Literature Review and Data Description

CIND820 – DJ0

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Literature Review

The following contains individual summaries of Articles/Journals/Papers looking at Emissions and Energy consumption and their significance on our lives today. Detailed citation provided in the references section.

CO2 Emissions

CO2 emissions have been widely recognized as the primary driver of climate change and this work provides a summary of historic and current data and look at three primary questions. Which countries are responsible for the highest emissions today? Including historical emissions which countries have emitted the most in total? And who emits the most on a per person average? Emissions have been continually going up year after year from a global perspective, we currently emit 51 billion tons of CO2 equivalent annually. Of the 36 billion tons of CO2 emitted in 2017, 53% came from Asia, 18% from North America, 17% from Europe, and 8% from Africa, South America, and Oceania. More than 50% of emissions comes from China, USA and European union with 27%, 15%, and 10% respectively. The top 10 emitters are responsible for 75% of the global emissions. Looking at historical emissions USA is responsible for 25%, EU 22%, and China 13%. Looking at per person averages can be misleading because the picture changes entirely, and it is noted that the major oil and gas producers in the world show the highest per person average for emissions. They also found that wealth is a huge indicator of our carbon footprint and as we gain wealth, we get access to a lot of modern amenities which increases our carbon footprint. The authors conclude that the richest countries in the world should take responsibility and use their resources and educated workforces to create low cost, low carbon solutions and that historically this will spread to other parts of the world who wish to trade with them. (Ritchie, H., & Roser, M. May 11, 2020)

World Greenhouse Gas Emissions in 2005

This paper summarizes the change in emissions by sector, industry, land use etc. in the year 2005 as compared to the year 2000. 12.7% emissions increase was observed Globally between 2000 and 2005. It also shows growth by different sectors that range from close to 0% to 40%. Emissions from change in land use increased by 4.1%. Transportation, cement, iron & steel were among the most significant increases. Changes due to increased electricity use and manufacturing saw emissions increase of 44%. Overall, this data shows consistent increase in emission across the board from the year 200 to 2005 (Herzog, T, 2009)

Greenhouse Gas Emissions from Global Cities

With more than 50% of the world population residing in urban areas in 2009 this study looks at data for 10 global cities: Bangkok, Barcelona, Cape Town, Denver, Geneva, London, Los Angeles, NY City, Prague, Toronto. It summarizes emissions in these cities with respect to ground transportation fuels, GHG emissions from waste and Methane emissions from landfill waste, and other sources some which seem negligible. (Kennedy, C., Steinberger, J., Gasson, B., Hansen, Y., Hillman, T., HavránekM., Pataki, D., Phdungsilp, A., Ramaswami, A., & Mendez, G. V. , 2009)

ICT Energy Consumption – Trends and Challanges

With the growth of information and communication technology this work looks at emissions as a result of ICT energy consumption and finds its responsible for the same amount as global air travel. Cell phone use has grown by a large factor from 1991 over the next 15 years and internet servers went up by a factor of 1000. They found electricity consumption doubling in households over a 4 to 5 year period. In 2005, 3% of the global energy consumption was due to cell phones, networks and the internet. At this rapid rate several solutions are proposed to manage this growth ecologically to reduce the energy consumption (Fettweis and Zimmermann, 2008).

Estimation of Energy Consumption in Machine Learning

This work looks at including energy efficiency as a factor in Machine Learning and deep learning. It states that researchers have been focused on producing highly accurate models without considering energy consumption as a factor. They believe in existing machine learning frameworks like Tensorflow, Caffe2, and Pytorch it is possible to look at the energy efficiency as a factor and gain insight on this as well. (García-Martín, E., Rodrigues, C. F., Riley, G., & Grahn, H. ,2019)

Data Description

The following is a summary of the data and a look at the year-by-year emissions and energy consumption by sector.

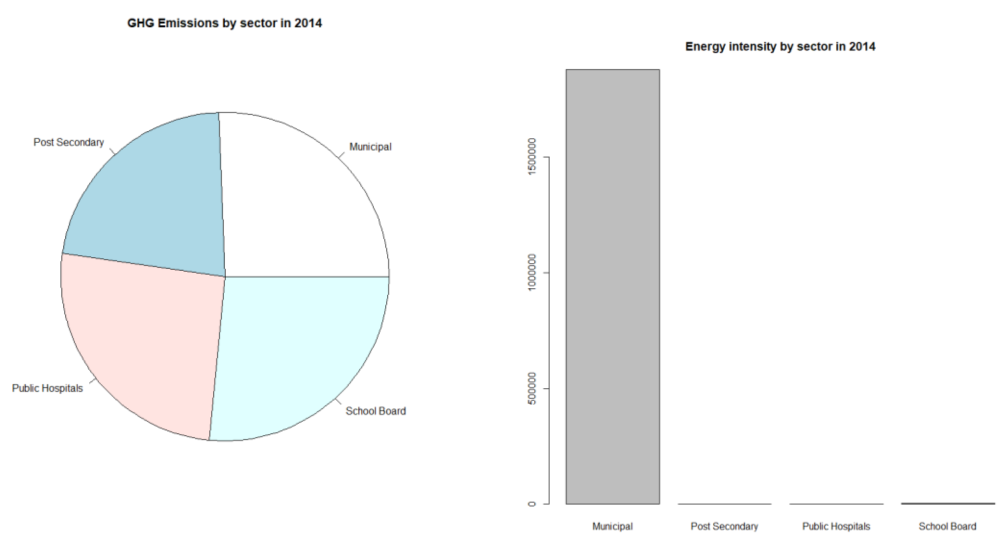


Figure 1.1 – 2014

Sector	GHG Emissions (Kg)	Energy Intensity (GJ/m^2)
Municipal	751683710	1875675.183

Post-Secondary Educational Institution	649641034	1286.305
Public Hospital	756500552	1074.657
School Board	778306857	3953.466

Table 1.1 - 2014

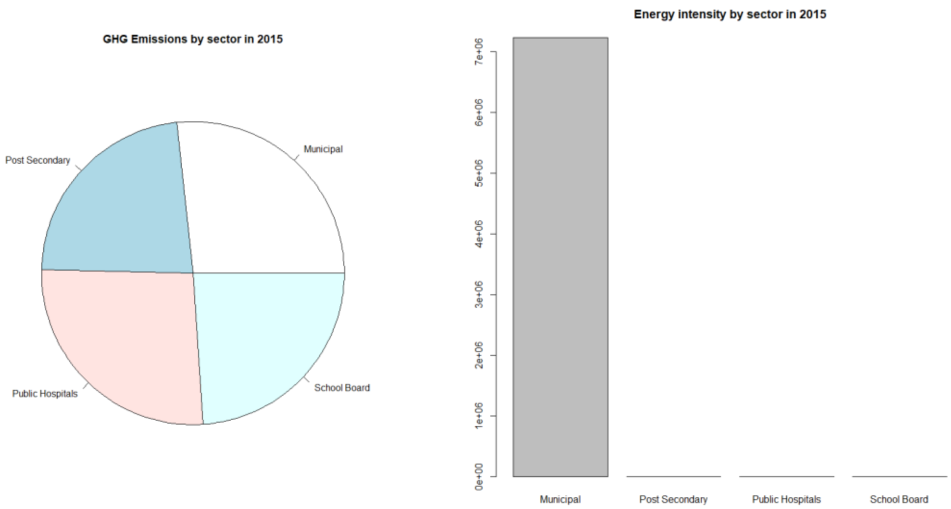
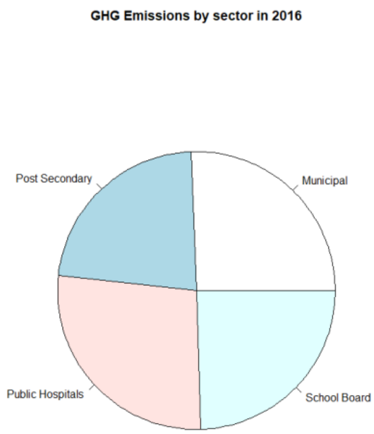


Figure 1.2 – 2015

Sector	**GHG Emissions (Kg)**	**Energy Intensity (GJ/m^2)**
Municipal	737670586	7229288.402
Post-Secondary Educational Institution	633699889	1176.964
Public Hospital	729999245	1138.012
School Board	660689336	3434.418

Table 1.2 – 2015



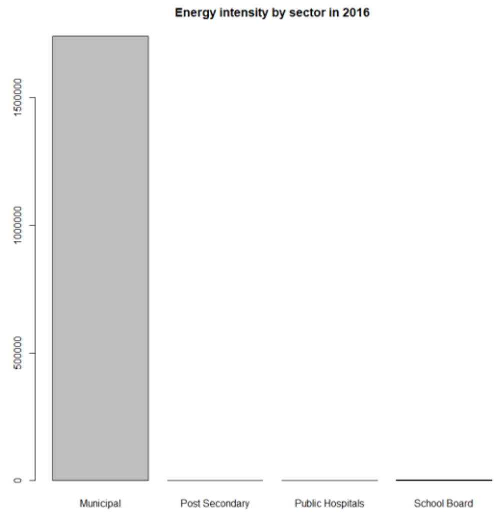


Figure 1.3 – 2016

Sector	**GHG Emissions (Kg)**	**Energy Intensity (GJ/m^2)**
Municipal	676237901	1741181.737
Post-Secondary Educational Institution	598826060	1086.419
Public Hospital	717111081	1140.490
School Board	647550174	3403.888

Table 1.3 – 2016

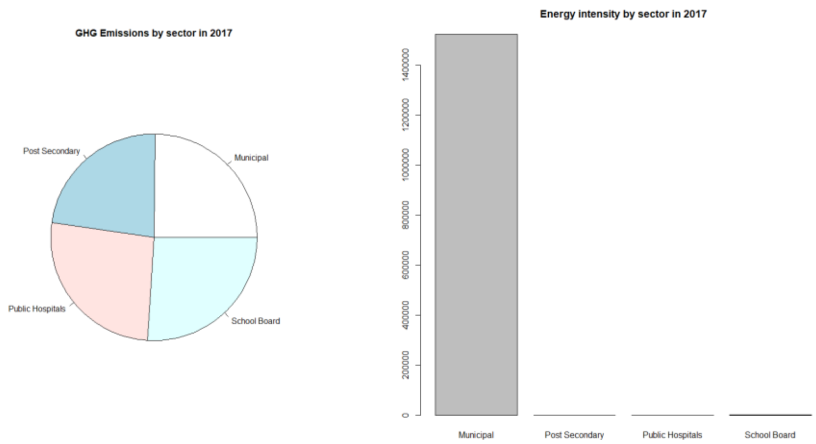


Figure 1.4 – 2017

Sector	**GHG Emissions (Kg)**	**Energy Intensity (GJ/m^2)**
Municipal	627359630	1522086.944
Post-Secondary Educational Institution	578894549	1103.270
Public Hospital	664344181	1043.568
School Board	657144923	3670.521

Table 1.4 – 2017

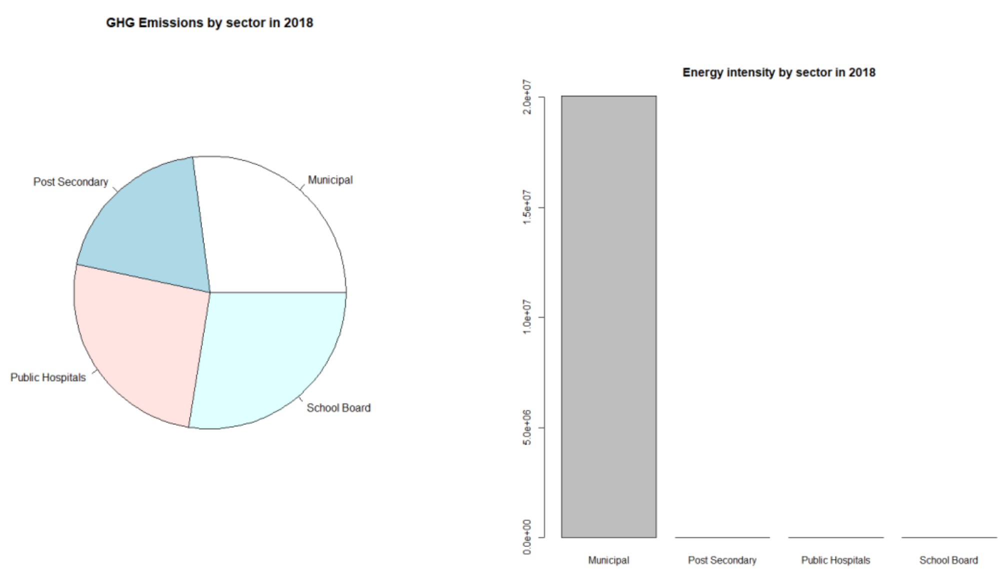
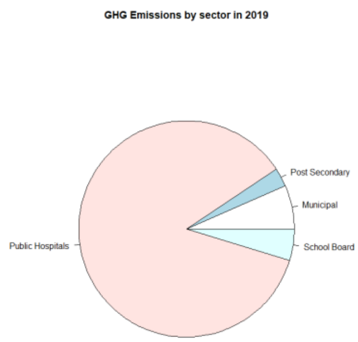


Figure 1.5 – 2018

Sector	GHG Emissions (Kg)	Energy Intensity (GJ/m^2)
Municipal	700497850	20046380.566
Post-Secondary Educational Institution	507316432	1101.285
Public Hospital	667819901	7235.668
School Board	712605606	3708.285

Table 1.5 - 2018



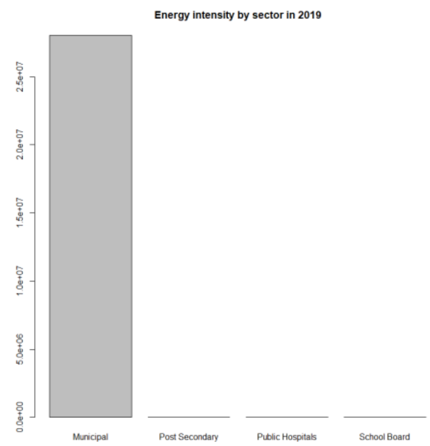


Figure 1.6 – 2019

Sector	GHG Emissions (Kg)	Energy Intensity (GJ/m^2)
Municipal	805447325	28033216.581
Post-Secondary Educational Institution	341921719	1079.828
Public Hospital	10606982648	5157.810
School Board	585149330	3183.761

Table 1.6 – 2019

Figures and Tables show Emissions and Energy Consumption by year. There seems to be a significant increase in emission by Public Hospitals in 2019 which will be investigated. The following is a summary of both these variables over the 6 years.

2014 GHG emissions summary

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.

0	6266	35825	170467	113522	99665401

2015 GHG emissions summary

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0	5263	30571	156375	97573	99444636

2016 GHG emissions summary

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0	4504	27347	150292	93419	92778381

2017 GHG emissions summary

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0	3438	27170	149138	95844	87235316

2018 GHG emissions summary

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0	5117	35082	159600	108288	76117439

2019 GHG emissions summary

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0	4328	30170	739100	95710	7.217e+09

2014 Energy Intensity summary

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0	0.6	0.9	119.8	1.4	388006.2

2015 Energy Intensity summary

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0	0.6	0.8	449.2	1.4	1207413.2

2016 Energy Intensity summary

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0	0.5	0.7	99.5	1.2	326995.1

2017 Energy Intensity summary

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0	0.49	0.77	90.15	1.24	201149.03

2018 Energy Intensity summary

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0	0.5	0.8	1249.7	1.3	1904607.9

2019 Energy Intensity summary

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0	0.5	0.8	1630	1.4	1.44e+06

Methodology

- Data Preprocessing:
    - From the 41 columns in each of the 6 datasets extract the columns with sufficient information(Operation, Sector, Operation Type, City, Total indoor space, Unit of measure, GHG Emissions(KG), Energy Intensity(GJ/m2)
    - Drop duplicates based on unique column “Operation”, convert indoor space to the same unit Sq.m, drop unit of measure columns
    - Replace all division by zero errors and nan values to zero in the numeric columns for year 2014 and create a clean dataframe, add Emissions and Energy Intensity columns by year to clean dataframe with empty values.

- Rename columns in all dataframes to match with the year values in clean dataframe, set index to unique value column “Operation” and update clean dataframe with values from each dataframe.
    - Clean commas, errors and convert numeric columns to numeric datatype, remove rows containing 0 in the 2014 or 2019 GHG and Energy Intensity Columns.
    - Create two new columns for GHG results, and Energy Intensity results and fill with zeroes. Compare values in 2014 to 2019 and change value to 1 if they have been succesful in having less emissions and Energy usage in 2019 respectively.
- Create a train and test division and complete a decision tree algortihm.
- Complete a Logistic regression model.
- Evaluate the performance of the two models.

References

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