Introduction

In the final assessment in the CCIA course is to analyze the exposure unit of icy days where temperature is less than 0°C for months September, October, and November in Toronto, Ontario. All future temperature analyses are compared to an observed baseline period form 1981-2010. The assessment methods that were used to compare different models was AR4 and AR5.

Methodology and Results

As mentioned before, the basis for all analysis done in this assessment was based on an exposure unit that looked at all the days in September, October and November, in a certain time period, that had maximum temperatures less than 0°C. This exposure unit was considered during the second and third parts of the CCIA assessment.

The first step of the CCIA process is to determine a proper baseline period. To do so, temperature data from 1961-1990, 1971-2000 and 1981-2010 where graphed in an annual temperature distribution plot. For each time period, the statistical significance of the data was assessed by using Excel's regression analysis to determine R^2 values, Pearson R-value, mean values, and standard deviations. By basing the conclusion off these statistical parameters, the statistical significance of the data can be determined and so the baseline can be confidently established. Based on the statistical significance, the baseline period chosen was 1981 – 2010 and its associated temperature distribution is shown in Fig 1.

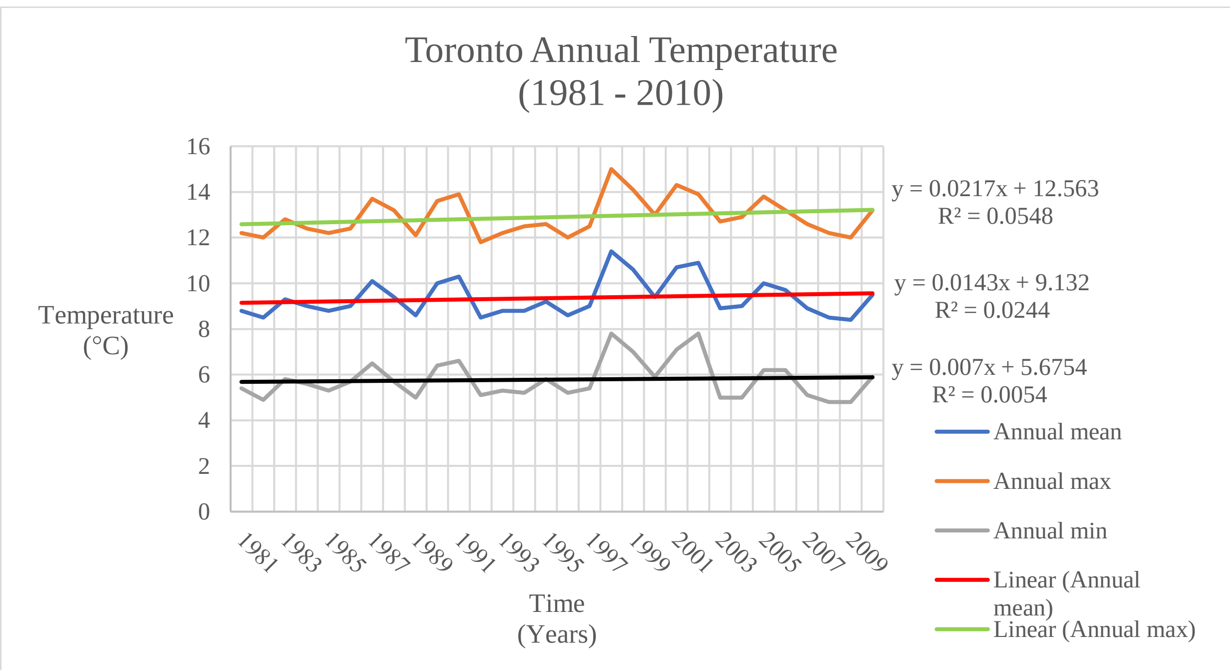

Figure 1: Annual temperature distribution for 1961-1990 with Annual mean, max, and min curves.

The second part was to rank different climate models to determine the top 3 that would be best suited for further assessments. In this part, AR4 and AR5 assessments with their associated climate models were being ranked. There were two methods of ranking used: absolute differences and GF Confidence Index.

For absolute differences, it was between the observed average Tmax data and model average baseline temperature data for 1971-2000 and 1981-2010. The observed data values used are summarized in the table below. Average baseline temperature values were determined for each model using excel integrated functions.

Table 1: Statistical data on 1972-2000 and 1981-2010 time period

	Tmax For 1971 - 2000	Tmax For 1981 - 2010
Average	12.66666667	12.9
Std. Dev	0.794087346	0.816214982

After determining the absolute difference for each model, the list of values was ordered from smallest to largest with their associated models. The top 3 ranked values would be the top 3 smallest absolute difference value. The GF Confidence Index is defined as and calculated using:

$$GF = \frac{\left| \begin{matrix} Obse\ Avg \\ Tmax \end{matrix} - \begin{matrix} Model\ Avg \\ Baseline\ Temperature \end{matrix} \right|}{\begin{matrix} Std.Dev\ of \\ Observed\ Tmax\ data \end{matrix}} = \frac{Abs\ \Delta T}{\begin{matrix} Std.Dev\ of \\ Observed\ Tmax\ Data \end{matrix}} \qquad [1]$$

Where if GF > 1 the value is considered suspect and if GF < 0.5 then one can have confidence that the value is acceptable

Below is a summary table of the top 3 ranked models with their associated GF index values and absolute difference values. It is worth nothing that the GF index is proportional and related to the absolute difference values. Therefore, the model with the smallest absolute difference would also have the smallest GF index value. As it can be seen in Table 2 that the absolute difference values are not the same as the GF index values for each associated modelling method. The top 3 ranked values describe how good the model is at being close to real world data.

Table 2: A summary table of the top 3 ranked models.

Data Set	Model	Avg Baseline (degC)	Abs ΔT	Ranking	GF index	GF Confidence Index
AR4 - 1971-2000	CGCM3T47(Run 3)	12.7905	0.123833333	1	0.155944222	Confident
	CGCM3T47(Run 5)	12.4851	0.181566667	2	0.228648231	Confident
	CGCM3T47(Mean)	12.4484	0.218266667	3	0.274864809	Confident
AR4 - 1981-2010	CGCM3T47(Mean)	12.89853333	0.001466667	1	0.001796912	Confident
	CGCM3T47(Run 5)	12.89773333	0.002266667	2	0.002777046	Confident
	CGCM3T47(Run 1)	12.9266	0.0266	3	0.032589453	Confident
AR5 - 1971-2000	MIROC5(Run 2)	12.6156	0.051066667	1	0.064308627	Confident
	ACCESS1-3(Run 1)	12.7343	0.067633333	2	0.085171151	Confident
	MIROC5(Mean)	12.8292	0.162533333	3	0.204679415	Confident
AR5 - 1981-2010	ACCESS1-3(Run 1)	13.133	0.233	1	0.285464008	Confident
	FIO-ESM(Run 3)	12.649	0.251	2	0.307517021	Confident
	FIO-ESM(Run 1)	12.540725	0.359275	3	0.440172023	Confident

The third part has two sections. The first section is to determine future temperature projections for time periods 2011-2020, 2041-2050, and 2051-2080. First, the Toronto city daily temperature dataset was filtered for temperatures that were less than 0°C for September, October and November were extracted by using Excel pivot tables. As expected, only the month of November met the criteria of the exposure unit. Anomalies for each month were taken down from Climate Change Hazards Information Portal (CCHIP) website for experiments RCP4.5, RCP6, and RCP8.5 and are summarized in Table 3.

Table 3: Summary of anomalies taken from CCHIP

Month	Experiment	2020 Projection Avg	2050 Projection Avg	2080 Projection Avg
Sep	RCP4.5	22.7	23.9	24.5
	RCP6	22.5	23.7	25
	RCP8.5	22.9	24.8	27.3
Oct	RCP4.5	15.3	16.4	17.1
	RCP6	15.1	16	17.4
	RCP8.5	15.5	17.4	19.6
Nov	RCP4.5	9.2	10	10.5
	RCP6	8.9	9.8	10.9
	RCP8.5	9.2	10.7	12.7

These anomalies for each experiment, for each projection would be added to each of filtered Toronto temperature, as mentioned before, to get the projections for 2011-2020, 2041-2050, and 2051-2080.

The second section of part 3, to re-evaluate the models on how they can assess future climate. In this case the future periods being analyzed are 2041-2070 and 2071-2099. This is done by using a ranking method like part 2 but only basing the rankings off the top 3 smallest GF index value. This re-evaluation was done for assessments AR5 (2011) and is summarized in Table 4.

Table 4: Rankings for AR5.

Assessment	Time Period	Model	Avg Temperature change (°C)	GF Index	Ranking
AR5 (2011)	2041-2070	HadGEM2-CC(Mean)	4.3483	10.47726419	1
		HadGEM2-CC(Run 2)	4.2952	10.54232058	2
		HadGEM2-CC(Run 3)	4.2069	10.65050286	3
	2071-2099	HadGEM2-CC(Run 3)	7.902	6.123386744	1
		HadGEM2-CC(Mean)	7.7232	6.342446678	2
		HadGEM2-CC(Run 2)	7.2927	6.86988125	3

To find the new exposure unit for the new time periods, the temperature change for each model was added to every Toronto city max temperature data point. This procedure is repeated for all the other models. Then by using pivot tables filter for the top 3 ranked models for the data points for September, October, and November for temperatures < 0°C. The following tables, Table 5 and Table 6, summarizes the average temperature change and the number of temperatures <0°C for each model for each time period.

Table 5: Average temperature for each model for each time period

Assessment	Experiment	Model	Avg Temperature (°C) Baseline (1981-2010)	Avg Temperature Change (°C) (2041-2070)	Avg Temperature Change (°C) (2071-2099)
AR5 (2011)	RCP8.5	HadGEM2-CC(Mean)	9.9138	17.44885672	20.82375672
		HadGEM2-CC(Run 2)	10.1167	17.39575672	20.39325672
		HadGEM2-CC(Run 3)	9.8884	17.30745672	21.00255672

Table 6: Number of temperatures that follow the criteria of the icy day exposure unit, for each model, for each time period

Assessment	Experiment	Model	Count (1981-2010)	Count (2041-2070)	Count (2071-2099)
AR5 (2011)	RCP8.5	HadGEM2-CC(Mean)	26	1	0
		HadGEM2-CC(Run 2)	26	1	0
		HadGEM2-CC(Run 3)	26	1	0

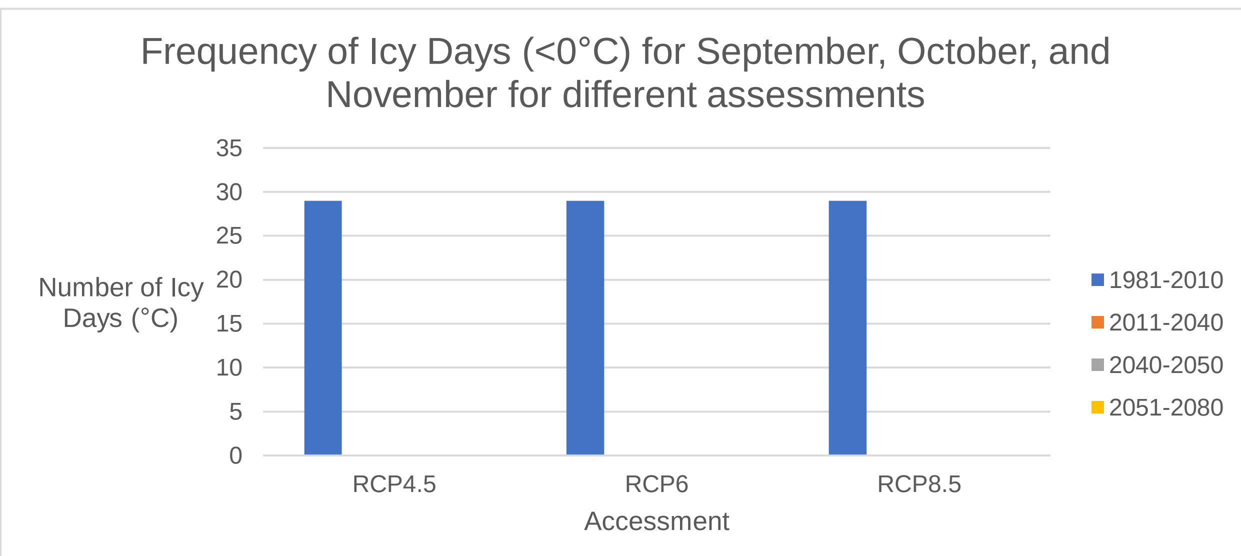

Figure 1: Frequency of icy days for September, October, and November for different experiments, for different time frames in comparasion to the blue baseline period. The number of icy days for September, October, and November are non-applicable to the definition of the exposure unit, after applying anaomaly projections summarized in Table 3.

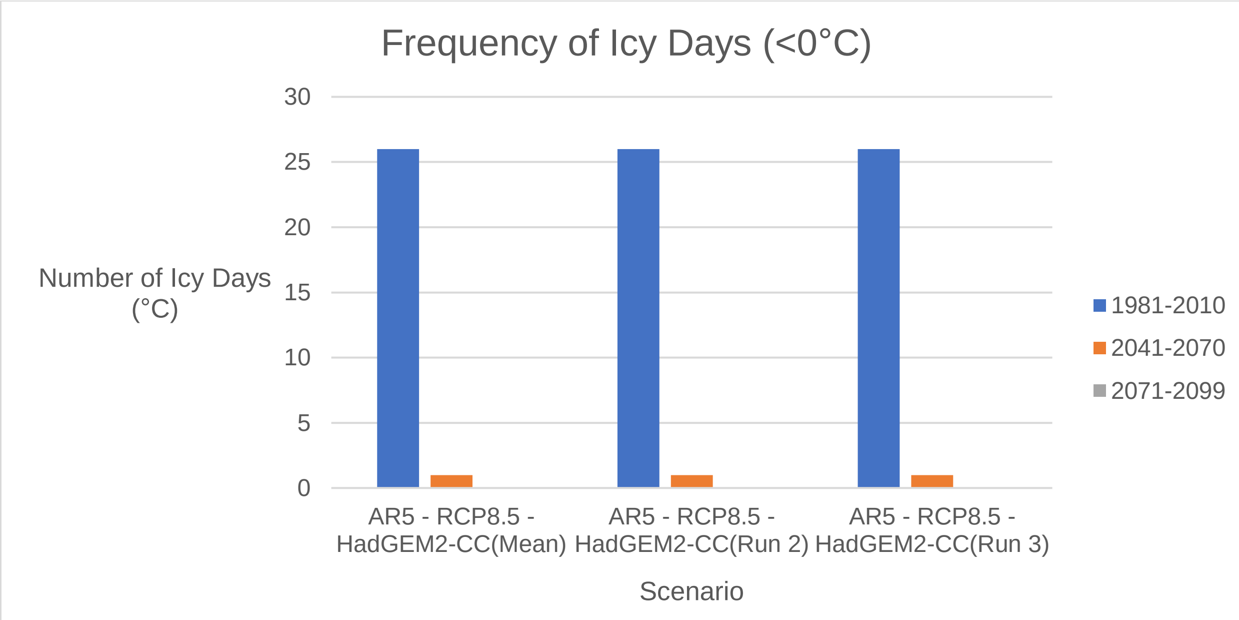

Figure 2: Frequency of icy days for future periods, compared against the baseline period.

Discussion

As seen in Fig. 6, after the re-evaluation, the number of icy days for September, October, and November also decrease such that they become non-existent. Which, qualitatively, is consistent with the result seen in Fig. 5. At first Fig 5-6 seem to be quite alarming that in the future, summer like temperature will also be very likely in September, October, and November. However, each of the data points used in Fig. 5 and Fig. 6 were increased by a fixed amount. For example, for Fig. 5, the anomalies are such large positive values, adding it to a small negative number will still result in a positive number. For example, November 21 (1987) it had a maximum temperature of -4.4°C and by adding a 9.2°C projection it would give a result of 4.8°C. Therefore, the projections show that temperatures less than 0°C for September, October, and November should not be expected for 2011-2020, 2041-2050, and 2051-2080. This effect also affects Fig. 6 since it is based on the 1981-2010 baseline period which all have small negative numbers. The one big difference between Fig. 5 and Fig. 6 is that Fig. 6 has been shifted by each model's temperature value compared to the projections given by CCHIP shifting the data in Fig. 5. Even so, both graphs show that in the future, it is not expected that September, October, and November have temperatures < 0°C.

In terms of the reliability of each forecast given from the second and third parts, no one is better than the other. Since both forecasting's use a similar ranking method which is GF index and they both qualitatively show the same thing, there is no huge difference in which forecasting method is chosen. It can be said that the second forecasting could be more realistic and thus more reliable since its assessment is based on AR5. According to the paper written by Vuuren (2011), AR5 is a compressive assessment and it was the most recently developed compared to AR4. To be more specific about each assessments process, AR4 uses SRES models while AR5 uses RCP models. In addition, AR5 uses average surface temperature whereas AR4 uses average global temperature. Both assessment methods incorporate the affects of the increasing amounts of greenhouse gases (GHG) in their models. However, the advantage of AR5 is that it integrates anthropogenic forcing's and its model is more sensitive to the effects of GHG on the climate. These advantages are not offered when using AR4 assessment method. In summation, AR5 considers more complex parameters that the world inherently has which ultimately makes future temperature estimates more realistic. It is important to note that for both forecasting's, the top 3 ranked models are not the same.

With the results seen in Fig. 5 and 6 showing a climate change in Toronto, it could be that the definition of the exposure unit might have to be re-defined. The overall trend from part 1 to part 3 shows a decreasing trend in icy days and this is supported by Mohsin's paper where it is said that the increasing urbanization of Toronto is contributing to the increase in winter annual minimum temperature (2009).

Mitigation and Adaptation Measures

In terms of mitigation measures, one of the measures was for land use where the implementation of a carbon tax for every metric ton of carbon dioxide produced, there is a fee that the producer must pay. In the paper by Mu et al. they found that a carbon tax reduced "total forest and agriculture greenhouse gas (GHG) annual flux by 15% and 9%, respectively" (2015). In addition to their findings was that crop management adaptation increased GHG emissions by 1.7% (Mu et al., 1993). In summation, if mitigation measures were implemented exclusively, then GHG emissions decreased while adaptation measures increased GHG emissions. In my opinion, I believe that adaptation is not effective because GHG is still being produced even if it is a slower rate. Whereas, the carbon tax acts as a deterrent that if a company wishes to produce an item that produces lots of GHG then they will have to incur costs and dwindling profits.

A paper written by Gunawansa and Kua, they compare "mitigation and adaptation strategies" for the construction industry (2011). They studied how Singapore, Miami, and San Francisco directed eco-friendly initiatives such as green buildings. One of the results they came to was that initiatives that pushed for green building design and construction had a direct impact on lowering GHG emission (Gunawansa & Kua, 2011). They also emphasized the implementation of community involvement in planning and implementation of adaptation measures to bolster efficiency and effectiveness of the proposed measure (Gunawansa & Kua, 2011). Ultimately, they suggest that if climate change adaptation and mitigation was given to local governments to handle, that it could be more effective (Gunawansa & Kua, 2011).

References

Gunawansa, A. Kua, W. H. (2011, August 16). A comparison of climate change mitigation and adaptation strategies for the construction industries of three coastal territories. *Sustainable Development, (22)1*, 52-62. doi: 10.1002/sd.527

Mohsin, T. Gough, A, W. (2009, October 2). Trend Analysis of long-term temperature time series in the Greater Toronto Area (GTA). *Theoretical and Applied Climatology, 101*(3-4), 311-327. doi: 10.1007/s00704-009-0214-x

Mu, E. J. Wein, M. A. McCarl, A. B. (2015) Land use and management change under climate change adaptation and mitigation strategies: a U.S. case study. *Mitigation and Adaptation Strategies for Global Change, (20)*, 1041-1054. doi: 10.1007/s11027-013-9514-7

Vuuren, D., P., Edmonds, J., Kainuma, M., et al. (2011). The representative concentration pathways: An overview. *Climatic Change, 109*(1-2), 5-31. doi: 10.1007/s10584-011-0148-z