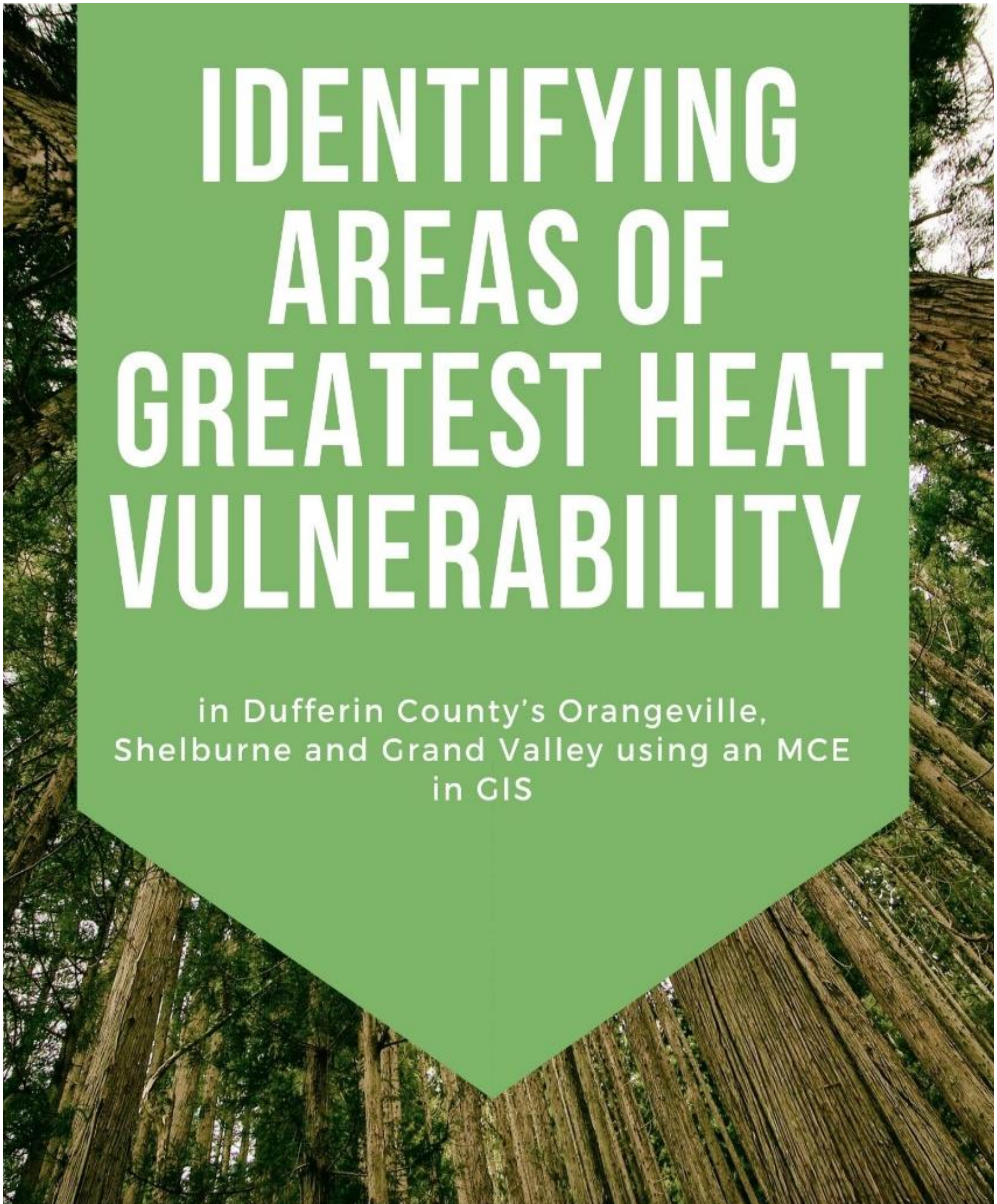


IDENTIFYING AREAS OF GREATEST HEAT VULNERABILITY

in Dufferin County's Orangeville, Shelburne and Grand Valley using an MCE in GIS

AUTHORS: JAMIE BARNES, ALEXANDER BOEKESTYN, AND ANETA BRYNKUS
APRIL 16, 2021
GEOG*4480

Abstract

In this study, we partnered with Dufferin County's Climate Office to aid their climate change action plan initiatives by investigating the most heat vulnerable areas in the county's major urban centres. The Urban Heat Island (UHI) effect is becoming an increasingly detrimental phenomenon to human well-being and the environment and requires adaptation and mitigation planning strategies. Increasing vegetation in urban areas has been identified as the most effective method in creating a cooling effect within cities as their natural structure creates natural cooling methods. Therefore, using GIS and a Multi-Criteria Evaluation (MCE) model, we identified the most heat vulnerable areas at the dissemination area (DA) level in Dufferin County's major town centres Orangeville, Shelburne, and Grand Valley. The variables in our model consisted of material deprivation, dependency, population density, proximity to cooling centres and, existing canopy cover, all of which were standardized to the DA level scale. Members of the Dufferin County's Climate Office helped us choose our weights of importance for our MCE model based on their professional experience of study areas. These weights were standardized and used in the model to generate the areas in the county per urban centre that were the most heat vulnerable. Once the weights were inputted, the MCE model was run and generated results. The results of the MCE model identified the DA from each study area that is most vulnerable to heat, based on our inputted variables. Aside from visualizing the most vulnerable DA per study area, our choropleth maps created to visualize the results also demonstrate different levels of vulnerability for each DA per study area. This information helps the Office in their decision-making process of the areas that are in the greatest need of an increase in urban vegetation.

Table of Contents

Introduction

The impacts of climate change are becoming felt on a global scale more intensely than ever before. Urban centres all around the world are at the forefront of these impacts. In a reciprocal relationship, climate change and urban activities have resulted in a phenomenon referred to as urban heat island (UHI) effect (Kleerekoper et al., 2012). A UHI occurs when the temperature of an urban centre is higher than the average temperatures of its surrounding rural environments (Filho et, al., 2017). The physical make-up of infrastructure and materials as well as anthropogenic activities are highly responsible for the UHI effect (Grimmond, 2007).

Therefore, it is understood that as urbanization and expansion continue, we will see an increase in UHI effects globally (Filho et, al., 2017). Anthropogenic activities that occur in urban centres are key drivers to climate change and their effects can be felt on a global and regional scale due to their greenhouse gas (GHG) contribution (Grimmond, 2007). The consequences of UHI can be felt by humans in a variety of heat-related illnesses (Filho et, al., 2017); (Kleerekoper et, al., 2012).

Research shows that the most effective method to create a cooling effect in urban centres is by adding vegetation in the forms of urban forests (parks) and street trees (Kleerekoper et, al., 2012); (Rahman, et, al., 2020). Applying natural ways of providing shade there will be an increase in evapotranspiration opportunities that contribute towards a microclimate cooling effect (Kleerekoper et, al., 2012 and Rahman, et, al., 2020). Moreover, an increase in vegetation also contributes to reversing the consequences brought on by deforestation and urbanization by increasing carbon sinks that are necessary for offsetting the GHG emissions that are brought on by urban centers (Grimmond 2007 and Rahman, et, al., 2020). Increasing urban vegetation is an adaptation strategy as well as a mitigation strategy that is widely recognized as a useful tactic that not only will relieve the effects felt by heat-vulnerable populations but also contribute to reversing climate change by increasing our global carbon sinks.

For the basis of this project, in a collaborative effort, we worked closely with Dufferin County Climate Office to determine which areas within the county are most vulnerable to heat. More specifically, members Sara Wicks and Allison Myles were a crucial part of our weight allocation decision making process. Major town centres, Orangeville, Shelburne, and Grand Valley are projected to undergo the greatest expansion in the county in the next ten years due to migration patterns away from the GTA (Wicks, 2021: personal communications). The Dufferin County Climate Action initiatives are interested in determining which areas will benefit the most from the addition of municipality planted trees.

Geographic Information Systems (GIS) is the most appropriate research tool for the basis of this project as it is an important analysis tool that will be key in identifying the spatial variability of socioeconomic and biophysical components of heat vulnerability in Dufferin County. Specifically, an MCE analysis will greatly enable us to combine numerous variables together to help in identifying the heat vulnerable areas (Coutinho-Rodrigues et, al., 2009). GIS can analyze data efficiently and effectively, which is appropriate for our data sets (Coutinho-Rodrigues et, al., 2009). With regards to GIS applications to planning departments, they can be user friendly, affordable and the data can be easily interpreted once completed and presented in the form of maps and visualizations (Coutinho-Rodrigues et, al., 2009).

Through a combined effort from members of Dufferin County we aim to provide a detailed GIS analysis of the most heat vulnerable areas in Orangeville, Shelburne and, Grand Valley to demonstrate the areas that would benefit the most from municipal planted trees.

Research Purpose

The purpose of our research is to provide the Dufferin County Climate Office with an MCE analysis that determines the areas within Dufferin County's major urban centers that are most vulnerable to heat.

Research Objectives

1. Identify the variables that influence heat vulnerability the most.
2. Prepare our data and create maps that illustrate the most vulnerable areas per variable for Orangeville, Shelburne and Grand Valley.
3. Apply our MCE model to determine the overall most heat vulnerable areas in Orangeville, Shelburne and Grand Valley.
4. Evaluate the strengths and weaknesses of the model.

Study Area

Our study area includes Dufferin County, a rural and agriculturally intensive area, with a focus on towns Orangeville, Shelburne, and Grand Valley (see *figure 1.0*). Since it is projected that all three towns will undergo rapid urban expansions in the next ten years it is important to establish sustainable planning strategies and initiatives that can help mitigate the increase in heat caused through anthropogenic activity. By determining the most heat vulnerable areas we can help Dufferin County in their development of heat mitigation strategies that ultimately will set them on track to achieve a low emission climate projection scenario.

Figure 1.0: This image shows our study area displayed at the DA level. Dufferin County is displayed in green and town centre Orangeville, Shelburne, and Grand Valley are displayed in pink.

Methods and Research Approach

Research Approach - Objective 1

The data comes in different resolutions; therefore, it must be aggregated. The data that is derived from Statistics Canada, Public Health Ontario and Dufferin County will be aggregated to the DA level and our results will also be provide at the DA level. Data sets such as the marginalization index and population density already come scaled at the DA level but datasets such as canopy cover will require manipulation.

The following are multiple biophysical and socioeconomic variables that have an influence on heat vulnerability that will be included in our analysis.

Existing canopy cover: A lack of canopy cover means more exposure to surfaces that absorb heat during the day and release the heat at night (Morakinyo et, al., 2020). An increase in canopy cover from vegetation results in more shaded areas that not only provide relief to citizens allowing them to have an easier time controlling their body temperature, but also contributes to a micro-scale cooling effect (Rahman, et, al., 2020). This data will be derived from Tree Inventory data and Wooded Area 2020 Data provided to us by Dufferin County and will be rescaled to the DA level (Town of Orangeville, 2020 and Dufferin County, 2020)

Dependency: Dependency is a measurement of area-level concentrating of people that typically share qualities of not having an income due to no employment; senior and children whose are not work compensated are included in this measurement (Matheson & Ingen, 2016). Increased temperatures in UHI are responsible for a variety of heat-related illnesses (Smoyer-Tomic et, al., 2002). Some of the more common illnesses are heat stroke, heat syncope, respiratory diseases and in extreme cases, morality (Smoyer-Tomic et, al., 2002). The age gaps that are most vulnerable to heat-related illnesses are elderly and infants due to their difficulty to regulate body temperature when exposed to extreme heat (Voelkel et, al., 2017and Smoyer-Tomic et, al., 2002). This data will be derived from Public Health Ontario and is already scaled to the DA level (Matheson & Ingen, 2016).

Proximity to cooling centres: People that do not have access to a personal cooling system (HVAC technologies) will oftentimes use public cooling areas such as community centres and public pools to escape the heat. But according to research, their proximity to these centres can be extremely uneven in urban areas due to physical barriers of access (Fraser et, al, 2016). This results in a lesser opportunity to access cooling centres to help in regulating their body temperatures (Fraser et, al, 2016). Defined by our Dufferin County community partners, we will perform a network analysis at the DA level on manually selected points within our study area to obtain average distance to cooling centres per DA level.

Material Deprivation: Material Deprivation is a measurement that is closely related to poverty as it references people's ability and communities to access basic needs (Matheson & Ingen, 2016). Data shows that people of lower incomes are more vulnerable to heat (Reid et, al., 2009). This is because of their lack of access to HVAC home utilities that allow for cooler environments (Voelkel et, al., 2017). Without air-condition (HVAC) cooling technologies, they are more at risk of struggling to regulate their body temperature and therefore are more likely at feeling the effects of heat more (Smoyer-Tomic et, al., 2002). This data will be derived from Public Health Ontario and is already scaled to the DA level (Matheson & Ingen, 2016).

Population density: The UHI is greatest in areas that experience the most amount of anthropogenic activity (Grimmond, 2007). Therefore, these will produce more GHG that contribute to warming and have surfaces that contribute to the UHI effect. Areas with higher population density have higher rates of anthropogenic activity. This data will be derived from Statistics Canada and is already scaled to the DA level (Statistics Canada, 2016).

Research Approach - Objective 2

The second objective is preparing the variables discussed in objective 1. Each variable was aggregated to the DA to conduct an MCE at the dissemination scale. Preparing the variables required different methods for each factor. Each variable includes joining the data to the Dufferin DA boundaries.

The dependency and material deprivation data were retrieved from the Ontario Marginalization index in the form of data tables and were joined to the Dufferin DA boundary shapefiles. Applying population density to the DA level required dividing Dufferin County's population by the county's DAs. This outcome was then divided by the area of each DA. The area of each DA was then calculated using the calculate geometry feature found in the attribute table.

Distance to cooling centers and tree canopy cover required more steps than the dependency, material deprivation, and population density variables. To determine the average distance to cooling centers per DA, a layer was created with georeferenced data points for the cooling centers. To calculate the average distance to cooling centers, we followed a generalized network method presented by Deaton, & Vyn (2010), where we utilized a cost distance function on a rasterized road network of Dufferin County. This allowed us to calculate the distance to the nearest cooling center; we were then able to use the per cell distances and aggregated them to the DA boundaries using the zonal statistics function. The canopy cover variable is composed of a tree inventory of Orangeville and a county-wide file that displays wooded areas. The tree inventory data required some geoprocessing efforts; buffers were produced for each tree point based on the tree canopy radius. The tree canopy radius was not constant, as tree size and type within the tree inventory affected the size of the canopy. The two variables were then merged and dissolved; this allowed us to compare the tree canopy area and the total DA area from this single layer. We derived the canopy cover area as a percentage per DA.

All the data was clipped to the three areas of focus in Dufferin County and then standardized using a basic linear transformation. This displayed the criteria as percentages and ensured the values were all on the same measurement. The tree canopy cover layer was already in the percentage format and only required subtracting the variable from 100 to determine the inverse percentage of the area without canopy cover. Refer to the flow chart, *figure 2.1* in the appendix to see an overview of the steps taken.

Research Approach - Objective 3

The third objective included developing the MCE model. This process consisted of multiple steps, such as creating a pairwise table to determine the weights, calculating the consistency ratio, and applying them. The weights were decided using a pairwise table as well as input from Sara Wicks and Allison Myles, two members of the Dufferin County Climate Office. The weights were standardized so that their total will equal 1. To ensure that the weights are logical, we checked the consistency ratio of the pairwise table; if our ratio is above 0.1, the weights do not follow the logic and are too inconsistent. Once the weights are chosen, they were applied; however, all variables must first be joined to the same attribute table. The weights were applied, and the variables will be added to determine the heat vulnerability per DA. This will effectively display urban heat vulnerability. The areas of highest heat vulnerability will be of interest as they will be recommended for tree planting. See the flow chart, *figure 2.2* in the appendix for an overview of the steps taken.

Research Approach - Objective 4

The fourth objective is to identify and evaluate the strengths and weaknesses within our MCE model. MCE models are often used in the environmental and urban assessment field because it is suitable for complex decision problems that involve multiple conflicting objectives and criteria like our model (Jiang and Eastman, 2000).

An advantage of the MCE model is that it allowed us to allocate different weights to each variable. Our communications with Dufferin County Climate Office were advantageous in deciding the allocation of weights to each variable. Additionally, a pairwise table was used to reach accurate and effective results.

A disadvantage of this model is that the outcome of our MCE (DA most vulnerable to heat) depends on the weights assigned. By ranking the variables differently and assigning different values, the results may be skewed. This illustrates the importance of ranking variables with certainty. Including Wicks in the ranking processes ensures a professional opinion and expertise that represents Dufferin County accurately.

Results and Discussion

Objective 1

The variables selected in this analysis were important, but further research into other variables could have the potential to provide a more detailed analysis with a different outcome. In future research, it would be helpful to consider a few more variables in our model. Some other variables that can be considered are surface type (land classification), a more detailed tree inventory data to ensure all trees are accounted for in the county, and data of the age of homes or number of homes with HVAC cooling technologies.

Surfaces that are darker and not permeable, exacerbate the UHI effect as darker surfaces absorb more heat and their non-permeable make-up results in little to no evapotranspiration. Classifying land types in our study areas added to our analysis by showing which areas naturally absorb and release more heat (Filho et, al., 2017). Moreover, a more detailed tree inventory covering both private and public lands would have eliminated assumed gaps in our data; our data consisted of trees on publicly owned land. Finally, having insight on which homes have HVAC cooling technologies and which homes do not would have allowed us to get a more detailed overview of which people in the community do not have personal access to air-conditioning (Filho et, al., 2017). These additional variables would have contributed to a more detailed analysis of heat vulnerability throughout our study areas.

Objective 2

The data preparation revealed the values for each variable at the DA level. The layers produced maps of the individual variables to the town centre DAs of Dufferin County. A map was produced for each variable and can be seen in *figures 1.1- 1.6.* We indexed the results to 10 % intervals to display the range in values of each variable.

Figure 1.1 indicates the canopy cover per DA; Orangeville experienced the greatest variance in canopy cover due to its higher population density and increase in urban-like areas.

Grand Valley is largely rural and has less development, resulting in more canopy cover. It is important to note that 100% indicates an absence of canopy cover. The distribution of canopy cover is consistent with the development in Dufferin County, as Orangeville, the largest town centre is the most developed town centre.

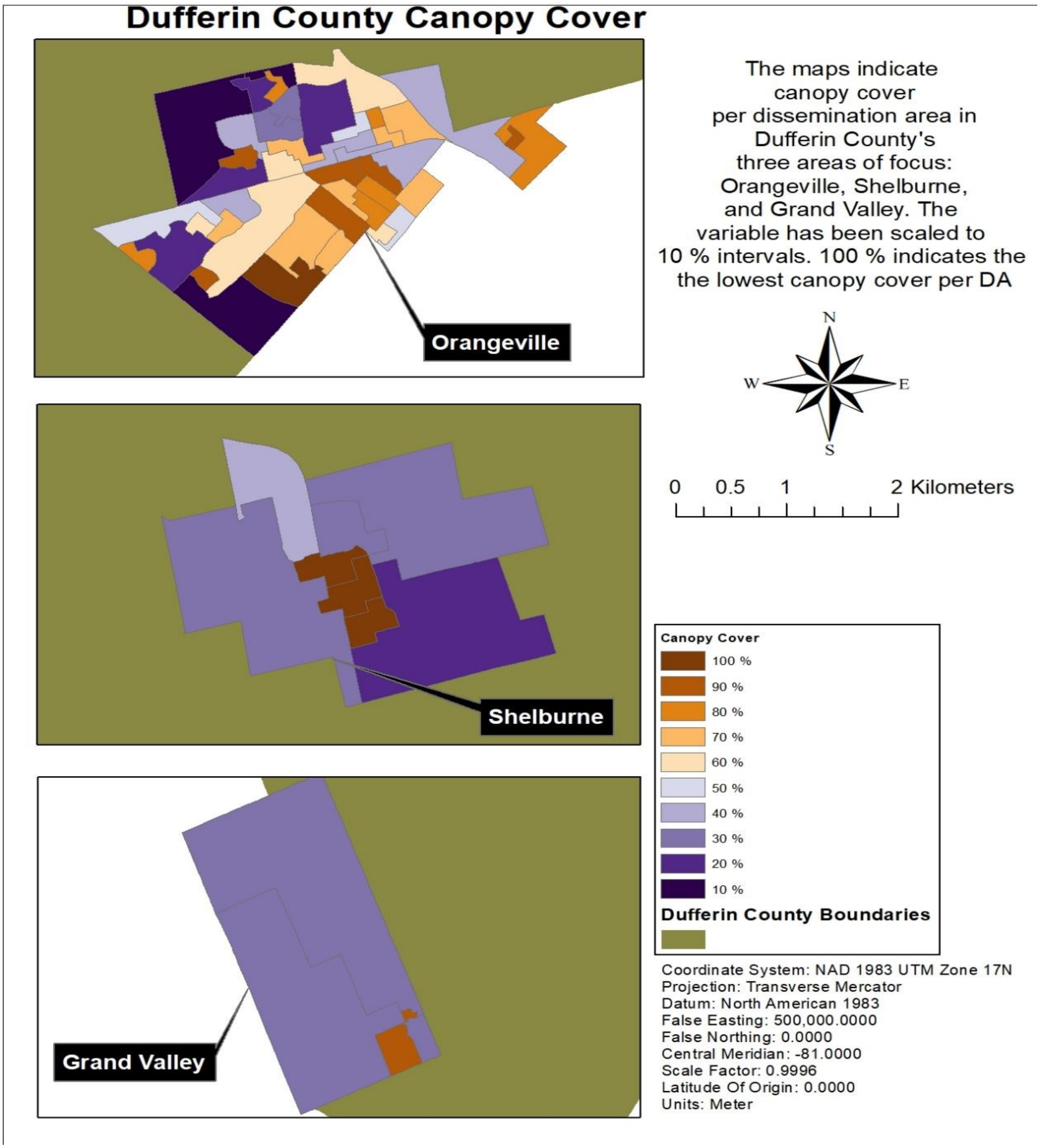


Figure 1.1: Dufferin County Canopy Cover for Orangeville, Shelburne and Grand Valley

In *Figure 1.2* the dependency variable is mapped. Orangeville has some of the highest values. These areas are indicative higher proportions of populations over 65 and a high dependency ratio (total population 0-14 and 65+ /total population 15 to 64) (Matheson, 2016). Orangeville has higher rates of dependency, which may be due to the larger population, as seen in the population density analysis.

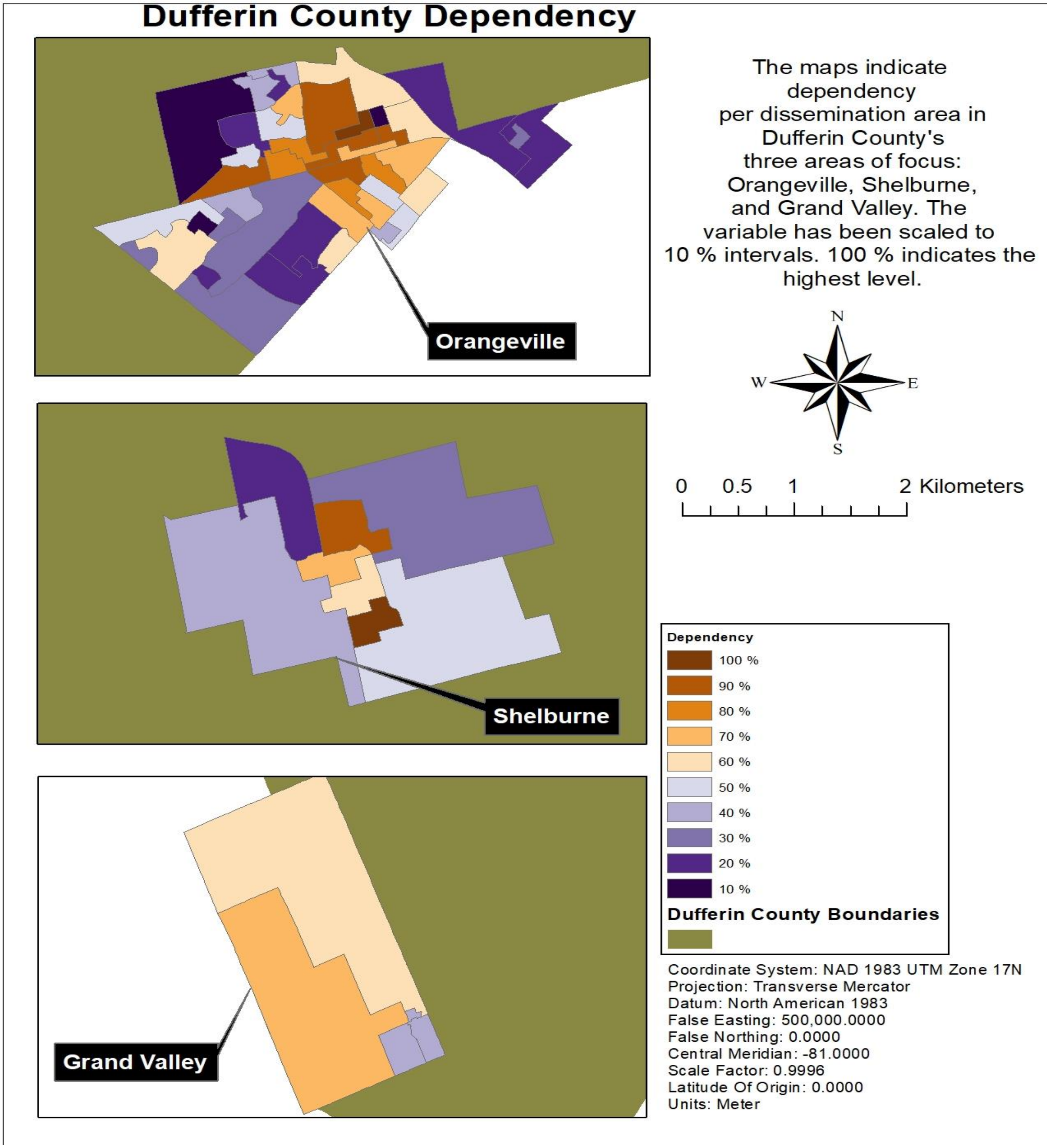


Figure 1.2: Dufferin County Dependency for Orangeville, Shelburne and Grand Valley

As seen in Figure 1.3 the average distance to cooling centres per DA is mapped. Grand Valley has the highest average distance due to the rural nature of the town centre. Orangeville and Shelburne have relatively lower distances to cooling centres because of their smaller DA size. DAs typically range from 400-700 people, therefore Grand Valley has larger DAs because of its lower population density (Stats Canada, 2016).

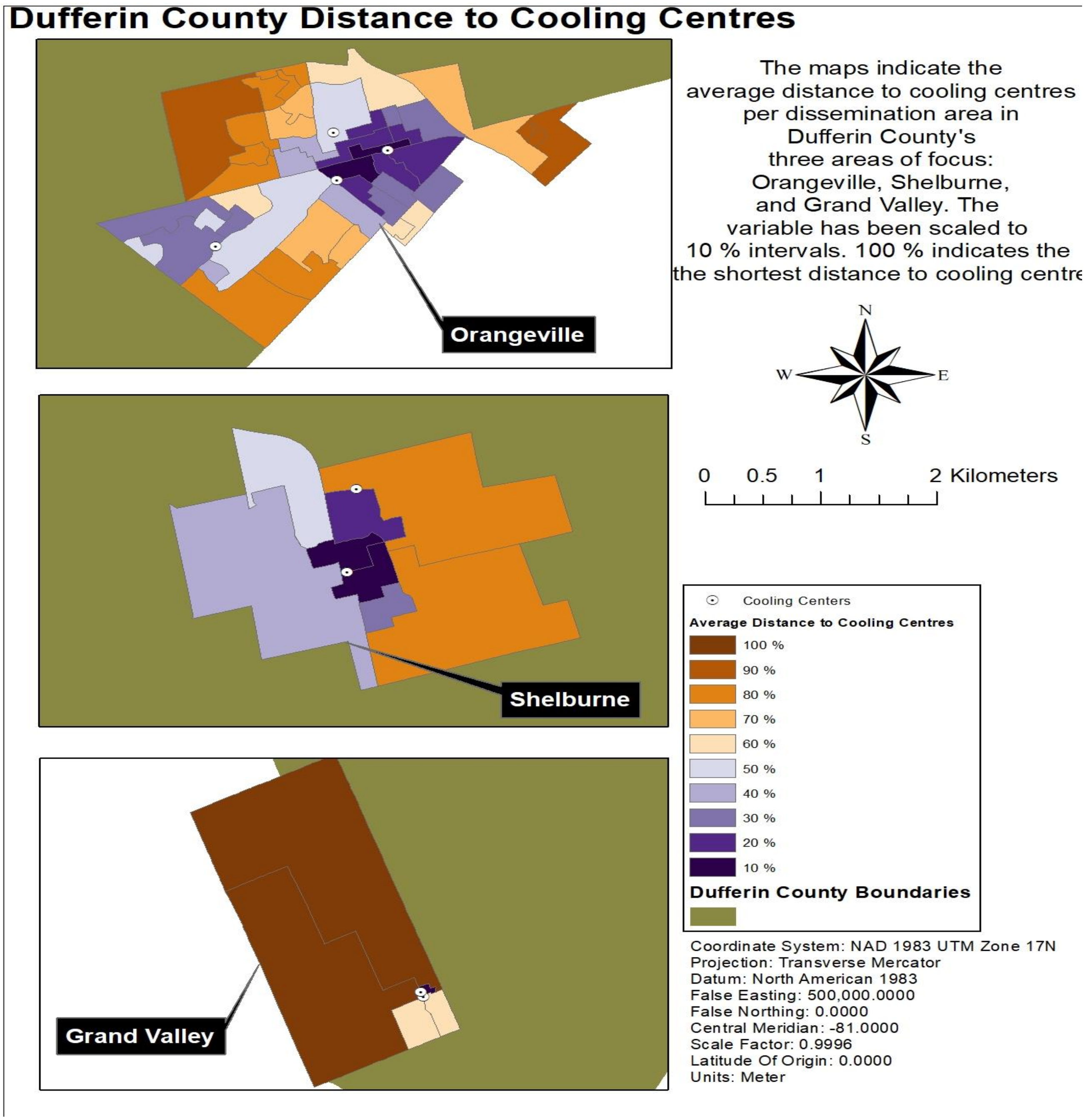


Figure 1.3: Dufferin County Distance to Cooling Centre for Orangeville, Shelburne and Grand Valley

As seen in Figure 1.4 material deprivation per DA was mapped. This variable was retrieved from the Ontario Marginalization index. Its multidimensionality addresses poverty without directly using income (Matheson, 2016). The marginalization index utilizes six indicators to determine material deprivation. They include the following: proportion of population aged 20+ without a high-school diploma, proportion of families who are lone parent families, proportion of total income from government transfer payments for population aged 15+, proportion of population 15+ who are unemployed, and proportion of the population considered low-income (Matheson, 2016). Using income alone is not enough to justify poverty.

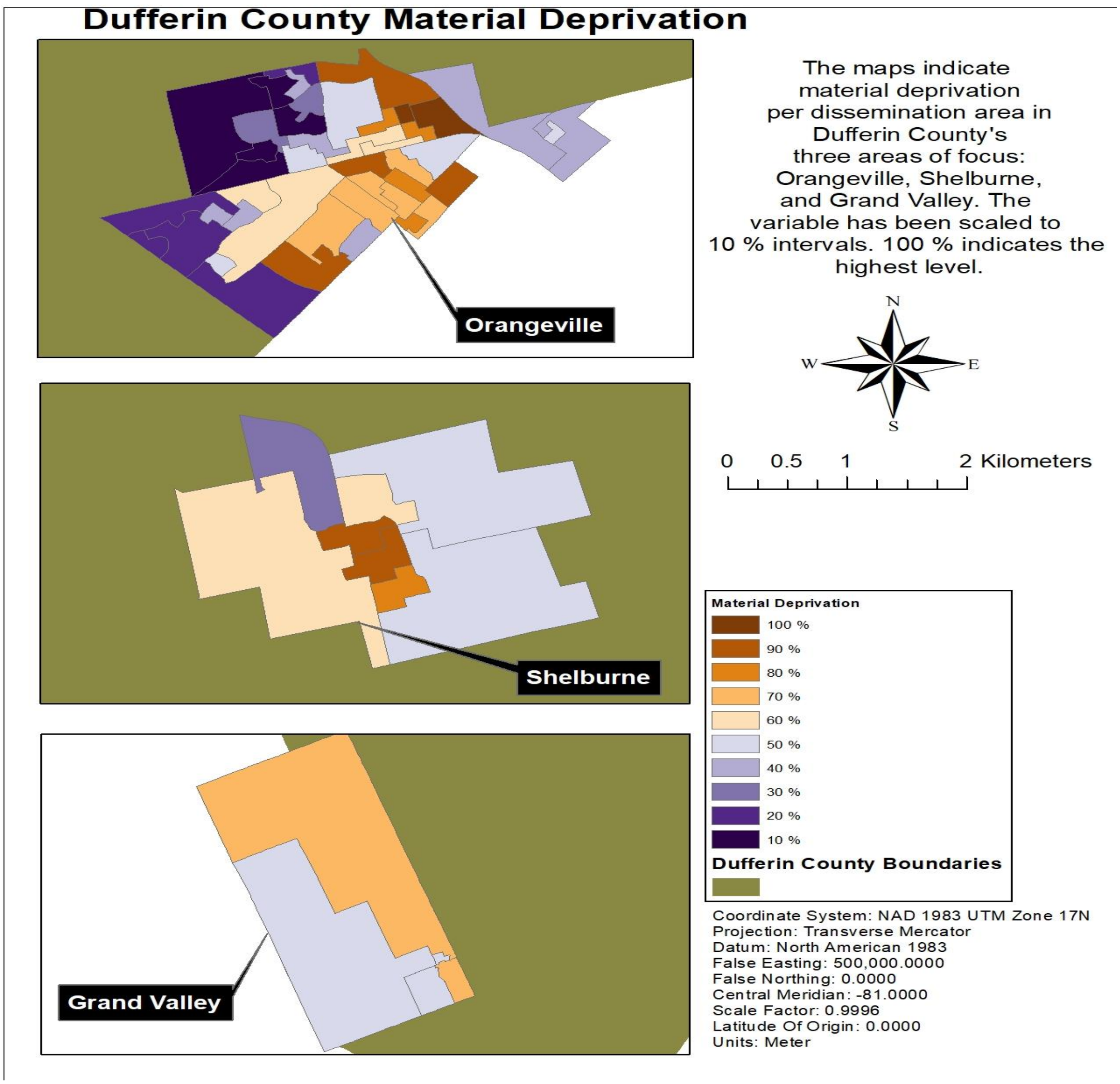


Figure 1.4: Dufferin County Material Deprivation for Orangeville, Shelburne and Grand Valley

In *Figure 1.5* Population density is lowest in Grand Valley, due to its ruralness. Within Orangeville, we see a large range in the level of population density. This may be due to the mixed types of homes within the town of Orangeville. Moreover, Shelburne is experiencing significant development (Wicks, S; Personal Communication, 2021), henceforth there appears to be sprawling development occurring in the town centre.

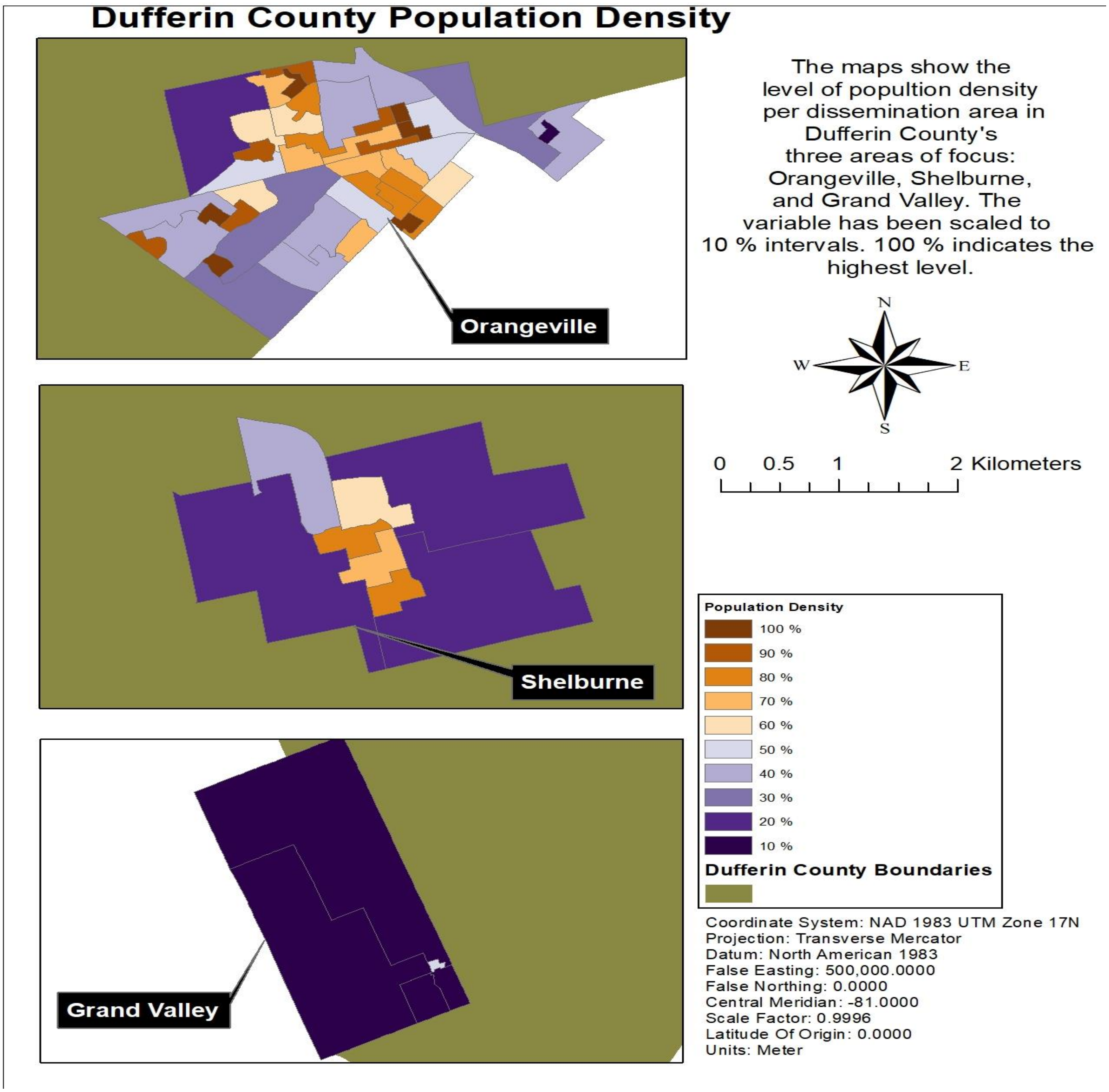


Figure 1.5: Dufferin County Population Density for Orangeville, Shelburne and Grand Valley.

Objective 3

The pairwise table calculated the weights by comparing the variables to one another, the calculations can be found in the appendix in *figure 1.7.* Members from Dufferin County Climate Office, Sara Wicks and Allison Myles, decided the weighting in an interview. The weights were standardized into individual weights, as seen in *figure 1.8.*

We then determined the consistency ratio to ensure the variables were logically made, as seen in *figure 1.9.* To determine the consistency ratio, we subtracted five from lambda and divided it by four (Ergu et al, 2011). The equation below visualizes how the consistency ratio was determined. N is five because we chose 5 different variables.

$$\text{Consistency ratio} = (\lambda - n)/(n - 1)$$

The consistency ratio was 0.0059 which fell well below 0.1. If the ratio were greater than 0.1 it would be deemed illogical. After applying the weights and producing the MCE model, we determined the areas with the highest level of heat vulnerability. The heat vulnerability is displayed as a choropleth map indicating the degree of heat vulnerability per DA. We highlighted the areas with the greatest heat vulnerability in each town centre. This allowed us to make recommendations for each urban center in addition to the overall county.

Within F*igure 1.6* heat vulnerability is aggregated to the DA level. Shelburne has the DA with the highest level of heat vulnerability. Grand Valley experienced the lowest level of heat vulnerability; our model is best suited for town centres and Grand Valley may be too rural for ideal analysis. Orangeville experienced the greatest range in heat vulnerability, due largely to its large range of values for each variable.

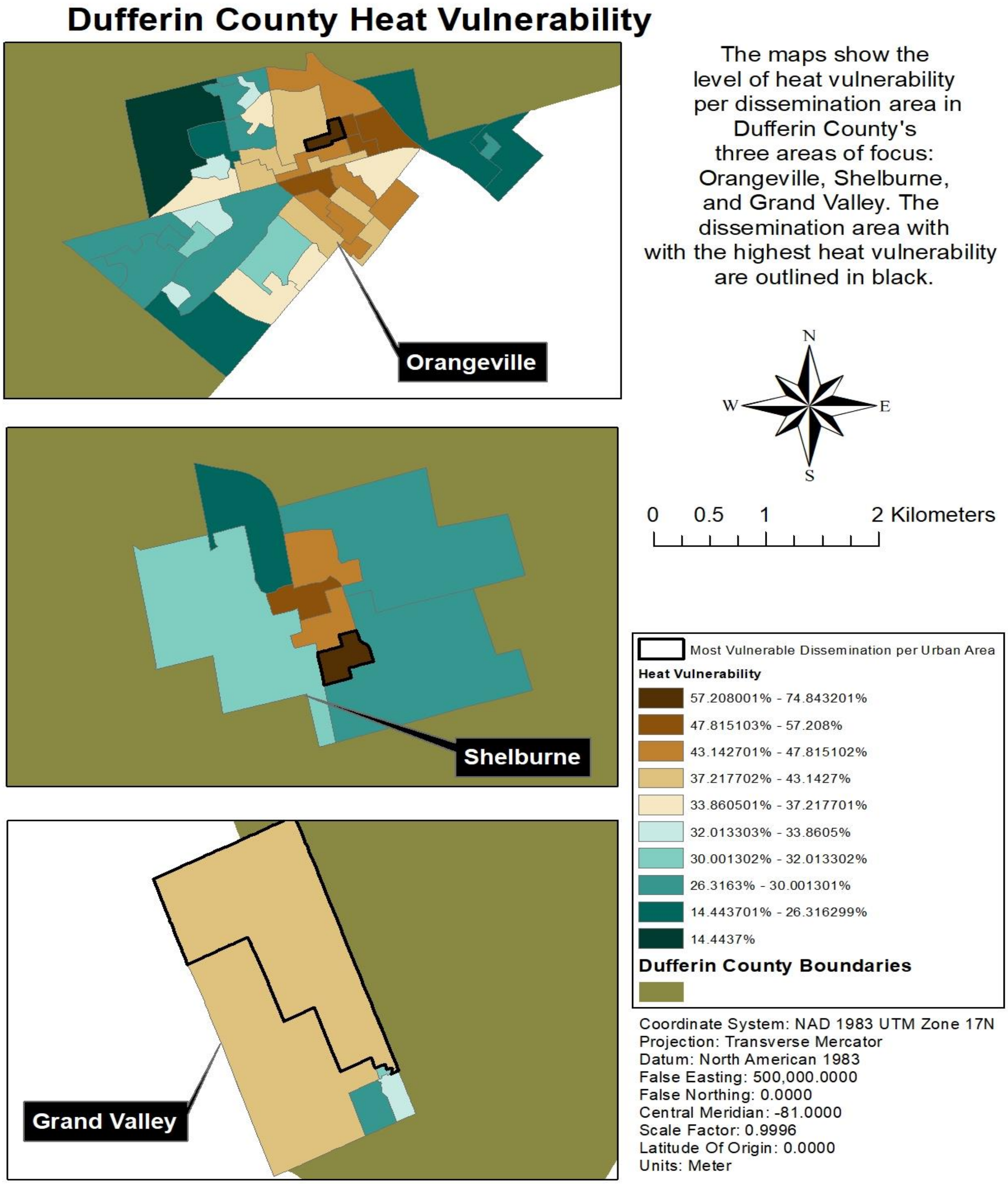


Figure 1.6: Dufferin County Heat Vulnerability for Orangeville, Shelburne and Grand Valley

Objective 4

In the MCE model we identified areas where heat is most vulnerable in Dufferin County's town centres Orangeville, Shelburne, and Grand Valley. The advantages when running an MCE model is that it allowed us to weigh our variables, since mitigating heat is a very complex topic that may have different influences based on region or county. To achieve accuracy, we asked Sara Wicks who has been conducting Climate work within Dufferin County to rank the importance of each variable from most importance to least important in terms of priority and influence. The ranking of the variables from most to least weighted were as follows: dependency, material deprivation, forest canopy, population density and proximity to cooling centers. With this ranking, we then conducted calculations to assign weights to each variable which can be seen in *figure 1.7 And 1.8* in the appendix. Our decision to use five variables was for simplicity in our model; selecting too few variables could result in an underestimate in our results and too many variables could result in an overestimation of heat vulnerability. Therefore, picking five variables that represent/influence Dufferin County will give us accuracy within our model. Another advantage of our model is that it is very cost effective, the programs used, and data set used were public meaning no funding was needed.

However, our model does have its weaknesses, most of which are due to the lack of recent data or access to data. Since our data sets are public records from 2016 or data sets, we created ourselves(proximity to cooling centers), there could be missing data that has not been accounted for. For example, our tree coverage variable illustrated three DAs with no tree coverage. This could be because these areas simply do not have any tree coverage, or these areas have not been surveyed or updated, so we simply just do not know unless we visit the site. Another reason can be that these DAs are majority private land, since our model focuses on public/ city owned land, our tree coverage data only account for trees planted in public areas. Another weakness within our model is the fragile nature of the MCE weights. The outcome or final product of our MCE emphasizes the areas where heat is most vulnerable based on the rankings of our variables. Changing the rankings of our variables will impact the level of heat vulnerability per DA. So, in other words, the DAs of the final product are highly influenced by the opinion of the person ranking the variables. For example, Dufferin County's Climate Office employee might have different views/ ranks than a County's Financial Advisor. To ensure the models accuracy, it is important to account for Dufferin County's overall ranking. Due to time constraints, we relied on Wick's and Myles' expertise and experience they have with Dufferin County. With that said our MCE model was specifically built for Dufferin County and their requirements, if another County or Region was to adapt this model, they would have to re-weigh each variable to receive the most accurate results.

Conclusion

The UHI effect is becoming an increasingly detrimental phenomenon to human health and the environment. Urban centers are the epicenters of anthropogenic activity because they are major contributors to GHGs which contribute to the UHI effect. Research shows that the most effective method to reverse the UHI effect is by adding more vegetation to urban areas. Vegetation provides natural methods of cooling as well as works towards reversing an increase in CO2 by creating an increase in carbon sinks.

Using GIS and a combined effort of members of the Dufferin County Climate Office, we were able to effectively create an MCE model that demonstrates which areas in Orangeville, Shelburne and Grand Valley are most vulnerable to heat. Factors including, material deprivation, dependency, population density, proximity to cooling centres and pre-existing tree canopy, created results that accurately represent and model the socio-economic and environmental concerns that are affected by heat thus creating heat vulnerability.
Upon the completion of our analysis, through the use of maps, we identified the top greatest heat vulnerable areas in all three town centres of Dufferin County.

Our results will aid the Office in their future climate action initiatives by providing the areas in the community that would benefit from an increase in both private and public trees. Our research, although tailored to what the community partners needed from us, has the potential to be explored more in-depth. In future research, it would be useful to also create a suitability analysis to show exactly the best places to plant trees are and looking into which tree species would be most adaptable to the changing environments. The constraints to completing these analyses in this study were due to lack of time but are still highly encouraged in future research as it would develop the movement in this project creating stronger justifications to climate change adaptability.

Appendix

Variable	Population Density	Material Deprivation	Dependency	Distance to Cooling Centres	Forest Canopy
Population Density	1.000	0.33	0.25	2.00	0.50
Material Deprivation	3.000	1.00	0.50	3.00	2.00
Dependency	4.000	2.00	1.00	4.00	3.00
Distance to Cooling Centres	0.500	0.33	0.25	1.00	0.33
Forest Canopy	2.000	0.50	0.33	3.00	1.00
Sum	10.500	4.16667	2.33333	13.00000	6.83333

Figure 1.7: Pairwise Comparison Table

Variable	Population Density	Material Deprivation	Dependency	Distance To Cooling Centres	Forest Canopy	Total Weights
Population Density	0.0952	0.08	0.10714286	0.153846154	0.073170732	0.1019
Material Deprivation	0.2857	0.24	0.21428571	0.230769231	0.292682927	0.2527
Dependency	0.3810	0.48	0.42857143	0.307692308	0.43902439	0.4072
Distance to Cooling Centres	0.0476	0.08	0.10714286	0.076923077	0.048780488	0.0721
Forest Canopy	0.1905	0.12	0.14285714	0.230769231	0.146341463	0.1661
Sum	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Figure 1.8: Standardization of Weights

Variable	W*Sum	Consistency vector	
Population Density	1.069735	4.809607995	
Material Deprivation	1.052877	4.886619431	
Dependency	0.950246	5.414398531	
Distance to Cooling Centres	0.93721	5.489705624	
Forest Canopy	1.13494	4.533285852	
Sum	5.1450		
		Lamda	5.026723487
		Consistency index	0.006680872
		Consistency Ratio	0.005965064

Figure 1.9 - Determining the Consistency Ratio

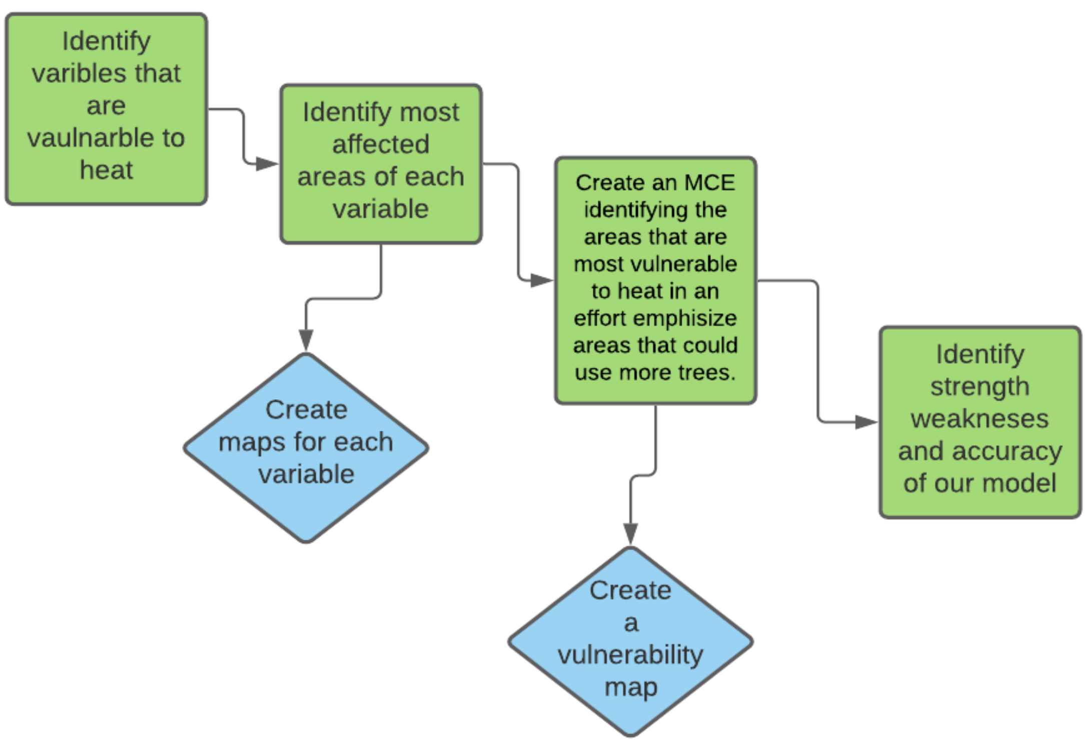
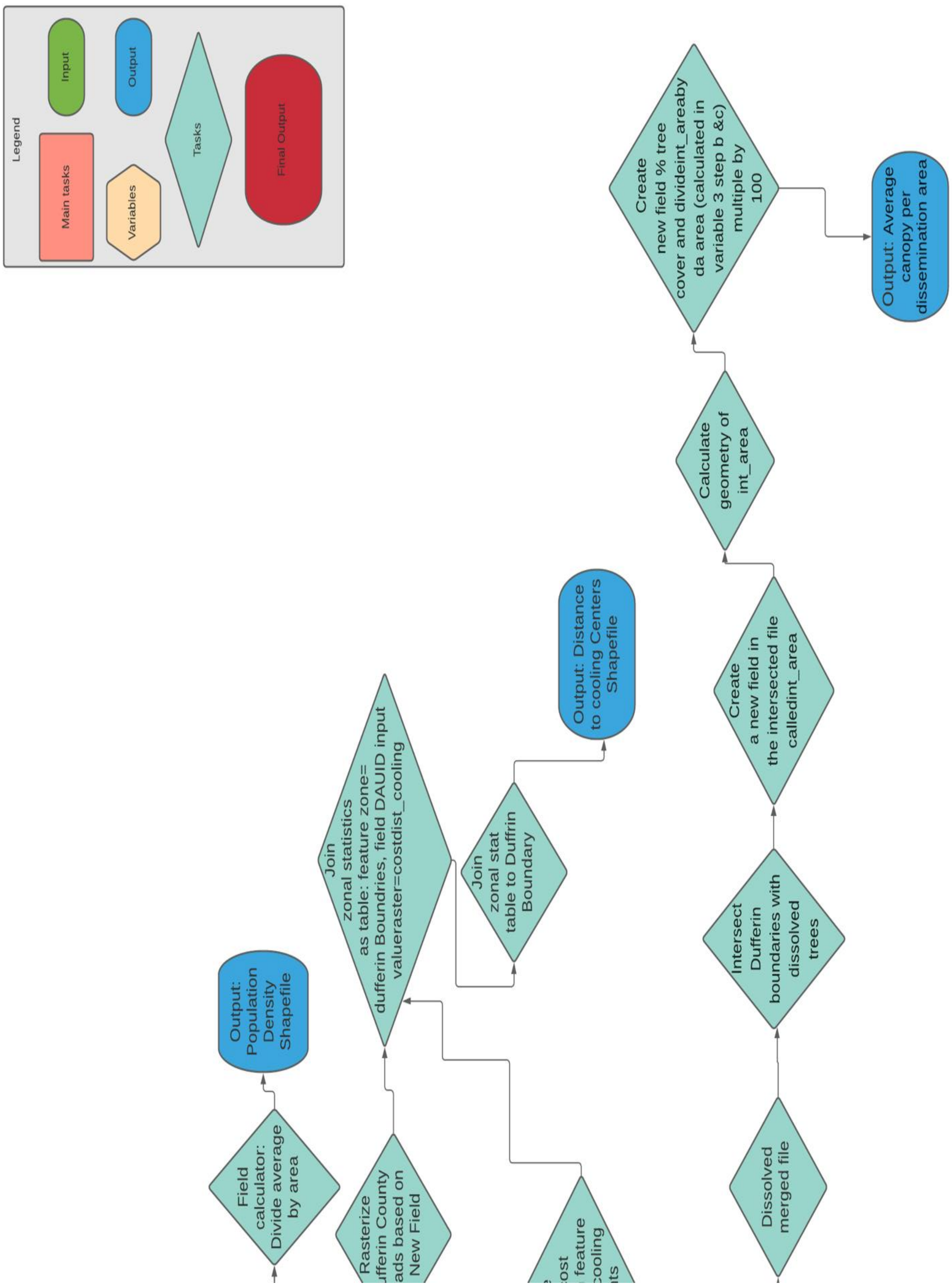


Figure 2.0: Concept flow chart. Flow Chart A.


Legend
Main tasks
Input
Output
Variables
Tasks
Final Output
Field calculator: Divide average by area
Output: Population Density Shapefile
Join zonal statistics as table: feature zone= dufferin Boundries, field DAUID input valueraster=costdist_cooling
Join zonal stat table to Duffrin Boundary
Output: Distance to cooling Centers Shapefile
Dissolved merged file
Intersect Dufferin boundaries with dissolved trees
Create a new field in the intersected file calledint_area
Calculate geometry of int_area
Create new field % tree cover and divideint_areaby da area (calculated in variable 3 step b &c) multiple by 100
Output: Average canopy per dissemination area

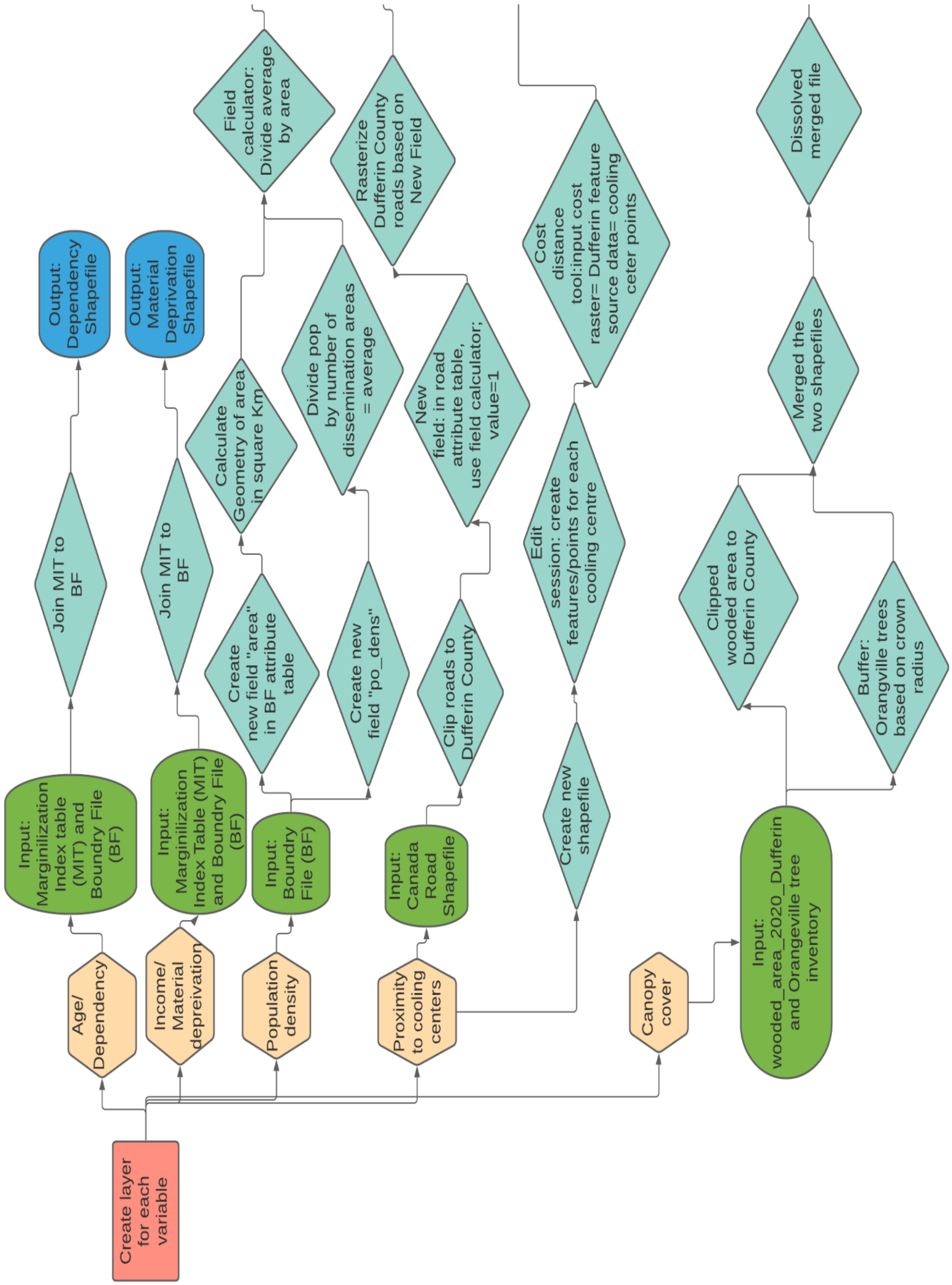


Figure 2.1: Flow chart for objective two illustrating variable process and shapefile outputs. Flow Chart B.

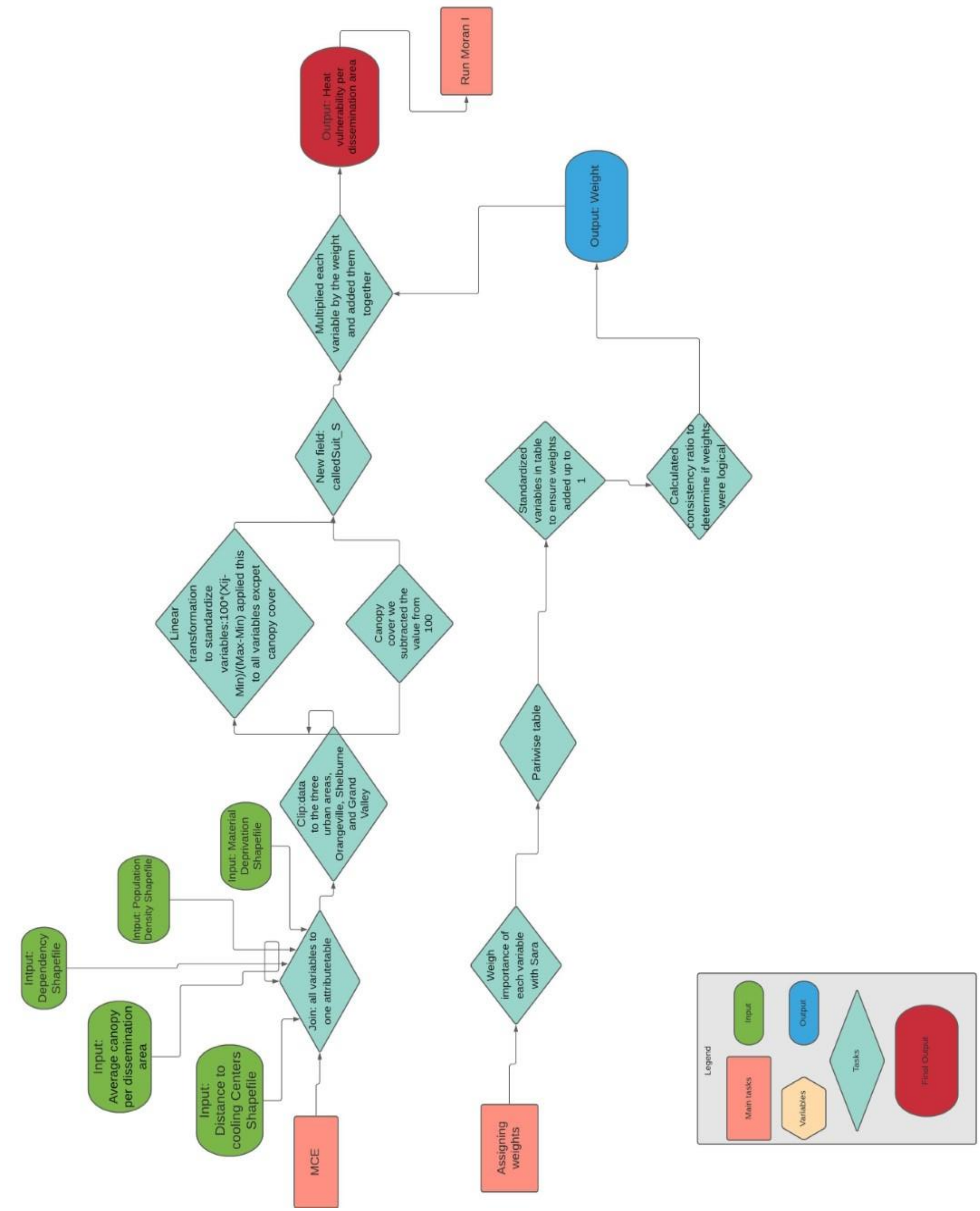


Figure 2.2: Flow chart for objective three illustrating the final MCE process and final output.
Flow Chart

References

Coutinho-Rodrigues, J., Simão, A. & Henggeler Antunes, C. (2011). A GIS-based multicriteria spatial decision support system for planning urban infrastructure. Decision Support System, 51, p. 720-726. DOI:10.1016/j.dss.2011.02.010

Deaton, J., & Vyn, R. (2010). The Effect of String Agricultural Zoning on Agricultural Land Value: The Case of Ontario's Greenbelt. *American Journal of Agricultural Economics, 92, 941-955.* https://onlinelibrary-wiley-com.subzero.lib.uoguelph.ca/doi/full/10.1093/ajae/aap022?sid=vendor%3Adatabase

Dufferin County. (2020). Wooded Area 2020 Dufferin.

Eastman, J. R. (1999). *Multi-criteria evaluation and GIS* (N.d). Abridged. https://www.geos.ed.ac.uk/~gisteac/gis_book_abridged/files/ch35.pdf.

Ergu, D., Gang, K., Peng, Y., & Shi, Y. (2011) A simple method to improve the consistency ratio of the pair-wise comparison matrix in ANP. *European Journal of Operational Research,* 213, 1, 246-259. https://www.sciencedirect.com/science/article/pii/S0377221711002256

Filho, W. L., & Morgan, E. A., (2018) Coping with the impacts of urban heat islands. A literature-based study on understanding urban heat vulnerability and the need for resilience in cities in a global climate change context. *Journal of Cleaner Production,* 171, 1140-1149. https://wwwsciencedirectcom.subzero.lib.uoguelph.ca/science/article/pii/S0959652617323806?via%3Dihub

Fraser, A.M. et, al. (2017). Household accessibility to heat refugees: Residential air condition, public cooled space, and walkability. Environment and Planning B: Urban Analytics and City Science, 44(6), p. 1-36-1055. https://doi.org/10.1177/0265813516657342

Grimmond, S. (2007). Urbanization and global environmental change: local effects of urban warming. *The Geographical Journal*, 173(1), 83-88. https://doi.org/10.1111/j.1475-4959.2007.232_3.x

Jiang, H., & Eastman, J. R. (2000). Application of fuzzy measures in multi-criteria evaluation in gis. *International Journal of Geographical Information Science, 14*(2), 173-184. doi:10.1080/136588100240903

Kleerekoper, L., van Esch, M, & Baldiri Salcedo, T. (2020). How to make a city climate-proof, addressing the urban heat island effect. *Resources, Conservation and Recycling*, 64 pp/ 30-38. https://doi.org/10.1016/j.resconrec.2011.06.004

Matheson FI, van Ingen T. 2016 Ontario marginalization index: user guide. Toronto, ON: St. Michael's Hospital; 2018. Joint publication with Public Health Ontario. https://www.publichealthontario.ca/-/media/documents/O/2017/on-marg-userguide.pdf?la=en

Morakinyo, T. E., Ouyang, W., Lau, K. K., Ren, C., & Ng, E. (2020). Right tree, right place (urban canyon): Tree species selection approach for optimum urban heat mitigation - development and evaluation[ZA1] . *Science of The Total Environment, 719*, 137461st ser. doi:https://doi.org/10.1016/j.scitotenv.2020.137461.

Rahman, M.A., et.al. (2020). Traits of trees for cooling urban islands: A meta-analysis. Building and Environment, 170. https://doi.org/10.1016/j.buildenv.2019.106606

Reid, C.E., et, al. (2009). Mapping community determinants of heat vulnerability. *Environmental Health Perspective*, 117(11) word length, 6178. https://go-gale-com.subzero.lib.uoguelph.ca/ps/i.do?p=AONE&u=guel77241&id=GALE|A212769463&v=2.1&it=r

Smoyer-Tomic, K.E., kuhn, R. & Hudson, A. (2003). Heat Wave Hazards: An Overview of Heat Wave Impacts in Canada. *Natural Hazards,* 28(2-3), 465-468. https://doi.org/10.1023/A:1022946528157

Statistics Canada. (2016) Census Boundary Files. Dissemination Areas. https://www12.statcan.gc.ca/census-recensement/alternative_alternatif.cfm?l=eng&dispext=zip&teng=lda_000b16a_e.zip&k=%20%20%20%2090414&loc=http://www12.statcan.gc.ca/census-recensement/2011/geo/bound-limit/files-fichiers/2016/lda_000b16a_e.zip

Town of Orangeville, (2020) Street Trees in the Town of Orangeville. https://services3.arcgis.com/pCmV4YWmyIH9CmGq/arcgis/rest/services/Trees/FeatureServer

Voelkel, J., Hellman, D., Sakuma, R. & Shandas, V. (2018). Assessing Vulnerability[ZA2] to Urban Heat: A Study of Disproportionate Heat Exposure and Access to Refuge by Socio-Demographic Status in Portland, Oregon, International journal of environmental research and public health, 15(4), p 640-654. DOI:10.3390/ijerph15040640

Wicks, Sara. (2021). Personal Communications