy include:

- Limitations in the ability of computer models to predict the exact location, timing and spatial extent of air masses and their movement,
- The role of large-scale teleconnections such as the El Niño/Southern Oscillation and the Pacific Decadal Oscillation,
- Understanding the interactions between multiple variables and scales of weather patterns, and
- Determining the best way of calculating measures of drought severity."

Due to the difficulty with forecasting/predicting drought, we used historical drought conditions within the study area at different levels of drought intensity as classified by the CDM program.

Within the three years of this study, there was a limited number of droughts that occurred resulting in the need to expand the timeframe over which historical drought data were collected and analyzed. Four years were selected that held different climate conditions for the study area and represented the different CDM class conditions over most of the growing season (i.e., May – August). We used 2017 as our baseline year for comparison as there were no drought conditions experienced in the Greenbelt region during the growing season of that year (Figure 9). Abnormally dry conditions (D0) were identified in 2018, whereby portions of the Greenbelt were in D0 in June and all of the Greenbelt was in D0 in July with portions of the Bruce Peninsula in D1. Moderate drought conditions (D1) dominated the growing season in 2007 with most of the Greenbelt in some level of drought over the entire growing season. More than half of the Greenbelt was in D1 in June and nearly all of the Greenbelt was in D1 or D2 in July and August of 2007. The greatest spatial and temporal coverage of severe drought conditions (D2) occurred in 2016, whereby three quarters of the Greenbelt was in D2 in June, approximately one-third in July, and two-fifths in August. Among the drought data recorded by CDM, we were unable to identify conditions of extreme (D3) or exceptional drought (D4) in the Greenbelt region.

Figure 9: Canada Drought Monitor coverage for the Greenbelt over the May-August growing season. A) Baseline Scenario, absent of drought conditions, 2017; B) abnormally dry condition (D0) scenario, 2018; C) moderate drought condition (D1) scenario, 2007; and D) severe drought condition (D2) scenario, 2016.



The drought scenarios were incorporated into the EPIC model by first running EPIC for a 15-year spin-up phase. This spin-up phase replicated the 2017 (no drought) year annually to ensure each scenario was initialized with the same starting conditions. Then a single year representing one of four different drought conditions was incorporated as the 16th year of a model run.

For the municipal regression models, the climate data contained within a “drought year” was extracted from daily gridded rasters and applied to the nested regression models to predict water taking during a drought scenario.

These drought scenarios were then further incorporated into population growth scenarios examined below.

4.5.2 Estimating Population Growth

Population was estimated for scenarios based on the yearly growth rate between census years 2011 and 2016 for each CSD. For a given CSD, the low-growth scenario was defined as the yearly growth rate from 2011 to 2016 extended over 20 years, whereas the high-growth scenario was defined as double the yearly growth rate from 2011 to 2016 extended over 20 years. Population growth was used as an input into the regression models to predict how municipal water taking will increase in the future (Table 5).

Table 5: Population figures by CSD over time

Census Subdivision	2011	2012	2013	2014	2015	2016	2017	20-year Low Growth	20-year High Growth
Ajax	109,600	111,615	113,631	115,646	117,662	119,677	121,692	162,000	202,308
Aurora	53,203	53,651	54,100	54,548	54,997	55,445	55,893	64,861	73,829
Brock	11,341	11,401	11,461	11,522	11,582	11,642	11,702	12,906	14,110
Burlington	175,779	177,286	178,793	180,300	181,807	183,314	184,821	214,961	245,101
Caledon	59,460	60,868	62,277	63,685	65,094	66,502	67,910	96,078	124,246
Clarington	84,548	86,041	87,534	89,027	90,520	92,013	93,506	123,366	153,226
East Gwillimbury	22,473	22,777	23,080	23,384	23,687	23,991	24,295	30,367	36,439
Erin	10,770	10,904	11,038	11,171	11,305	11,439	11,573	14,249	16,925
Georgina	43,517	43,897	44,277	44,658	45,038	45,418	45,798	53,402	61,006
Halton Hills	59,013	59,443	59,872	60,302	60,731	61,161	61,591	70,183	78,775
Hamilton Township	10,702	10,750	10,798	10,846	10,894	10,942	10,990	11,950	12,910
King	19,899	20,822	21,744	22,667	23,589	24,512	25,435	43,887	62,339
Milton	84,362	89,515	94,668	99,822	104,975	110,128	115,281	218,345	321,409
Mono	7,546	7,759	7,971	8,184	8,396	8,609	8,822	13,074	17,326
Mulmur	3,391	3,408	3,426	3,443	3,461	3,478	3,495	3,843	4,191
Orangeville	27,975	28,160	28,345	28,530	28,715	28,900	29,085	32,785	36,485
Scugog	21,569	21,579	21,588	21,598	21,607	21,617	21,627	21,819	22,011
St. Catharines	131,400	131,743	132,085	132,428	132,770	133,113	133,456	140,308	147,160
Uxbridge	20,623	20,734	20,844	20,955	21,065	21,176	21,287	23,499	25,711
Vaughan	288,301	291,887	295,474	299,060	302,647	306,233	309,819	381,547	453,275
Whitby	122,022	123,293	124,564	125,835	127,106	128,377	129,648	155,068	180,488
Whitchurch-Stouffville	37,628	39,270	40,912	42,553	44,195	45,837	47,479	80,315	113,151

Employment rates in each CSD for a given water taking category (Commercial, Industrial, Aggregates, and Construction) were assumed to increase proportionally with population growth with the assumption that the distribution of employment across sectors within a CSD were stable over time.

4.5.3 Agricultural Adaptation Scenarios

The list of agricultural adaptation actions is extensive and many of these are represented as agricultural best management practices.[12] Among these practices, soil health has been promoted by reducing the exposure of soil through no-till applications (that limit the erosion of nutrients and sediments and the addition of organic matter) and the slow-release of nutrients through the application of compost. To evaluate the combined effects of these two BMPs (i.e., no-till and compost additions), we parameterized the land-management operations of EPIC to represent non-BMP and BMP scenarios.

The non-BMP scenario applies standard tillage, fertilization, and pesticide applications (Table 6). In contrast, the BMP scenario does not till the land and uses a drill planter as well as compost applications in the spring (early June, 80 kg / ha). The compost was created as a new fertilizer type, comprising 1.1% N, 0.3% P, 0.8% K, whereby 0.1% of the N exists as NH_3 (Ammonia), and 23.2% organic carbon. These additions decrease the bulk density of the soil and increase the soil water holding capacity and cation exchange capacity of the soil in addition to increasing the available nutrients.

Table 6: Land management activities with general dates and amount of nutrient and pesticide applied to soil polygons for corn growth.

Month	Activity	Amount	Units
	Tillage		
	Ferlizer Application		
	Potassium (K) 280 kg/ha	280	kg / ha
	Phosphorus (P) 134 kg/ha	134	kg / ha
	Nitrogen (N) 290 kg / ha	290	kg / ha
May	Pesticide		
	Atrazine (0.16 kg / ha)	0.16	kg / ha
	Planting		
	Density	8.9	plants / m2
	Ferlizer Application		
	10-20-10	11	kg / ha
November	Harvest		

4.6 Cost-Benefit Analysis of Soil Health Improvements for Corn

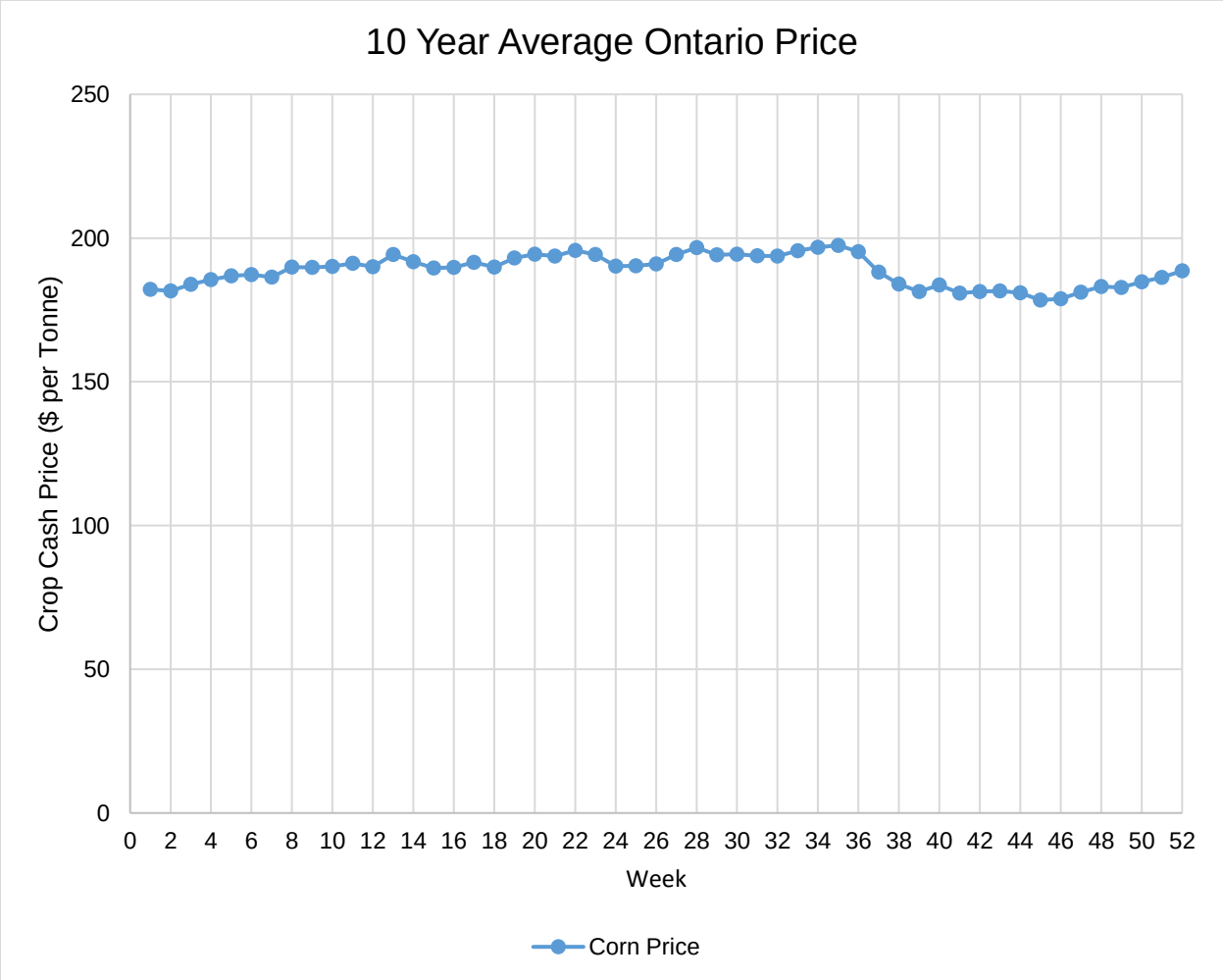
Outputs of the EPIC model provide the basis for completing a cost-benefit analysis of potential agricultural adaptation actions to drought. The crop model projected corn yields

[12] http://www.omafra.gov.on.ca/english/environment/bmp/series.htm, Last Accessed December 16, 2019.

based on different drought scenarios and whether soil health practices were used for each soil polygon containing corn within the study area. The outputs of the modelling allowed for an analysis of how yields changed because of drought, and the use of soil health practices to adapt to droughts.

From these yield predictions, a cost-benefit analysis was developed by estimating the production of corn within each soil polygon. This is determined by the modelled yield output times the area comprising corn within each soil polygon. The monetary value of crop production was then determined by multiplying the total crop production by the 10-year average price of corn (Figure 10). These calculations were done for all drought scenarios both with and without the use of adaptation actions. Taking the difference between the value of corn production with and without the use of adaptation actions, provides an estimate of the benefit provided by those actions.

Figure 10: 10-year average price of Corn in Ontario[13]



[13] Source of price data: OMAFRA Field Crop Statistics. Prices for Chatham-Kent area http://www.omafra.gov.on.ca/english/stats/crops/index.html

Costs associated with the soil health practices were determined based on assumed average values (measured in $/ha) to implement specific soil health practices (Table 7). The average costs were based on detailed data provided by the USDA and include all relevant costs associated with the actions (e.g. labour, machinery usage, materials, and other inputs, etc.). All cost values were converted to 2018 CAD. The research conducted developed an average value for a wide range of soil health practices as shown in Table 7 for the purpose of expanding the model in the future. For the cost-benefit analysis presented in this report, the focus is on the additional cost resulting from two actions (no-till, and compost additions) in relation to the additional benefit received in terms of increased crop production. Specifically, the analysis assumed a no-till cost of $41 per ha and a nutrient management cost (compost addition cost) of $34 per ha for a total cost for the adaptation actions of $75 per ha.

Table 7: Cost estimates for soil health practice adaptation actions[14]

Adaptation Action Cost Estimates	Description of Action	Average Cost per Hectare
Conservation Tillage	No-Till/Strip-Till	$ 41
	Residue and Tillage Management, Reduced Till	$ 49
Cover Crops and Conservation Cover	Cover Crop - Basic (Organic and Non-organic)	$ 127
	Cover Crop - No Termination Needed, Basic and organic/non-organic	$ 75
	Native Species	$ 355
Compost, mulch, manure additions	Natural Material (Mulch), Full Coverage	$ 2,153
	Basic Nutrient Mgmt (Non-Organic/Organic)	$ 16
	Basic Nutrient Mgmt with Manure and/or Compost (Non-Organic/Organic)	$ 34
	Precision Nutrient Mgmt (Non-Organic/Organic)	$ 96
Crop rotations	Basic Rotation Organic and Non-Organic	$ 23
	Specialty Crops Organic and Non-Organic	$ 62
	Irrigated to Dryland Rotation Organic and Non-Organic	$ 233

Since all production and cost values are calculated on a per soil polygon basis, the net benefit can also be presented by soil polygon, summed to CSDs, or presented for the whole Greenbelt study area.

[14] Source of cost data was USDA:
https://www.nrcs.usda.gov/wps/portal/nrcs/detail/national/programs/financial/?cid=nrcseprd1328426

5. Results

5.1 Water Taking Predictions for the Greenbelt Region

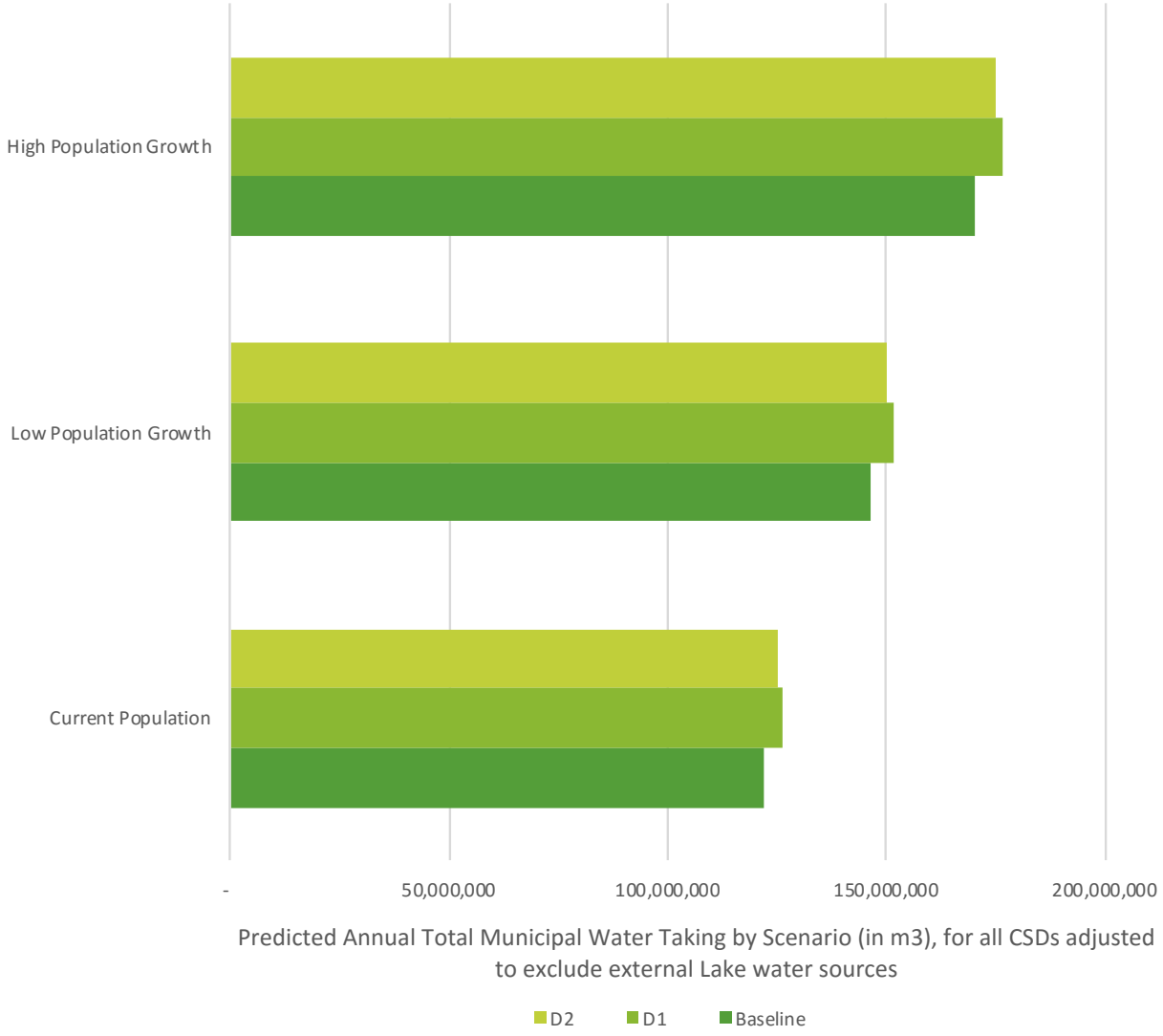
This section presents the results of the water taking predication across the study area resulting from the drought and population growth scenarios. The analysis provides an assessment of the regional water use context and how that water use could change under drought conditions and future population and economic growth.

5.1.1 Municipal Water Taking

Using the results of the regression analysis, total water taking predictions for each CSD were estimated based on applying the assumed drought conditions. These results were then averaged to a total water taking per person based on current population. Water taking for each CSD under increased population pressure was then determined by multiplying the average water taking per person by projected future population under low and high population growth assumptions.

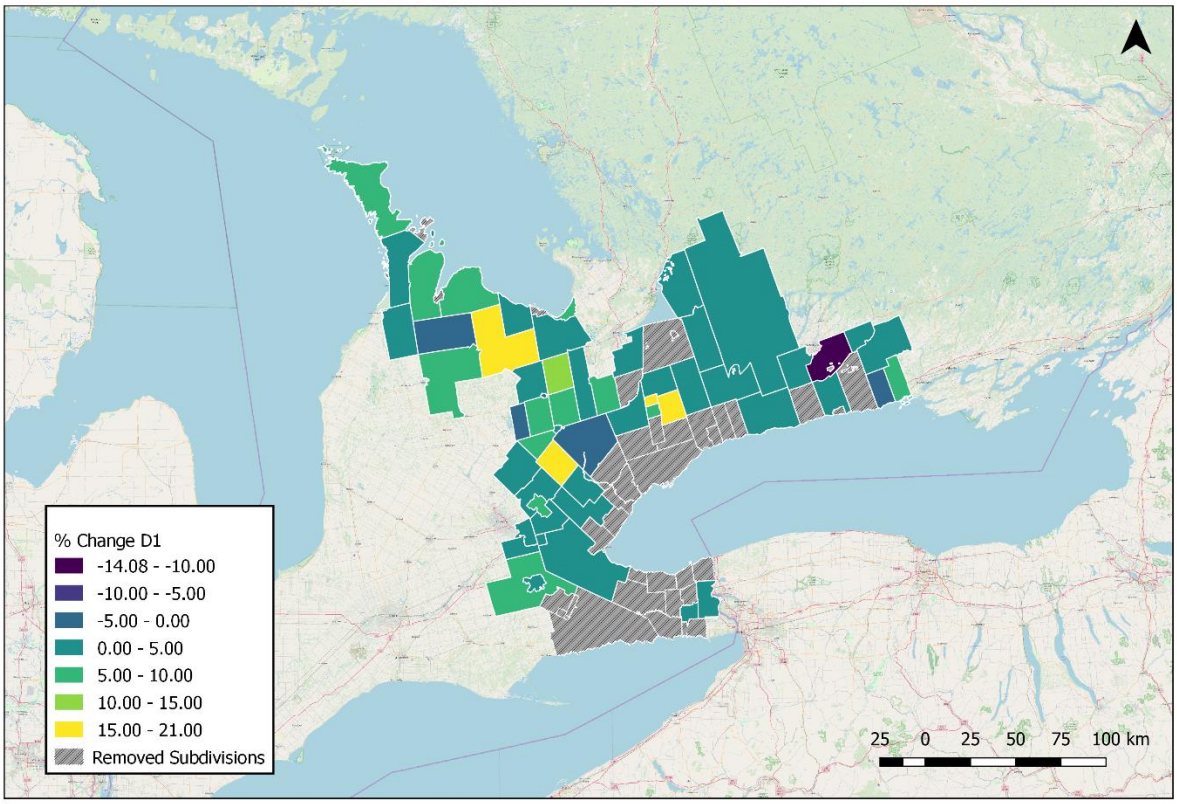
Figure 11 shows the results of municipal water use prediction within our study area. As one would expect, our results indicate that during drought conditions the total water use increases. However, the more severe drought scenario (D2) uses less water than the D1 drought scenario. In addition, increased population growth translates into increased water use. The findings demonstrate that municipal water use will increase as populations grow within the study area, and if drought conditions become more frequent, water demand will put additional pressure on the water supply. The degree to which supply can meet this projected increased demand was not explicitly analyzed and should be the focus of future research.

Figure 11: Predicted Annual Municipal Water Taking by population and drought scenarios



The percent change in water use was evaluated for D1 and D2 Scenarios relative to baseline conditions. The average change among all CSDs is an increase of 4% in water use during a D1 drought relative to the Baseline Scenario. Figure 12: 2 provides a map of the estimated percent change in municipal water use under a D1 drought.

Figure 12: Map of the percent change of predicted water taking in a D1 Scenario

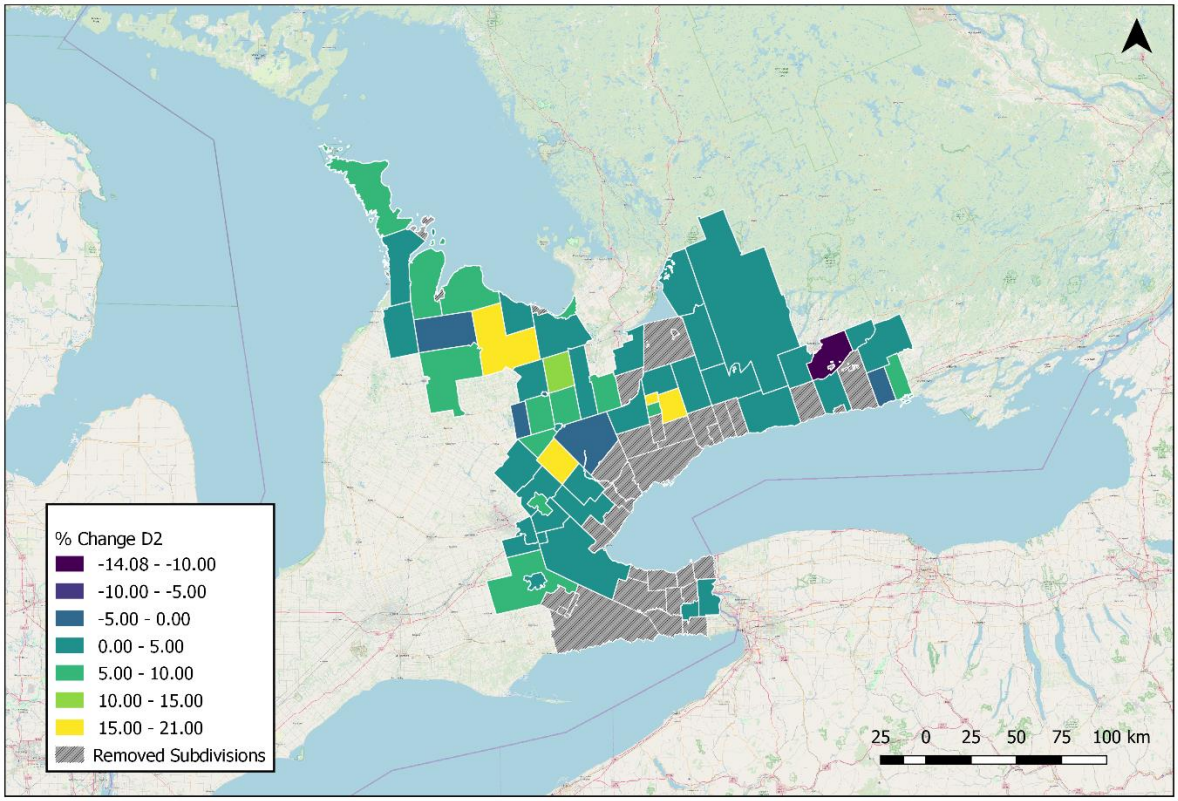


The relative change between the baseline and D2 drought conditions resulted in an average increase in water use by 2.36%. A similar pattern to the D1 scenario is observed with the same CSDs and caveats where extreme values tend to be from models with less certainty. However, Brighton, and Wasaga Beach have R-squared values above 0.46 and 0.90, respectively, with an approximate increase of 6.3% and 6.9%, respectively. Figure 133 provides a map of the estimated percent change in municipal water use under a D2 drought.

CSDs such as Erin, Grey Highlands, Whitchurch-Stouffville, Newmarket and Mulmur have the highest percent change with a 10-21% increase in water use under both drought scenarios. These CSDs have R-squared values of less than 0.22. Mulmur and Whitchurch-Stouffville models have total precipitation as a significant variable, however, the rest of the variables in these models are not significant. This means that while the models are predicting an increase in these CSDs, the accuracy of these models should be interpreted cautiously. There were some CSDs that showed a decrease in water use during a D1 drought, however, these CSDs also exhibit similar issues to the CSDs with a large positive percent change. The less extreme percent change values (closer to the mean), exhibit higher R-squared values and variable significance, suggesting these values are more realistic and indicative of the study area. For instance, Uxbridge and

Orangeville are 100% within the Greenbelt boundary and have R-squared values of 0.54 and 0.72, respectively. Uxbridge had a percent increase in water use of 3.8% (for D1) and 3.6% (for D2). Orangeville had a percent increase in water use of 1.4% (for D1) and 2.0% (for D2). Overall, the results from the change in water use from all scenarios generally show an average increase in water use under drought conditions.

Figure 13: Map of the percent change of predicted water taking in the D2 Drought Scenario



5.1.2 Commercial, Construction, Industrial and Aggregate Water Taking

Using the water use intensity ratios (described in Section 3.3.2), commercial, construction, industrial, and aggregate water use was estimated for future population growth scenarios for each CSD. Figure 14 shows the spatial distribution of water use under the Baseline Scenario along with percent changes in water use under the two growth scenarios.

Figure 14: Map of commercial, construction, industrial and aggregate water use under the Baseline Scenario (m3) and the percent change from economic and population growth scenarios

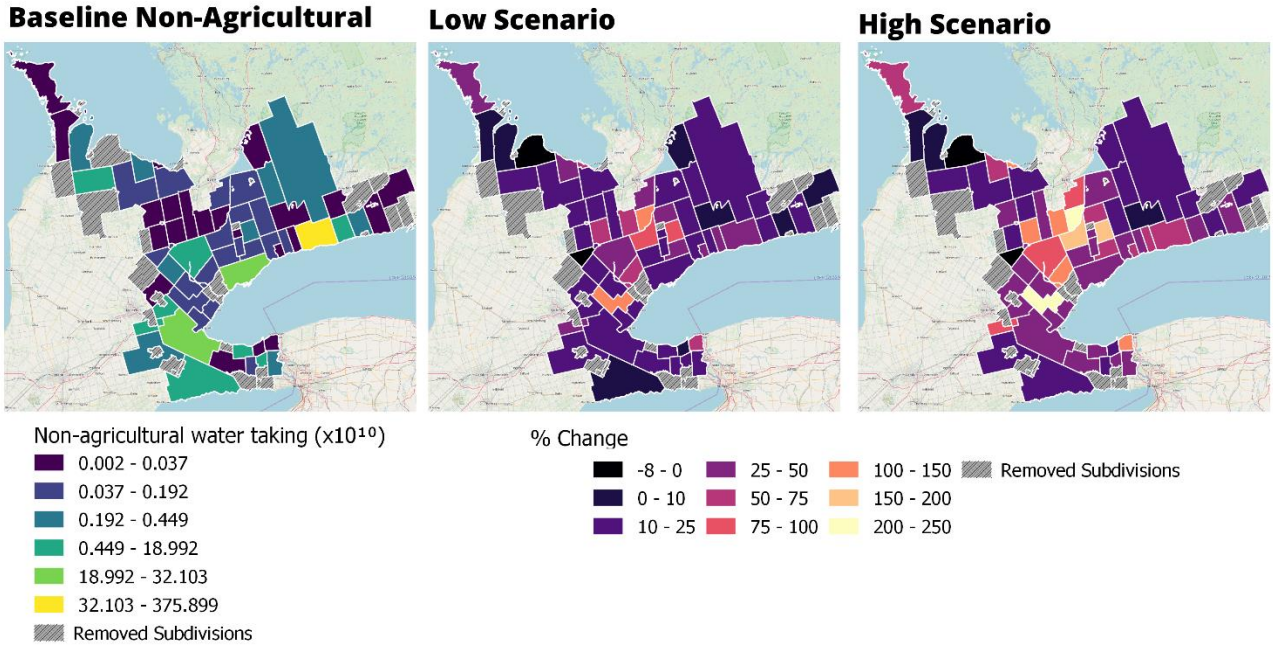


Table 8 provides the aggregated totals for the whole study area. Overall, these other sectors are using 4,612 million m^3 per year of water which could increase by 30% to 60% over the next 20 years depending on how and where the economic growth focuses water use extraction. Future modelling effort should focus on refining the estimation of commercial and industrial water use to more accurately simulate the spatial specificity of different future economic growth scenarios.

Table 8: Total commercial, construction, industrial and aggregate water use within the study area

Scenario	Total Water Use (Million m^3 / yr)	Percent Change from Baseline
Baseline	4,612	NA
Low growth scenario	6,087	32%
High growth scenario	7,562	64%

5.1.3 Agricultural Water Use

We initiated our estimate of agricultural water use by deriving water use coefficients that quantify water use over all activities associated with a specific crop (Table 9). By combining these different activities, we derived a unit value of litres per square metre per

year and applied that value to the areal coverage of the crop as represented in the annual crop inventory data generated by AAFC. The AAFC data demonstrate that 20 different crops were farmed within the Greenbelt study area. These crops represent approximately 45% of the Greenbelt area, with the remainder of the area residing in forest (~32%), urban and transportation (~10%), wetland (~5%), shrubland (~4%), exposed and barren land (~2%), and water (~2%) as well as small fractions of other land cover types (e.g., fallow 0.04%).

Based on the water use coefficient or inventory approach, we estimated that the 20 crops within the Greenbelt area use approximately 9.2 billion litres of water per year. The bulk of agricultural water use resides in specialty crops (sod farms and nurseries; 7 billion litres per year; 75.5%) followed by orchards (1.4 billion L per year; 15%). The remaining 9.5% (880 million litres) of annual water use is consumed by vegetables and vineyards (827 million litres; 9%), field crops (47.5 M litres per year; 0.5%), and pasture (5.5 M litres per year; 0.05%). Despite the water use ordering, the areal occupation of these crops is nearly reversed, with the majority of the agricultural lands within the study area comprising pasture (50.9%, Table 9), field crops (42.8%), vegetables and vineyards (4.0%), orchards (1.4%), and sod and nurseries covering 0.9%. Due in part to localized high water use by crops that occupy a small proportion of the Greenbelt, the spatial distribution of agricultural water use in the Greenbelt appears nearly uniform except for clusters of high-water use in the Simcoe region to the northeast, around Hamilton to the south, and Grimsby to the southeast (Figure 15 and Figure 16). The combination of the areal representation of crops and water use estimates demonstrate that in just over 6% of the agricultural area of the Greenbelt, fruit and vegetable and other crops, account for over 99% of the Greenbelt's agricultural water use.

Table 9: Agriculture and Agri-Food Canada (AAFC) annual crop inventory (ACI) land cover classes with associated water use activities within the official Greenbelt boundary. Water use coefficients acquired from De Loë (2005) and fraction of area irrigated from Ecologistics (1993). Vineyards represented by grapes and orchards represented by apples in data from De Loë (2005). Equipment washing and other water use values require refinement and should be used with caution. Agricultural land cover classes representing less than 0.0001% of the area are excluded. Pasture and forages ACI class likely contains misclassification errors with hay crops and therefore the area in pasture is likely substantially lower.

AAFC ACI class	Area (ha)	Percent Area of Green Belt	Irrigation Water Use (L/yr)	Spray Water Use (L/yr)	Equipment Washing (L/yr)	Other Water Uses (L/yr)	Total Water Use (L/yr)	Percent of Greenbelt Water Use
Pasture and Forages	187,535	23.127%		5,485,401	5,485	27,427	5,518,313	0.060%
Barley	1,488	0.183%		220,897	221	1,104	222,222	0.002%
Oats	1,124	0.139%		166,956	167	835	167,957	0.002%
Rye	150	0.019%		3,372			3,372	0.000%
Triticale	11	0.001%		1,256			1,256	0.000%
Winter Wheat	22,649	2.793%		2,547,987	2,548	12,740	2,563,275	0.028%
Spring Wheat	551	0.068%		81,754	82	409	82,244	0.001%
Corn	52,470	6.471%		17,708,655	17,709	26,235	17,752,599	0.192%
Ginseng	3	0.000%	367,031	22,316	67		389,414	0.004%
Canola and Rapeseed	906	0.112%		203,837	204	1,019	205,060	0.002%
Soybeans	78,238	9.649%		26,405,474	26,405	132,027	26,563,906	0.288%
Peas	117	0.014%		52,650	105	2,340	55,095	0.001%
Beans	183	0.023%		186,813	374	21,978	209,165	0.002%
Potatoes	869	0.107%	658,228,804	13,858	11,316,000	435	669,559,096	7.258%
Other Vegetables	5,194	0.641%		7,011,522	41,592,096		48,603,618	0.527%
Blueberry	83	0.010%	69,866,615	233,656			70,100,271	0.760%
Vineyards	8,329	1.027%		38,356,519		191,783	38,548,301	0.418%
Sod	1,796	0.222%	4,867,489,848	398,741	1,595		4,867,890,184	52.766%
Nursery	1,470	0.181%	2,058,462,000	39,698,910	119,097		2,098,280,007	22.745%
Orchards	5,204	0.642%	681,387,357	58,821,637	605,076,934	33,408,281	1,378,694,209	14.945%
Total	**368,370**	**45%**	**8,335,801,656**	**197,622,206**	**658,159,088**	**33,826,613**	**9,225,409,563**	**100%**

Figure 15: Agricultural water use within the Ontario Greenbelt region based on land cover data provided by AAFC annual crop inventory for the year 2017. White areas are those that are non-agricultural or beyond the Greenbelt boundary.

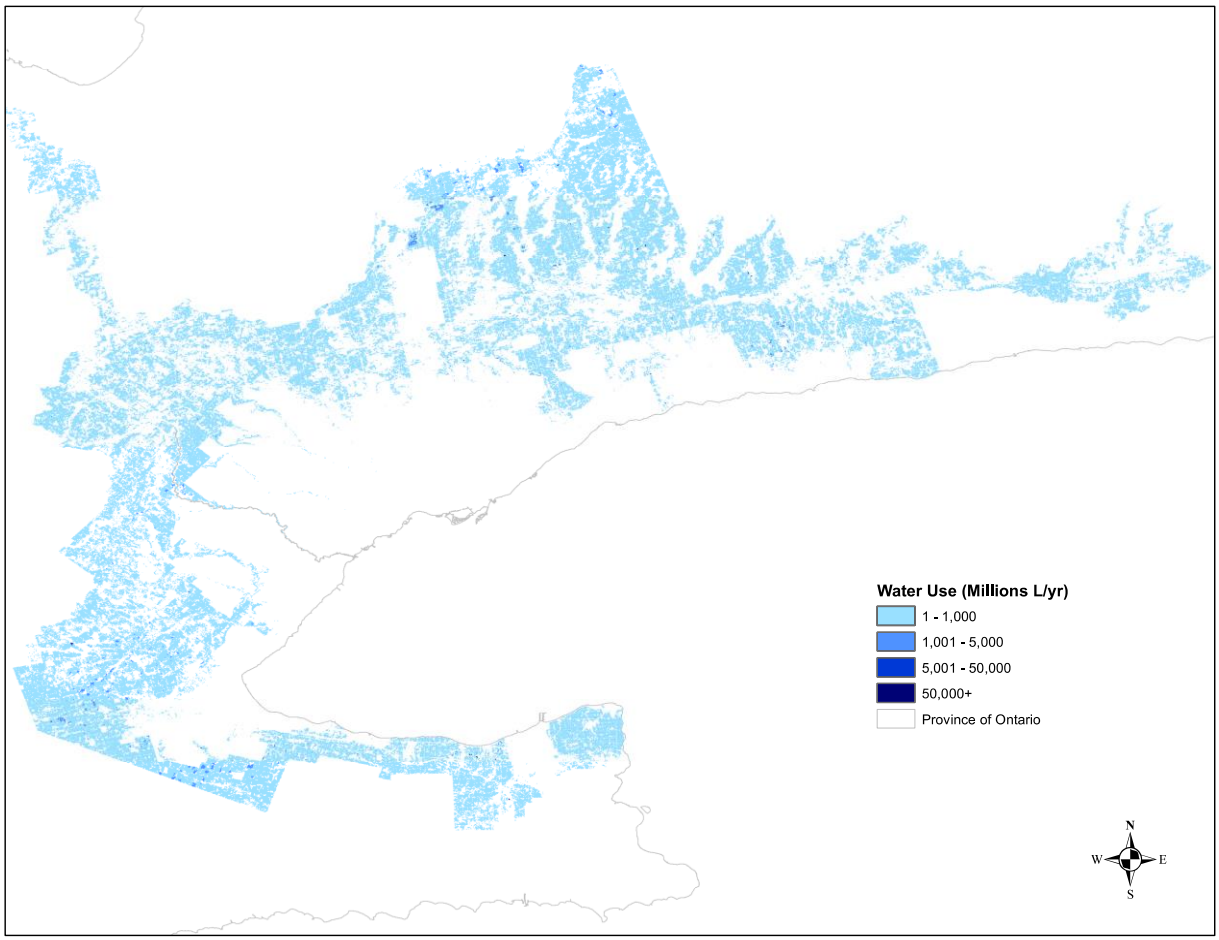


Figure 16: Map of agricultural water use by CSD. Appendix C provides a detailed breakdown of the agricultural water use by CSD and aggregated agricultural class.

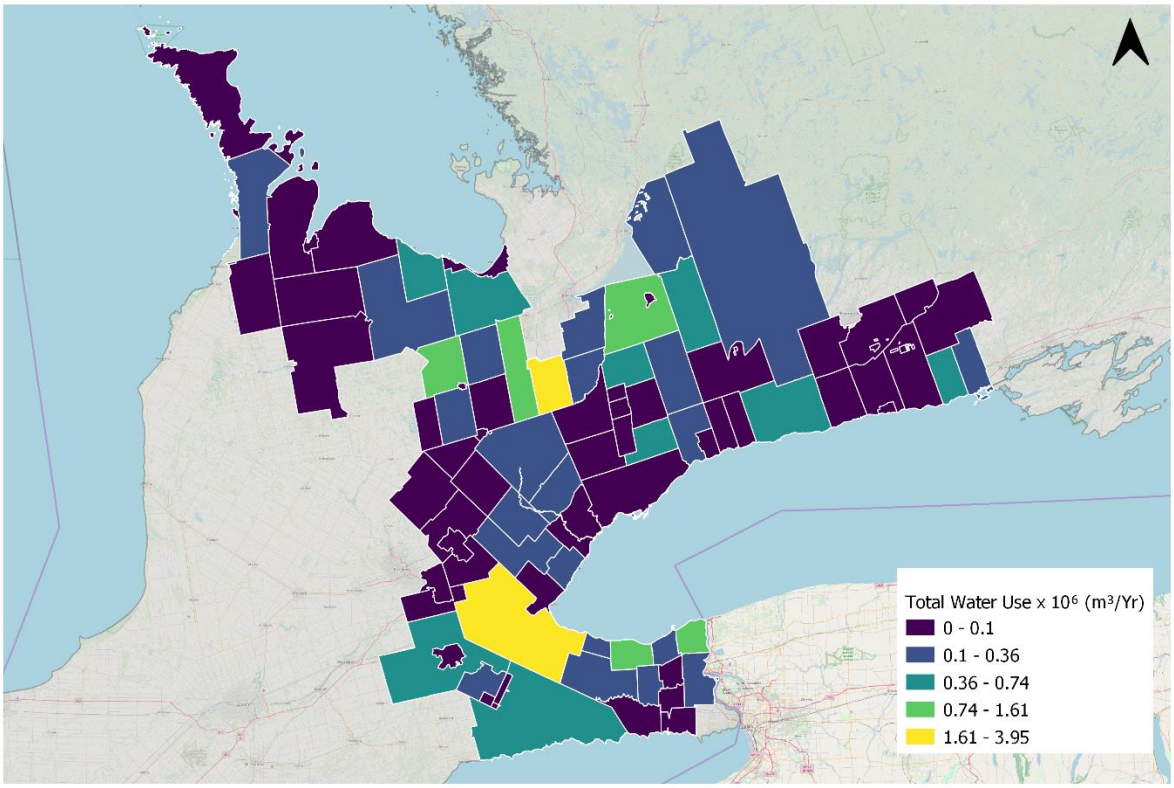
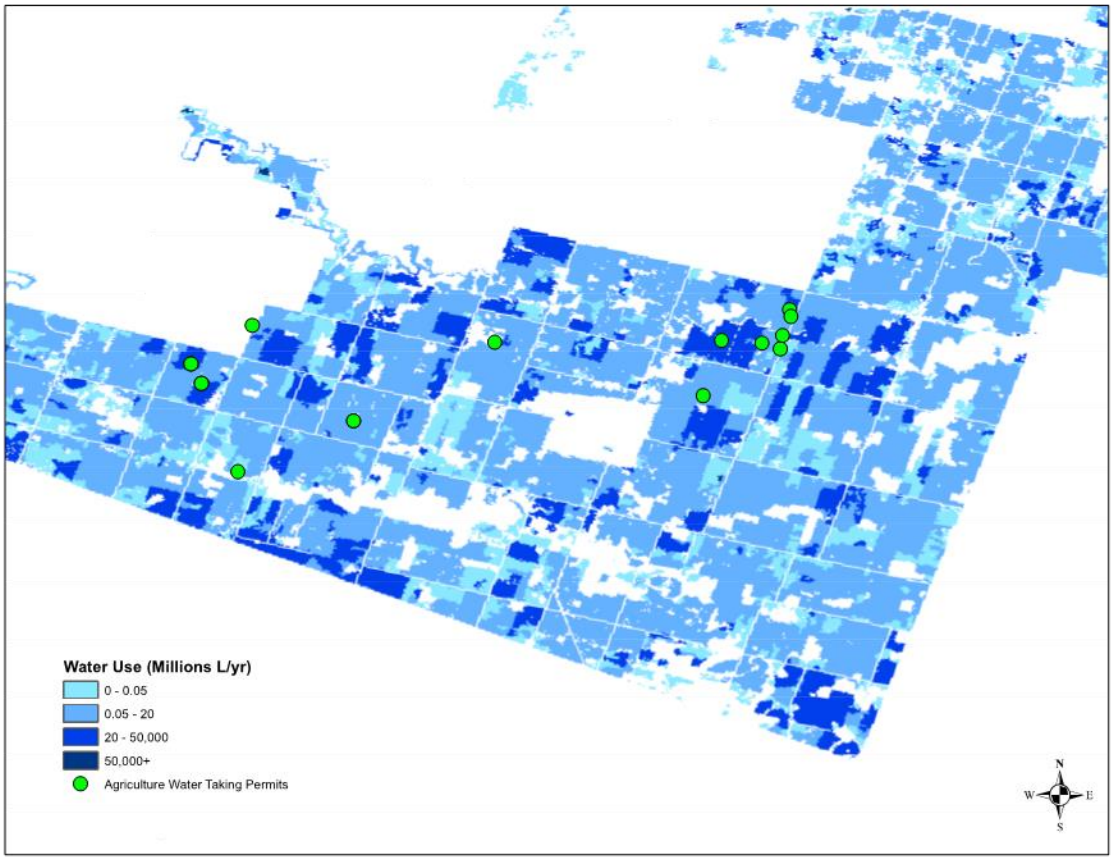


Figure 17 uses the water coefficients derived from the Greenbelt region in Table 9 (above) and applies these to the AAFC crop data across the whole study area. Hamilton and New Tecumseth (shown in yellow in Figure 16) have the highest total water use with 3.95 and 3.41 million m3/year, respectively. These two subdivisions contain high areas of fruits and vegetables in the study area and include high water use from potatoes and orchards. Georgina, Lincoln, Adjala-Tosorontio, Melancthon and Clarington have a total water use between 0.74– 1.61 million m3/year. The lower total water use subdivisions are typically more urban or have a smaller area.

Despite the static quantification of water use represented by the inventory approach, the water use coefficients (applied against the 2017 AAFC annual crop inventory data) compare well against the location of PTTW greater than 50,000 litres of water per day (Figure 17). Permits are located where a minimum of 50,000 litres are used annually and are not located where less than 50,000 litres are used annually based on the inventory approach. While the comparison does not provide a rigorous validation of the inventory approach, it does provide evidence that the results are consistent with water taking permit data.

Figure 17: Agreement between agricultural water consumption estimates derived from inventory approach and location of water taking permits for agricultural (> 50,000 L/day) for area southeast of Hamilton, Ontario. White areas are non-agricultural or outside the official Greenbelt area.



While the highest water use is clustered among a few crops and locations, the majority of the agriculture in the Greenbelt plays a critical role in terms of contributing to the supply of water. Since 94% of the agricultural lands (~345,000 ha) in the Greenbelt are composed of non-irrigated crops, these lands offer opportunity for water containment, groundwater recharge, and thus replenishment of the supply of water for other agriculture and non-agriculture uses. Water use coefficients are unidirectional and represent demand or use associated with growth, harvest, and food production, since the biophysical process of water capture and infiltration is more generally associated with soils. To investigate the contribution of agricultural lands to water supply and how drought conditions affecting water supply, use, and farm revenue as represented by crop yields, we evaluated the costs and benefits of improving soil health on non-irrigated agricultural fields using the EPIC model (Section 4.3).

5.1.4 Summary

Table 10 aggregates the results from sections 4.1.1 through 4.1.3 to estimate water use within the Greenbelt study area in the absence of drought conditions. Overall, roughly 4,760 million m^3 of water is used per year with potential increases from population and economic growth. Only the non-drought scenarios are rolled up to a study area total since it was not possible to estimate agricultural water use changes under drought conditions.[15]

Table 10: Total water use in the Greenbelt study area by use category and population growth scenario (in million m^3/yr) in the absence of drought conditions. Note: Excludes majority of municipal water supplies as they are from the Great Lakes.

Category	Current	Low growth	High growth
Municipal	122	146	170
Other Non-Agricultural*	4,612	6,087	7,562
Agriculture	25	25	25
Total	4,759	6,258	7,757

* Commercial, construction, industrial and aggregate

5.2 Analyzing Potential Changes in Water Supply Provided by Non-irrigated Agricultural Fields

Using the EPIC crop model, we simulated potential changes in yield and water supply on non-irrigated agricultural fields within the Greenbelt study region under four different drought scenarios (Section 3.5.1) as well as with and without the inclusion of adaptation practices (Section 3.5.3). Given the spatial variability in crop growth and water supply, we report average figures for the Greenbelt to facilitate a general understanding of the effects of drought and soil health improvement adaptation practices.

When adaptation practices were not included, percolation or groundwater recharge was reduced, the water use efficiency of corn decreased, and crops experienced more days of water stress (Table 11). These latter two components likely play a role in the decreasing corn yields that occurred with increasing drought. It is important to note that there are a variety of climate factors (e.g., temperature, rainfall duration, intensity, frequency, and seasonality) influencing these outcomes that were not individually evaluated. Therefore, we did not find a clear relationship between water supply variables (e.g., water stress days) and crop yields. Similarly, while we see a general decrease in percolation or ground water recharge with increasing drought conditions, there is variability due to the five climate factors.

[15] Note there is an implicit assumption built into the persistent water use for agriculture, which is that additional food requirements will be imported and that existing management practices will either remain the same or intensification will be offset by some other factors not discussed in this document.

Table 11: Outcome of potential changes in agricultural yields and water supply from combinations of drought and adaptation scenarios. Drought scenarios included no drought (Baseline), abnormally dry conditions (D0), moderate drought conditions (D1), and severe drought conditions (D2). Adaptation actions included no-till planting and the addition of compost. YLD = yield tonnes per hectare, PRK = percolation into ground water (mm), WUEF = water use efficiency of corn (kg/mm), WS = number of days crop experiences water stress.

Scenario		Average			
Adaptation	Drought	YLD	PRK	WUEF	WS
NO	Baseline	10.79	97.42	17.89	70
	D0	6.36	134.07	15.77	70
	D1	5.40	88.30	14.66	84
	D2	6.30	90.45	16.93	77
YES	Baseline	9.76	95.56	16.06	61
	D0	6.06	131.74	14.89	65
	D1	5.71	86.65	15.43	81
	D2	7.07	88.96	18.93	76

When adaptation practices were included, the water holding capacity of the soil was increased and there was less percolation and ground water recharge. The number of water stress days were reduced substantially when there was no drought, but this reduction became less as the level of drought increased. The water use efficiency of corn was lower with the addition of adaptation measures under no drought conditions (Baseline Scenario) relative to no-adaptation, but this reversed with increasing drought severity. A similar outcome was observed with crop yields, such that the general outcome was that adaptation measures were more beneficial for maintaining available water for crops under increasing drought severity.

An unexpected result of the scenario analysis was that the D2 Scenario shared similar output values to that of the D1 Scenario and some outputs were improved under the D2 Scenario relative to D1. We attribute these outcomes to our use of historical climate data for the study region to best represent the drought conditions. In using the historical data, it is difficult to obtain a year that solely experiences D1 or D2 conditions and therefore both are present in each scenario. However, in the D1 Scenario, some of the western portion of the study area is under D2 conditions. This area has substantial corn application and under the D1 Scenario experiences a reduced yield and supply improvements. In contrast, this same area remains under a D1 drought condition in the D2 Scenario; despite the D2 Scenario experiencing more areal coverage for a longer temporal period in D2 drought conditions. Therefore, we found more similar results between the D1 and D2 Scenarios than there are with the Baseline and D0 Scenarios.

Additional research improving the calibration of the EPIC model would facilitate partitioning the water budget among runoff, evaporation, evapotranspiration, and groundwater recharge. The additional partitioning of the water budget is required to gain a more complete understanding of the role of BMPs, like soil improvements, so that the

types of results reported in the presented research can be used by policy makers, crop extension specialists, and farmers to improve crop yields and soil health.

5.3 Cost-Benefit Analysis of Soil Health Practices on Non-irrigated Agricultural Fields within the Greenbelt Region

This section presents the results of the cost-benefit analysis. The cost-benefit analysis is based on projected yield outputs modelled in section 4.2 and examines the change in yield and associated production with and without the use of soil health adaptation practices during baseline and drought conditions.

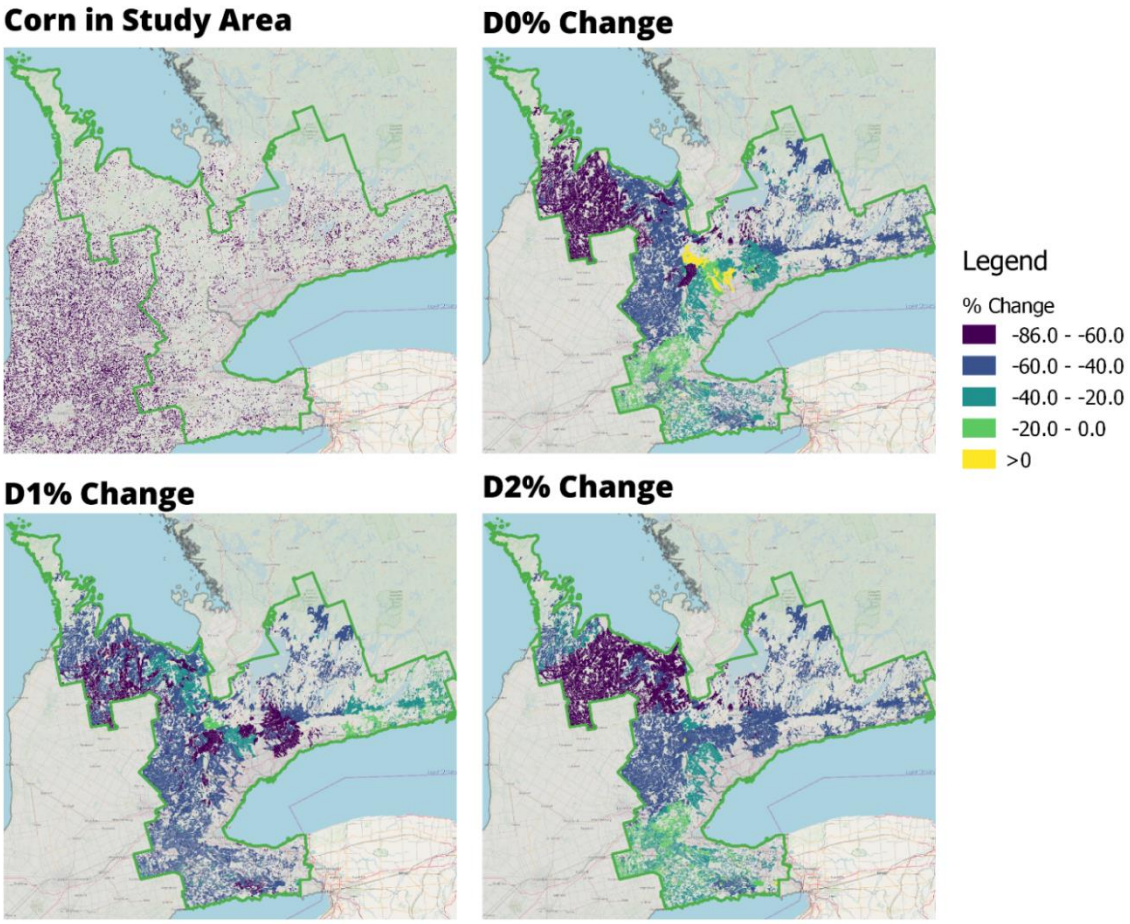
Table 12 provides a summary of corn production and value for the Greenbelt study area. Based on the crop modelling results, drought conditions put significant strain on corn production and value cutting it in half relative to the Baseline Scenario. The severity of the drought had limited impact on the size of the reduction in production and value. However, D1 and D2 Scenarios had a slightly larger negative impact than the D0 Scenario.

Table 12: Corn production and value in the study area with no soil health adaptation practices used

Scenario	Total Production (Tonnes of Corn)	Percent Change from Baseline	Value
Baseline	434,000	NA	81,910,000
D0	229,000	-47 %	43,149,000
D1	213,000	-51 %	40,149000
D2	216,000	-50 %	40,711,000

Figure 18 depicts the spatial distribution of the percent change by soil polygon that contained corn production. Note however, that the actual production only occurs on the corn fields as depicted on the upper left tile of the figure. As expected, the largest impacts from the assumed drought conditions on yield occur in the regions that correspond to the largest temperature and precipitation pressure associated with the given drought scenario (as defined in Section 5.1.1).

Figure 18: Map of corn areas and percent change in production from drought conditions relative to baseline conditions



Total corn production within the study area with and without soil health practices are summarized in Table 13. Based on the crop model outputs, a reduction in production is observed when using no till and compost and manure additions under baseline and minor drought conditions. However, these measures start to offset lost production under the more severe drought conditions of D1 and D2.

Table 13: Production summary with and without use of soil health adaptation practices

Scenario	Baseline	D0	D1	D2
Corn production (tonnes) No soil health adaptation used	434,000	229,000	213,000	216,000
Corn production (tonnes) Soil health adaptation used	406,000	222,000	225,000	243,000
Difference in production (tonnes)	-28,000	-7,000	12,000	27,000

The cost-benefit analysis for the study area is summarized in Table 14. The table highlights that despite productive gains provided using soil health practices during

drought conditions, those productivity gains are outweighed by the costs required to implement those actions. However, digging deeper into the results it was clear that while this conclusion holds in aggregate across the study area, there are numerous locations across the study area where the net benefit of soil health practices was significantly positive across all scenarios.

Table 14: Cost and benefit summary with and without use of soil health adaptation practices

Scenario	Baseline	D0	D1	D2
Corn production (value in $) No soil health adaptation used	81,910,000	43,149,000	40,149,000	40,711,000
Corn production (value in $) Soil health adaptation used	76,531,000	41,806,000	42,372,000	45,774,000
Difference in production (value in $)	-5,379,000	-1,343,000	2,223,000	5,063,000
Cost of implementing soil health actions	10,719,000	10,719,000	10,719,000	10,719,000
Net Benefit	-16,098,000	-12,062,000	-8,496,000	-5,656,000

Under the Baseline Scenario, there were 973 locations where soil health practices improved production for a total net benefit of $7.0 million. Under the D0 and D1 Scenarios, less locations exhibited a net benefit (358 and 370 locations with a net benefit of $3.0 and $3.1 million, respectively). Under the most severe drought modelled (D2), a total of 1,703 locations exhibited a positive net benefit from the use of soil health practices, for a total net benefit of $3.2 million. Of the areas that exhibited a positive net benefit from the use of soil health practices, the average benefit was $8.41 per ha under baseline conditions, $3.75 per ha during a D0 drought, $3.77 per ha during a D1 drought, and $5.77 per ha during a D2 drought.

6. Discussion

This chapter of the report presents and discusses challenges and limitations associated with the study as well as options for future research and analyses.

6.1 Challenges and Limitations

Several challenges were faced throughout the research project are discussed below. Like many projects, this one had a large scope of work with constraints of limited time and person hours. All of the challenges were connected in some way to the type or availability of data. For example, there is a tremendous lack of water taking data and the data that are available (e.g., PTTW) have obvious errors and/or unknown accuracy. Some climate and precipitation data from Environment Canada were not available during the project due to miscalculations in modelling steps of their gridded data (Personal Communication, ECCC, April, 2019). Based on a peer-review with Conservation Authorities within the Greenbelt and hydrogeological experts, it became obvious that there are inaccuracies with the PTTW database. Individual Conservation Authorities have indicated that some fields in the PTTW database are inappropriately allocated, for instance, whether water is taken from groundwater, surface water, or some combination of the two. As well, Conservation Authorities have found water taking purposes to not always be consistent. This may indicate data quality issues with the PTTW database, since most of the information in the database may be filled out by the permit holder who may not have the best available information or be limited by the forms to submit their data. In many cases, water taking estimates are reported by the permit holder rather than actual use. Many entries for a single taking demonstrate this approach to reporting as the reported values are identical over time. While some Conservation Authorities have corrected these data for their own uses, these corrections are not reflected in the main database housed by the Province, from which the data employed in this analysis was received. Furthermore, there are no data for agricultural water use less than 50,000 litres per day and therefore the water use coefficients, which are based on a small sample of measurements that have been modified over time (to reflect expert opinion), offer the most transparent and possibly the most valid empirical approach to water use estimation. In future modelling of municipal water taking data, understanding the relationships between various geographic areas may allow for better model specification. For instance, if it is understood that one larger CSD transfers a proportion of their water to another, smaller, CSD, then these relationships can be incorporated into the model.

The lack of water taking data for those not requiring a permit constrain the ability to calibrate and validate crop models like EPIC that can be used to pose ‘what-if’ questions to investigate the impacts of changes in climate, land management, and technology on crop yields and water supply. It is partly due to a lack of these data as well as a lack of behavioural data about land management and water use decisions, that water supply under non-irrigated corn as an example of its contribution to estimating water use and the impacts of drought was used. Dynamic crop growth models like EPIC are required to gain

a better understanding of the effects of climate (e.g., drought) on biophysical processes since simplified models like the water use coefficient approach do not account for: the effects of soil variability; hydrological connectivity and processes such as evapotranspiration, permeability, overland flow, and ground water flow and recharge; and land management activities.

Despite these challenges, the approach produced a wall-to-wall estimate of water use across the Greenbelt study area. It uses inventory (water use coefficients), statistical, and process-based models to represent multiple actors to derive a comprehensive coverage of water use that complements and differs from the engineering based approaches used in the generation of water budgets by Conservation Authorities. While, substantial additional work is required to refine both the methods and the results of the presented project, this work has laid a foundation upon which others can make improvements and generate comprehensive coverage of water use estimates for the Greenbelt or other study regions in Canada and abroad.

The initial scope of the project did not incorporate the use of a dynamic vegetation model like EPIC. However, the alteration of agricultural water use coefficients without empirical field measurements would be a qualitative undertaking that would be difficult to justify in the absence of extensive collaboration with crop extension specialists, crop scientists, farm organizations, and many others. While use of the EPIC model overcame the limitations of water use coefficients and demonstrated how their combined use can generate full spatial coverage water use estimates, the adoption and instantiation of a process model (like EPIC) is a formidable undertaking that often requires developers of the model to be involved for the model application to pass the level of rigor required of academic publishing (Bell et al. 2015). While the EPIC model has been applied in Ontario in the past (Rudra et al. 2011), individuals involved with running the model were not available for consultation. Communication with EPIC developers at Texas A & M verified that the model has been accurately setup and parameterized, however, additional validation work is required. Therefore, the results should be interpreted to have qualitative meaning (e.g., ranking of yield or water supply values will hold) but absolute values may differ as the model instantiation is refined in the future.

As previously mentioned, the research presented in this report has been designed to lay the foundation for a coupled natural and human systems model of agricultural land use and land management. EPIC was chosen not only because it integrates nutrient, water, and carbon cycles as well as land management activities, but also because it may generate output files that record the state of the system (e.g., soils) at a specified interval (e.g., annual). Therefore, the natural system as represented by the EPIC model may be manipulated by a human system model (e.g. an agent-based model) and respond to the different land management choices implemented by a human system model at an annual or sub-annual time scale. The coupling of human and natural systems models is essential if we wish to more fully understand how water use will differ under changing climate, policy, and technology (Robinson et al. 2018).

6.2 Future Research Directions

Given the wide number of actors and factors affecting water takings, future research may take a variety of pathways. Despite this expanse, the following directions would strengthen and build upon the original research proposal: synthesize water budget data provided by Conservation Authorities as part of the *Source Water Protection Act* to identify thresholds of water use beyond which there are cascading drought impacts; collect and analyse on-farm decision-making data; and construct a computational framework to modify the EPIC model temporally and spatially based on independent farm households or enterprises. Incorporation of existing source water protection data and available water supply data should take care to note assumptions and methodology used as this likely varies by area.

There is room to further refine the drought scenario assumptions and modelling. For instance, indices such as SPI, climate normals, and evaporative stress can be refined and improved. Specifically, the following challenges associated with working with these indices can be addressed: 1) data availability for the study area; and 2) data processing time.

The use of the EPIC model was not originally intended as part of the proposed research affiliated with this project. However, as mentioned above, it was necessary to represent processes associated with plant growth and its response to adaptation and drought conditions. The calibration and validation of a crop model for application across a large spatial extent, such as the Greenbelt, could be improved by comparison of yield and other output variables to observations spanning a geographical distribution across the Greenbelt. Future initiatives should seek to complete a rigorous calibration, validation, and sensitivity analysis of the model for continued application across the Greenbelt.

Given a more complete understanding of the EPIC model, future work should link the model to a simplified representation of human-decision making (e.g., an agent-based model). Human decision-making models are preferred over statistical models since they can represent the spatial variability not only in the agricultural environment, but also among the decision makers.[16] The EPIC model was chosen not only because of its detailed representation of crop growth and land management activities, but also because it is a field-based model, which represents the scale of agricultural decisions, and because it stores environmental state conditions that enable the model to be stopped and restarted with those conditions. These features of the EPIC model make it feasible to couple with a human decision-making model and provide further insight into the effects of policy adoption and the effects of inclusion or exclusion of adaptation practices by farmers across the Greenbelt region.

The combination of a crop growth model and a human decision-making model would allow for the examination of scenarios that were part of the project proposal but not

[16] Rounsevell, M., Robinson, D.T. and D. Murray-Rust (2012). From actors to agents in socio-ecological systems models. Philosophical Transactions of the Royal Society B 367: 259-269. DOI: 10.1098/rstb.2011.0187

incorporated in the evaluation. For example, crop rotation choices and changes in land management and infrastructure (e.g., irrigation) under different climate and policy conditions will differ spatially and temporally across the Greenbelt region. Through this type of model coupling, the efficacy of different on-farm decisions can be evaluated and analyzed in a way that is not possible with statistical models applied uniformly across the Greenbelt region. If we cannot understand the reasoning behind the types of decisions that agricultural water users are making, then policy incentives to nudge water use decisions will be less effective.

7. Conclusion

Collectively, the results demonstrate that during drought conditions and increased population growth, there is greater pressure placed on the water resources of the Greenbelt. These pressures can be offset to some degree by the role that agricultural producers can plan in helping recharge ground water.

- There is significant water use pressure within the Greenbelt region. While this project did not explicitly link water usage to water supply, it does provide important context around the volume of extraction associated with Greenbelt water resources.
- The crop modelling foundations laid out in this project set the stage for more detailed future modelling work and also demonstrates the implications of using soil health practices as a means to (i) help adapt to drought conditions, and (ii) improve contributions to ground water supply.
- The results indicate that the use of soil health practices does not guarantee a cost-effective solution to adapting to drought conditions, but rather the effectiveness of these practices (both from a production and cost perspective) depends on location specific conditions. In some cases, it can be highly beneficial. However, the cost-benefit analysis only focused on the costs and benefits to agricultural producers. There are broader regional water supply benefits that are also generated by these activities. There is spatial variation over these actions, which could be further refined with more spatially explicit drought scenarios or indices that link climate conditions to a specific area. Additionally, there may be other opportunities to reduce costs by cost-sharing programs from OMAFRA.

Appendix A – Model Coefficients and Significance by CSD

Census Subdivision	Variable	Estimate	Standard Error	P-value
		($x10^6$)	($x10^6$)	
Ajax	(Intercept)	1,582.57	158.76	0.00
Ajax	max_t	12.96	5.94	0.03
Ajax	sum_p	-2.52	1.06	0.02
Ajax	Spring	164.49	90.10	0.08
Ajax	Summer	376.08	95.55	0.00
Ajax	Winter	84.70	122.47	0.49
Aurora	(Intercept)	349.71	38.70	0.00
Aurora	max_t	-2.53	1.39	0.08
Aurora	sum_p	-0.67	0.27	0.02
Aurora	Spring	29.17	21.28	0.18
Aurora	Summer	63.24	22.86	0.01
Aurora	Winter	-30.60	30.28	0.32
Brock	(Intercept)	58.12	3.40	0.00
Brock	max_t	0.32	0.12	0.01
Brock	sum_p	0.00	0.00	0.31
Brock	Spring	8.09	1.88	0.00
Brock	Summer	8.47	2.03	0.00
Brock	Winter	2.06	2.71	0.45
Burlington	(Intercept)	2,227.02	252.70	0.00
Burlington	max_t	16.33	9.08	0.08
Burlington	sum_p	-1.32	0.56	0.02
Burlington	Spring	95.05	137.35	0.49
Burlington	Summer	582.63	142.36	0.00
Burlington	Winter	80.44	191.28	0.68
Caledon	(Intercept)	65.96	35.97	0.07
Caledon	max_t	3.27	1.29	0.02
Caledon	sum_p	0.01	0.02	0.56
Caledon	Spring	5.07	19.54	0.80
Caledon	Summer	-15.47	20.98	0.47
Caledon	Winter	40.39	28.17	0.16
Clarington	(Intercept)	349.77	19.06	0.00

Clarington	max_t	3.10	0.72	0.00
Clarington	sum_p	-0.04	0.01	0.00
Clarington	Spring	12.93	10.96	0.24
Clarington	Summer	56.97	11.73	0.00
Clarington	Winter	16.64	14.92	0.27
East Gwillimbury	(Intercept)	172.00	24.99	0.00
East Gwillimbury	max_t	0.83	0.89	0.36
East Gwillimbury	sum_p	-0.01	0.03	0.78
East Gwillimbury	Spring	-8.02	13.43	0.55
East Gwillimbury	Summer	23.48	14.46	0.11
East Gwillimbury	Winter	13.12	19.46	0.50
Erin	(Intercept)	24.77	7.75	0.00
Erin	max_t	-0.43	0.28	0.13
Erin	sum_p	-0.02	0.01	0.13
Erin	Spring	6.39	4.27	0.14
Erin	Summer	6.62	4.56	0.15
Erin	Winter	-5.30	6.20	0.40
Georgina	(Intercept)	246.59	12.11	0.00
Georgina	max_t	2.33	0.43	0.00
Georgina	sum_p	-0.02	0.01	0.00
Georgina	Spring	8.14	6.51	0.22
Georgina	Summer	42.72	7.00	0.00
Georgina	Winter	20.01	9.52	0.04
Halton Hills	(Intercept)	487.44	66.48	0.00
Halton Hills	max_t	0.48	2.31	0.84
Halton Hills	sum_p	-0.21	0.10	0.04
Halton Hills	Spring	36.54	34.96	0.30
Halton Hills	Summer	86.62	37.59	0.03
Halton Hills	Winter	-37.56	51.52	0.47
Hamilton	(Intercept)	3,227.45	2,598.67	0.22
Hamilton	max_t	78.31	92.02	0.40
Hamilton	sum_p	-0.22	0.84	0.80
Hamilton	Spring	844.79	1,379.03	0.54
Hamilton	Summer	281.06	1,428.89	0.85
Hamilton	Winter	1,249.80	1,931.08	0.52
Hamilton Township	(Intercept)	12.51	1.50	0.00

Hamilton Township	max_t	0.05	0.06	0.37
Hamilton Township	sum_p	0.00	0.00	0.21
Hamilton Township	Spring	1.70	0.87	0.06
Hamilton Township	Summer	0.22	0.93	0.81
Hamilton Township	Winter	0.91	1.19	0.45
King	(Intercept)	138.04	18.96	0.00
King	max_t	2.34	0.68	0.00
King	sum_p	-0.05	0.02	0.03
King	Spring	5.77	10.30	0.58
King	Summer	20.10	11.06	0.08
King	Winter	30.48	14.82	0.05
Milton	(Intercept)	21.77	2.07	0.00
Milton	max_t	-0.08	0.07	0.28
Milton	sum_p	0.00	0.00	0.14
Milton	Spring	-0.48	1.13	0.67
Milton	Summer	0.29	1.19	0.81
Milton	Winter	-3.16	1.58	0.05
Mono	(Intercept)	4.46	4.21	0.30
Mono	max_t	0.35	0.15	0.02
Mono	sum_p	0.00	0.01	0.35
Mono	Spring	-0.40	2.32	0.86
Mono	Summer	1.12	2.48	0.66
Mono	Winter	4.84	3.41	0.16
Mulmur	(Intercept)	5.87	1.61	0.00
Mulmur	max_t	0.07	0.06	0.20
Mulmur	sum_p	0.00	0.00	0.03
Mulmur	Spring	0.33	0.86	0.70
Mulmur	Summer	0.52	0.92	0.57
Mulmur	Winter	1.63	1.28	0.21
Orangeville	(Intercept)	88.02	9.20	0.00
Orangeville	max_t	1.21	0.33	0.00
Orangeville	sum_p	-0.01	0.02	0.47
Orangeville	Spring	1.55	5.12	0.76
Orangeville	Summer	14.27	5.49	0.01
Orangeville	Winter	12.05	7.49	0.11
Scugog	(Intercept)	61.30	24.15	0.01

Scugog	max_t	-1.61	0.89	0.08
Scugog	sum_p	0.00	0.02	0.82
Scugog	Spring	14.07	13.60	0.31
Scugog	Summer	19.61	14.68	0.19
Scugog	Winter	-15.83	19.10	0.41
St. Catharines	(Intercept)	1,497.42	102.69	0.00
St. Catharines	max_t	16.45	3.85	0.00
St. Catharines	sum_p	-1.04	0.34	0.00
St. Catharines	Spring	47.18	55.21	0.40
St. Catharines	Summer	256.58	56.93	0.00
St. Catharines	Winter	63.49	75.65	0.41
Uxbridge	(Intercept)	66.34	4.35	0.00
Uxbridge	max_t	0.77	0.16	0.00
Uxbridge	sum_p	-0.01	0.00	0.00
Uxbridge	Spring	3.24	2.39	0.18
Uxbridge	Summer	11.69	2.59	0.00
Uxbridge	Winter	6.78	3.40	0.05
Vaughan	(Intercept)	3.20	1.65	0.06
Vaughan	max_t	-0.10	0.06	0.10
Vaughan	sum_p	0.00	0.00	0.90
Vaughan	Spring	0.39	0.90	0.67
Vaughan	Summer	0.22	0.95	0.82
Vaughan	Winter	-2.07	1.25	0.11
Whitby	(Intercept)	1,735.53	127.25	0.00
Whitby	max_t	12.73	4.73	0.01
Whitby	sum_p	-0.72	0.43	0.10
Whitby	Spring	-26.46	72.09	0.72
Whitby	Summer	-10.28	77.37	0.89
Whitby	Winter	47.57	99.00	0.63

Appendix B – Permit To Take Water Metadata

PTTW Metadata
Ministry of the Environment and Climate Change August 27, 2013
Attribute Definitions for Permit to Take Water
PERMITNO: Permit Number for water taking
CLIENTNAME: Name of client requesting a permit
PURPOSECAT: Major Taking Category *
SPURPOSE: Specific Purpose **
EXPIRYDATE: Expiry Date of Permit
ISSUEDDATE: Date the Permit was issued
RENEWDATE: Date that a legacy permit was renewed ***
OLDCTYTWN: Former township name related to lot\concession
P_LOT: Lot where permit source is located
P_CON: Concession where permit source is located
P_MUNICIP: Current Municipality where permit source is located
P_UPPERT: Upper tier (county/district/regional municipality) where permit source is located
P_LOWERT: Lower tier (township/municipality) where permit source is located
SURFGRND: Origin of water taking: Surface, Ground, Both
SOURCEID: Description of exact location of water taking source (e.g. well 3, Mission River)
EASTING: Easting coordinates in UTM
NORTHING: Northing coordinates in UTM
UTMZONE: UTM Zone (15, 16, 17, 18)
MAXL_DAY: Maximum litres allowed per day
DAYS_YEAR: Number of days that water taking is allowed
HRS_DAYMAX: Maximum water taking in hours per day
L_MINUTE: Allowable water taking (in litres) per minute
AMENDED_BY: Previous Permit number
EXPIRED_BY: Previous Permit number
PERMIT_END: date of which the water permit ends
ACTIVE: Indicated whether the permit is active or expired (Yes/No) based on PERMIT_END and the date that data was extracted from the source database
LATITUDE: the latitude coordinates
LONGITUDE: the longitude coordinates

Daily Gridded Temperature and Precipitation Meta Data
Gridded 10km Canada Daily Temperature and Precipitation Dataset
ID DATA: PCP_DLY_1950_2015.tar, MAX_DLY_1950_2015.tar, MIN_DLY_1950_2015.tar
VERSION: ANUSPLIN V4.5 20170806
ORIGINATOR: LANDSCAPE ANALYSIS AND APPLICATION SECTION (LAAS)

GREAT LAKES FORESTRY CENTRE (GLFC), CANADIAN FOREST SERVICE (CFS),
NATURAL RESOURCES CANADA (NRCAN)
ID PARAMETERS: pcp, max, min
TIME INTERVAL: DAILY
PERIOD: 1950-2017
SPATIAL FORMAT: GRID
DATA FORMAT: ARC/Info ASCIIGRID
GRIDS DATUM: GEOGRAPHIC NAD83
SPATIAL RESOLUTION: 300 arc-second (~10 km)
GRIDS DOMAIN: 141.0 to 52.0W, 41.0 to 83.499N
ESRI ASCII RASTER FORMAT:
NCOLS 1068
NROWS 510
XLLCORNER -141.0
YLLCORNER 41.0
CELLSIZE 0.08333333767
NODATA VALUE -999
Units:
Temperature, Celsius degrees
Precipitation, millimeters (mm)
Notes:
All years were formatted as leap years with 29 days for February. The asciigrids for Julian day 60 are missing in the non-leap years.
The geographic.prj were included
The data quality over the latitude GT 60.0 is questionable.

Appendix C – Detailed Agricultural Water Taking (mil. m^3/yr) By CSD

Census Subdivision	Field Crops	Fruits and Vegetables	Other	Pasture
Adjala-Tosorontio	0.0023	0.6855	0.4809	0.0003
Ajax	0.0001	0.0030	0.0111	0.0000
Alderville First Nation	0.0000	0.0000	0.0000	0.0000
Alnwick/Haldimand	0.0021	0.0254	0.0237	0.0003
Amaranth	0.0025	0.2196	0.0788	0.0003
Arran-Elderslie	0.0058	0.0002	0.0095	0.0005
Asphodel-Norwood	0.0007	0.0009	0.0000	0.0002
Aurora	0.0000	0.0004	0.0000	0.0000
Bradford West Gwillimbury	0.0024	0.0992	0.0469	0.0001
Brampton	0.0010	0.0338	0.2058	0.0001
Brant	0.0145	0.4253	0.0759	0.0004
Brantford	0.0003	0.0831	0.0000	0.0000
Brighton	0.0014	0.0456	0.1140	0.0001
Brock	0.0040	0.0600	0.5259	0.0003
Burlington	0.0005	0.0336	0.0259	0.0001
Caledon	0.0049	0.0487	0.2674	0.0006
Cambridge	0.0005	0.0008	0.0039	0.0000
Cavan Monaghan	0.0018	0.0027	0.0037	0.0003
Centre Wellington	0.0058	0.0092	0.0030	0.0002
Chatsworth	0.0028	0.0011	0.0115	0.0006
Chief’s Point No. 28	0.0000	0.0000	0.0004	0.0000
Chippewas of Georgina Island First Nation	0.0000	0.0000	0.0000	0.0000
Clarington	0.0040	0.2625	0.4752	0.0004
Clearview	0.0054	0.4488	0.1251	0.0004
Cobourg	0.0001	0.0001	0.0000	0.0000
Collingwood	0.0000	0.0053	0.0000	0.0000
Cramahe	0.0015	0.1561	0.2853	0.0001
East Garafraxa	0.0020	0.0200	0.0000	0.0001
East Gwillimbury	0.0017	0.1146	0.5393	0.0001
Erin	0.0020	0.0009	0.0080	0.0003
Georgian Bluffs	0.0023	0.0006	0.0880	0.0006
Georgina	0.0014	0.0432	1.5701	0.0002

Grand Valley	0.0021	0.0133	0.0017	0.0001
Grey Highlands	0.0040	0.0980	0.0916	0.0009
Grimsby	0.0005	0.1579	0.0139	0.0000
Guelph	0.0001	0.0000	0.0004	0.0000
Guelph/Eramosa	0.0041	0.0014	0.0000	0.0002
Haldimand County	0.0196	0.0647	0.6024	0.0007
Halton Hills	0.0024	0.0152	0.2666	0.0002
Hamilton	0.0109	0.6881	3.2501	0.0006
Hamilton Township	0.0025	0.0045	0.0168	0.0002
Hiawatha First Nation	0.0000	0.0000	0.0000	0.0000
Innisfil	0.0029	0.1877	0.1217	0.0001
Kawartha Lakes	0.0111	0.0530	0.1643	0.0019
King	0.0019	0.0810	0.0218	0.0003
Lincoln	0.0012	1.2303	0.0468	0.0000
Markham	0.0013	0.0135	0.4622	0.0000
Meaford	0.0023	0.0377	0.0429	0.0006
Melancthon	0.0029	0.7578	0.2022	0.0003
Milton	0.0026	0.0109	0.1206	0.0003
Mississauga	0.0001	0.0027	0.0319	0.0000
Mississaugas of Scugog Island	0.0000	0.0000	0.0000	0.0000
Mono	0.0010	0.0636	0.0316	0.0003
Mulmur	0.0012	0.2751	0.0062	0.0003
New Credit (Part) 40A	0.0003	0.0000	0.0000	0.0000
New Tecumseth	0.0032	1.2272	2.1751	0.0002
Newmarket	0.0000	0.0000	0.0000	0.0000
Neyaashiinigmiing 27	0.0000	0.0002	0.0043	0.0000
Niagara-on-the-Lake	0.0002	1.1356	0.0393	0.0000
Niagara Falls	0.0011	0.1425	0.0011	0.0001
North Dumfries	0.0023	0.0043	0.0001	0.0001
Northern Bruce Peninsula	0.0005	0.0001	0.0015	0.0002
Oakville	0.0004	0.0026	0.1404	0.0000
Orangeville	0.0000	0.0001	0.0000	0.0000
Oshawa	0.0008	0.0015	0.0079	0.0000
Otonabee-South Monaghan	0.0019	0.0062	0.0002	0.0004
Owen Sound	0.0000	0.0000	0.0016	0.0000
Pelham	0.0011	0.2696	0.0004	0.0001

Pickering	0.0019	0.0100	0.2835	0.0001
Port Colborne	0.0010	0.0123	0.0040	0.0001
Port Hope	0.0022	0.0032	0.0032	0.0002
Puslinch	0.0011	0.0014	0.0125	0.0002
Ramara	0.0014	0.0046	0.1536	0.0003
Richmond Hill	0.0001	0.0014	0.1014	0.0000
Scugog	0.0039	0.0200	0.0375	0.0004
Shelburne	0.0000	0.0000	0.0000	0.0000
Six Nations (Part) 40	0.0014	0.0167	0.1138	0.0001
South Bruce Peninsula	0.0010	0.0001	0.1668	0.0004
St. Catharines	0.0002	0.1738	0.0499	0.0000
The Blue Mountains	0.0010	0.4080	0.0600	0.0002
Thorold	0.0006	0.0703	0.0153	0.0000
Toronto	0.0001	0.0020	0.0323	0.0000
Trent Hills	0.0027	0.0051	0.0000	0.0005
Uxbridge	0.0025	0.0961	0.2562	0.0003
Vaughan	0.0011	0.0131	0.0413	0.0001
Wainfleet	0.0033	0.0153	0.0000	0.0001
Wasaga Beach	0.0000	0.0000	0.0139	0.0000
Welland	0.0003	0.0127	0.0025	0.0000
West Grey	0.0063	0.0138	0.0205	0.0007
West Lincoln	0.0058	0.1070	0.1138	0.0002
Whitby	0.0007	0.0059	0.0690	0.0001
Whitchurch-Stouffville	0.0011	0.0346	0.0408	0.0001