CARBON CONSULTING

ELIMINATE. CONSERVE. MAINTAIN

CAMPUS SUSTAINABILITY PROJECT

FINAL REPORT

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Executive Summary:

For more than a decade, Denison has been proactive in the goal of reaching Carbon Neutrality by 2030. Since 2005, Denison has implemented multiple eco-friendly solutions to drop their CO_2 levels by 46% and CH4 levels by 33.3%. While Denison is on the right track to reach its goal, data management as well as the post-implementation analysis of solutions has been an obstacle; there seems to be a level of uncertainty when it comes to prioritizing the emission(s) that is contributing the most to Denison's total carbon footprint.

Throughout the course of this semester our team Carbon Consulting has moved forward through our goals to provide Jeremy King with usable scope 3 data and a thorough analysis of main contributors to carbon emissions on Denison University's campus. Because Scope 3 emissions had thus far been ignored in the statistical analyses done on campus there was a possibly significant portion of emission data missing. Scope 3 emissions, mainly commuting of faculty/staff which Denison has the data for and data of purchasing from Bon Appetit which has not been gathered, have not been analyzed. In order to accurately predict whether Denison is in the right direction to reach its goal of carbon neutrality by 2030, it would be useful to analyze scope 3 emission data as well as how introduction of major constructions and electricity consumption, like Eisner center, Whisler center, and new senior apartment building, will affect our goal.

Nevertheless, there are some emissions that have not been as well maintained as the others. Thus, we will be assuming some values based on their record of a particular year they were collected. All such assumptions have been clearly mentioned whenever assumption variable is being used in an analysis. It is important to note that we did not have enough data or resources to conclude whether Denison will reach carbon neutrality by 2030 or not. However, the main purpose of our project, as agreed by the client, is to analyze whether Denison is in the right direction and provide recommendations of how it can improve its chances to reach that goal.

Accomplishments:

- Data collection and organization for Scope 3 emissions
  - Commuter Data
  - Flight data
  - Bon Appetit purchasing data
- Evaluation of the most dominant source of emissions
  - Scope 1 Purchased Electricity
- Provide recommendations to reduce current campus emissions
- Analyze the most dominant emission source to see if it will be increasing or decreasing in the future.
  - Electricity forecasting
- Provide recommendation for communicate and spreading awareness of sustainability efforts on campus

- Infographics (Flights, Food, Electricity)

Process:

We began our project by analyzing the data provided by Jeremy King (access to SIMAP and Second Nature as well as his own personal fact book that included more recent data in excel sheets, as well as a Denison commuter study and flight data). We then gathered more data about Bon Appetit purchasing from Piper Fernway and further data about purchased electricity from Jeremy King (monthly electricity data and estimates for the new buildings on campus).

In order to analyze and organize the data, which in most cases was quite unorganized, we used R in Rstudio (a coding language often used in data analytics). We have provided the code that we used in a zipped file along with this document. In R we created and validated our models using the R^2 value and p-value. In order to organize our data in R we used regular expressions that sorted out portions of the data.

Figure 2: Final Status

Start	End	Task	Type	Completion
9/3	9/17	Initial Meeting	Milestone	Completed
9/17	9/28	Obtaining Initial Data	Task	Completed
9/24	9/29	Bid Proposal	Milestone	Completed
9/24	10/17	Gather More Data	Task	Completed
9/26	10/12	Clean Data	Task	Completed
9/26	10/20	Finalized Dataset	Milestone	Completed
10/22	11/5	Analyze and Compare	Task	Completed
10/29	11/16	Project Future Emissions	Milestone	Completed
11/26	12/10	Review	Task	Completed
11/26	12/20	Discussion and Presentation	Milestone	12/18

Orange: Phase 1 **Yellow**: Phase 2 **Blue**: Phase 3

Milestone refers to a success criteria and Task refers to a process that needs to be completed

Main Aproach

Identify the Dominant Contributor for Scope 1 Emission

From the S_eCO_2_sum.csv file, we gathered annual Scope 1 contributor's emission data from year 2005 to 2017, including other on campus stationary (also known as campus stationary sources), direct transportation, refrigerants & chemicals and fertilizer. To identify the dominant contributor for scope 1 emissions, we first calculated the annual total Scope 1 emission by sum up the contributors, then used R studio to perform the linear regression models and Pearson's r test for each of the contributors with the total emissions.
When the total Scope 1 emission was given, it was found that other on campus stationary with $\mathrm{r} = 0.998, \mathrm{p} < 0.01$, direct transportation with $\mathrm{r} = 0.685, \mathrm{p} < 0.01$, and refrigerants & chemical with $\mathrm{r} = 0.621, \mathrm{p} = 0.024$, were significant contributors. And fertilizer is not a significant contributor, $\mathrm{r} = 0.501, \mathrm{p} = 0.0814$.

Regression model fit for the other on campus stationary is $R^2 = 0.996$, for direct transportation is R^2 = 0.422, for refrigerants and chemicals is $R^2 = 0.329$, for fertilizer is $R^2 = 0.183$.

To read the result, we need to understand a few meanings behind the values:
The p-value is a number between 0 and 1, it determines the significant of the result. Generally, a p-value that is less than 0.05 is considered to be statistically significant.

The r value represents the correlation coefficient, it represents a statistical relationship between the variables. It's always ranged between -1 to 1, positive r value means positive relationship while the negative r value r means negative relationship. The more extreme the value is, the stronger relationship exist in between the variables. The R^2 value is also known as coefficient of determination, this is a statistical measure of how close the data are to the best fit line (Minitab Blog Editor, 2013, May 30). This value is always between 0 and 1, while 0 indicates that the model explains none of the variability of the present data points and 1 indicates all the variability of the data points can be explained by the model. Therefore, the greater the R-Squared value is, the better the best fit line represent the trend.

By comparing the r value for each linear regression test, we found that the other on campus stationary had the strongest positive relationship towards Scope 1's total eCO_2 emissions compared to the other factors. Figure 1 is the statistical result that created on R studio.

```
Call:
lm(formula = OtherOnCampusStationary ~ Scope1Total, data = Scope1)

Residuals:
    Min      1Q  Median      3Q     Max 
-345.86 -213.64   45.67  194.89  209.37 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -187.51199  228.24185  -0.822    0.429    
Scope1Total    0.97999    0.01928  50.827  2.1e-14 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 218.7 on 11 degrees of freedom
Multiple R-squared:  0.9958,	Adjusted R-squared:  0.9954 
F-statistic:  2583 on 1 and 11 DF,  p-value: 2.102e-14
```

Figure 1. Statistical results for linear regression model with Scope 1 total emission.

Therefore, the main contributor for eCO_2 emissions is the on campus stationary sources with the annual average emission of CO_2 equivalent from year 2005 to year 2017 equal to 10996.44 MT. The result is reasonable because this category includes natural gas, coal and propane, which were identified as the major producers of other greenhouse gases.

The scatter plot showed in Figure 2 is the other on campus stationary and the total eCO_2 emissions of Scope 1 contributors. The x axis represents the other on campus stationary while the y axis represents the total eCO_2 emission. There are 13 data points on the plot and each data point represents one year's the other on-campus stationary eCO_2 emission and total eCO_2 emissions. The line in the plot is the best fit line of the linear regression with the given two variables.

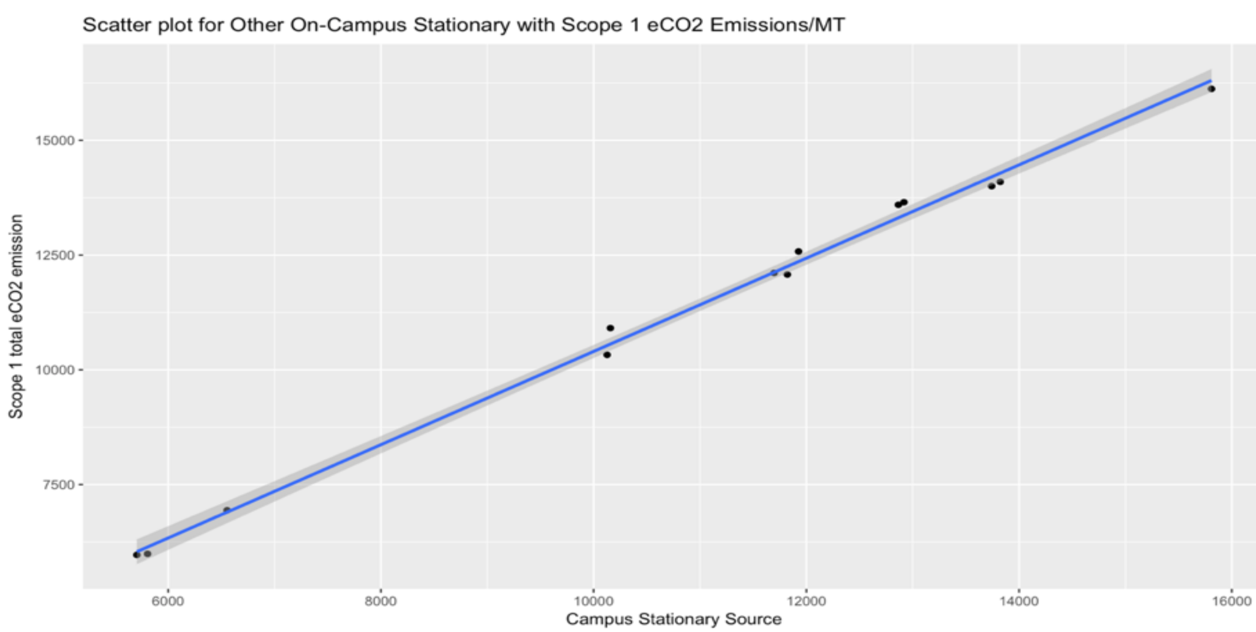


Figure 2: Scatter plot for Other On-Campus Stationary with Scope 1 total emissions.

Recommendation:

To perform a better linear regression model, we suggest to using a larger sample size. For example, using the monthly data for each year instead of yearly. In this way, the statistical result could be more accurate.

Faculty/staff commute analysis

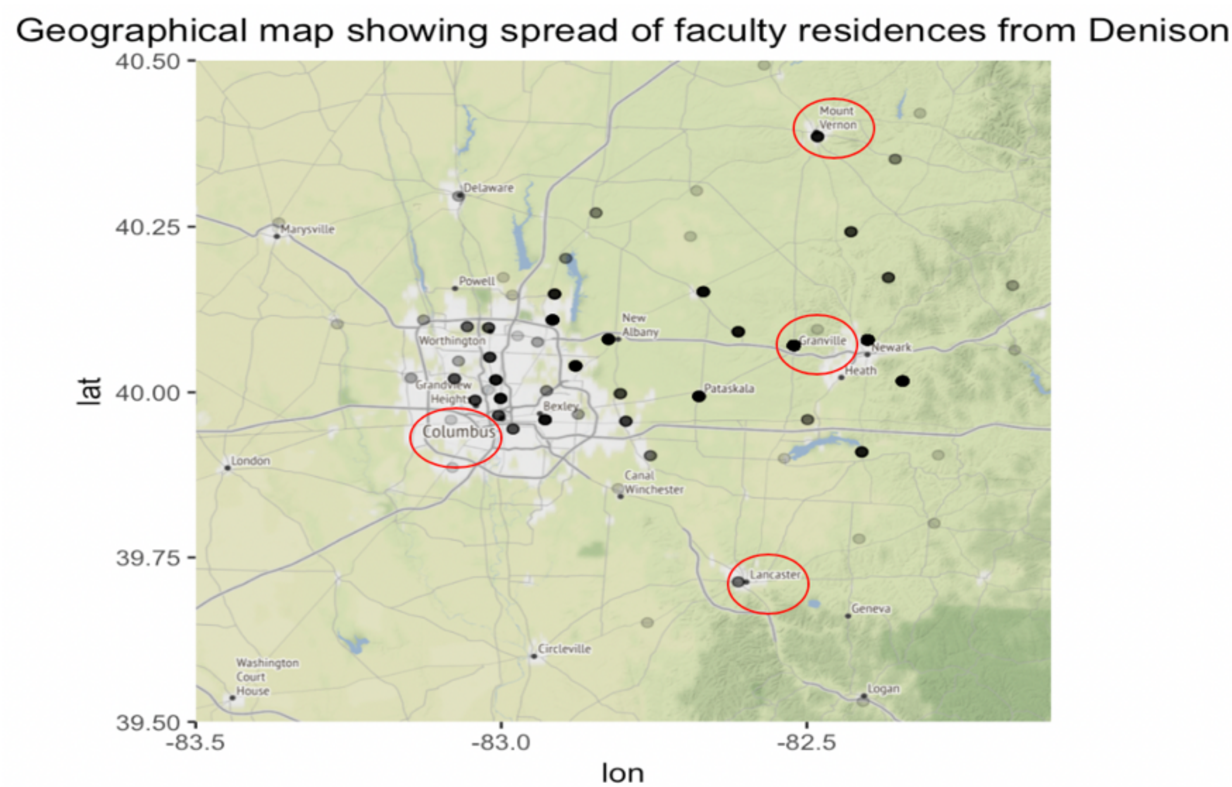


Figure 3: geographical map of staff/faculty commuters from Denison

Our analysis for the commute data of staff/faculty has been successfully completed. Our aim was to analyze the emissions per year that are caused by the vehicle commute of staff/faculty from their respective residences to reach Denison campus. This analysis will help the client realize whether the emissions from commute are significant or not to be looked at in the big picture.

The commute distance for faculty/staff ranges from 1 mile (just outside campus grounds) to 90 miles (Xenia, Ohio). On average, a Denison staff/faculty travels 11 miles to reach campus.

We realized that people living as far as 90 miles may not be coming to campus every day. Moreover, most staff/faculty do not come to campus every day of the year. After taking everything into consideration, we filtered out the large distance commuters and only considered travel of 7-8 months in a total year. We used equation 1 to calculate total distance travelled using longitude and latitude values. Total emissions of vehicles were calculated in SIMAP using the total distance travelled. One thing to keep in mind is that when the survey was taken in 2017, the response rate was 35%. Thus, to provide a fair value, and assuming that the people who did not respond live approximately as far as the 35% who did, we will be multiplying our final value by a factor of 3.

$$= Acos\left(\cos\left(Radians(90 - Latitude1)\right) \times \cos\left(Radians(90 - Latitude2)\right) + \sin\left(Radians(90 - Latitude1)\right) \times \sin\left(Radians(90 - Latitude2)\right) \times \cos\left(Radians(Longitude1 - Longitude2)\right)\right) \times 6371 Equation$$

Equation 1: obtained from https://www.contextures.com/excellatitudelongitude.html

Total miles travelled per day: **37,590 mi**

Total miles travelled per year: **6,76,6342 mi**

Total emissions from commute per year: **2.253 Mega Tonnes**

Compared to other emission sources, emissions from the commute of staff/faculty is negligible. To put this into perspective, Figure 3 is a bar graph comparing the primary emissions with the commute:

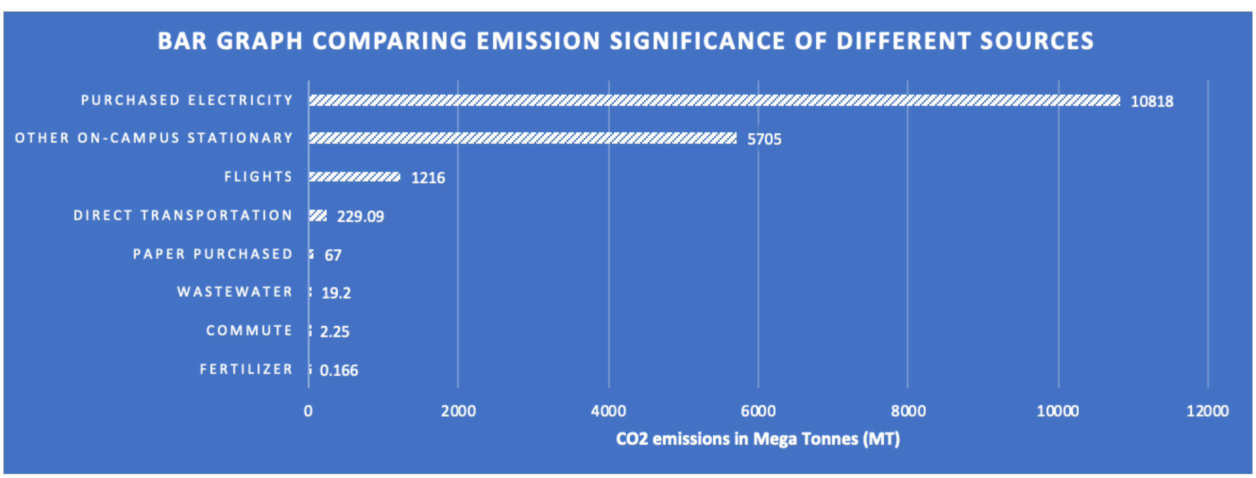


Figure 4: Bar graph comparing emission from different sources

Clearly, the commute emissions are negligible when compared with Purchased electricity and Other On-campus stationary emissions. Nevertheless, figure 4 removes the dominant emissions and compares our commute emissions with other scope 3 emissions, which are not as high as other scope emissions (as discovered in our previous progress report).

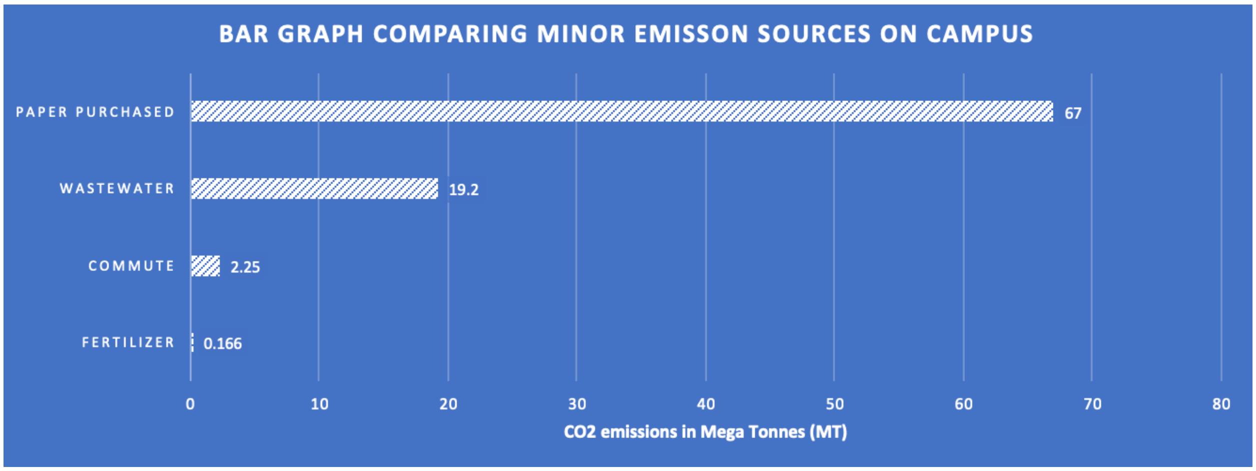


Figure 5: Bar graph comparing major scope 3 emissions

Looking at the figure 4, we can see that the commute emissions are negligible even compared to most scope 3 emissions as well. In fact, commute emissions make up for only **1/100,000** of the total emissions on campus.

Limitations and Recommendations:

We would recommend that our client need not focus much on emissions contributed by Commute of staff/faculty, since it is negligible compared to other primary contributors. Nevertheless, an updateable database will help keep track of the emissions and will provide a comprehensive scope 3 emissions database to be inputted into SIMAP, as that is one of the goals of our client.

Faculty/staff flights emission

Denison University faculty takes a lot of flights throughout the year for business purposes. To analyze and explore the emissions caused by a faculty member by taking a flight, we extracted the cost information from the data file we received from Jeremy King. We then uploaded the data into SIMAP (see next section Tools/software) which automatically converts the cost of a flight to the total eCO_2 emission caused by it.

The results we received were astonishing. We compared the flights emission of 2010 with the commute emissions of 2017, since we only have data for those particular years respectively. While the total emission per year caused by faculty car commute was 2.25 MT, the total emissions by flights per year was a staggering 1216 MT. It is even possible that the flights emissions can probably be significantly higher in 2017 than it was back in 2010.

average Emissions by flights per year: **1216 MT**

average cost of total flights per year: **$ 198,899**

Looking at Figure 3, we can see that the flight emissions are the third highest emissions overall. While we do realize that Denison should not be responsible for the entire emission of each single flight since multiple people are on board, we still feel that each person on board is equally responsible for the emission.

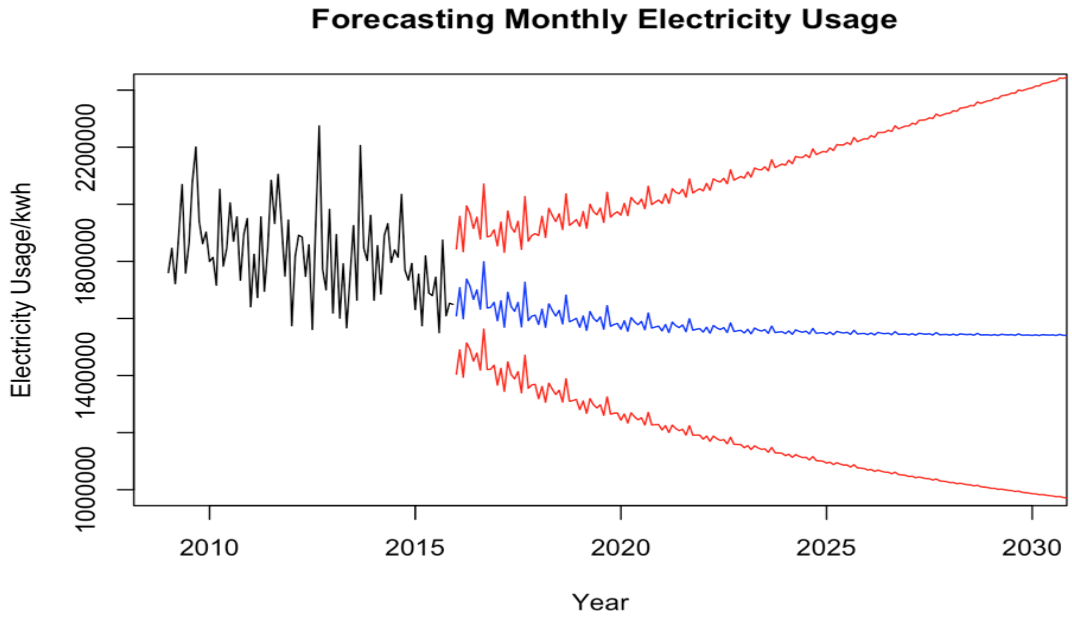
Limitations and Recommendations:

Use of flights by faculty/staff is definitely a major contributor to total emissions on campus, one that is possibly overlooked, since it is a scope 3 emission. A solution that we recommend be implemented is that faculty/staff should start opting for car travel than flight travel for small distances. This is because car travel contributes significantly less emissions than flight travel does. For instance, Denison spent $14,000 on flights to Chicago, a travel that should be easily undertaken by car. This would have reduced the emissions by 95 MT, which is more than **total Scope 3 emissions** (Paper purchased, commute, wastewater, fertilizer) per year.

Forecasting Model for electricity usage data

We also gathered the energy usage data from year 2008 to year 2015 from the office of sustainability in a excel file named "Consumables FY 15-16 9-2-16. xslx". This file contains not only the data, but also a few summary graphs. We mainly looked at the monthly data in the data set since it is more detailed, so it is a good option to perform a forecasting model with. But because all the data were stored and organized in fiscal year, which means every period starts with July 1st and ends with June 30th, we reshaped the data in the calendar year, so it can be read as time series by R studio.

We decided to focus on analyze the electricity usage, because it is the main contributor of CO_2 equivalent across all three scopes. Successfully projecting the electricity usage in the future years would provide us a better understanding about campus carbon footprint. We reorganized the data into calendar year and select the years without any missing data from any month to perform the ARIMA forecasting model. ARIMA is the abbreviation for Auto-Regressive Integrated Moving Average. It is the statistical model that we can use on time series data for forecasting (Upadhya, 2015).



Black Line: Past & Current Electricity Usage **Blue Line: Forecasting Usage from 2020 to 2030**
Red Line: Forecasting Confidence Interval (One Standard Deviation)

Figure 6. Forecasting model for Monthly Electricity Usage based on monthly data from year 2008 to 2015

We successfully created the forecasting model based on the cleaned version of the electricity usage data from 2008 to 2015. Figure 5 is the forecasting graph based on the statistical analyses. As shown in the figure, the line in black are the existing data from 2008 to 2015 that we gathered from the present cleaned data set. The blue line represents the forecasted electricity usage from 2015 to 2030. And the area in between the red line is the expected error range with one standard deviation. It means we expected the error of the prediction is limited in this given range. The uncertainty increase as time goes by, this is because projecting for 300 months is a very ambiguous, with the limited information, the underlying pattern is very likely to change over time. But with the given underlying patterns, we would perceive Denison community's monthly electricity usage after 2015 stay within the range **1400000 to 1900000 kWh.** The zig-zag pattern of monthly usage was also expected since the usage varies month to month. This model suggests the average monthly usage will be around **1600000 kWh** as time continues.

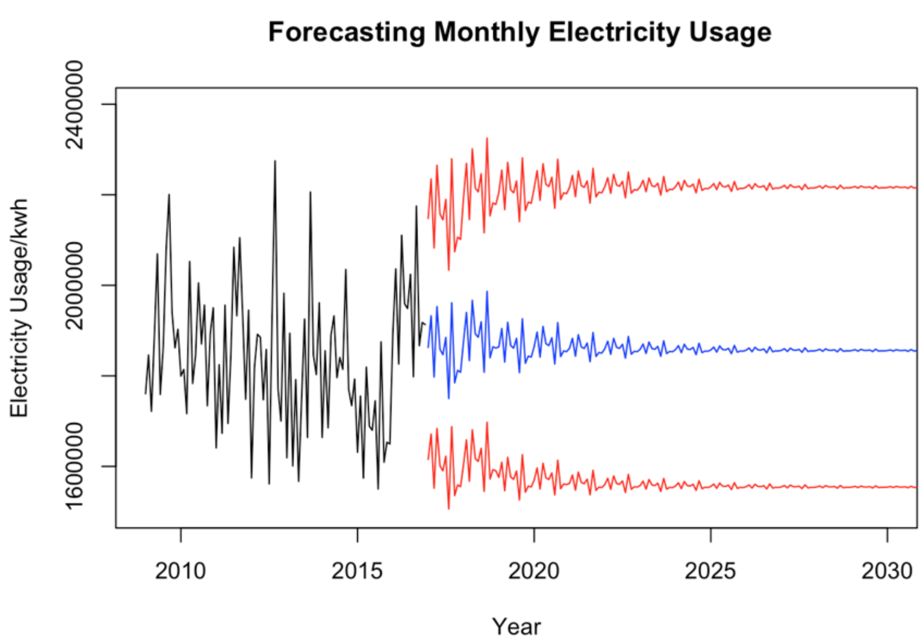
To validate this model, we ran the accuracy measure for the forecasting model in R studio. The statistics result is shown in Figure 6. In this result, ME stands for Mean Error, RMSE stands for Root Mean Squared Error, MAE stands for Mean Absolute Error, MPE stands for Mean Percentage Error, MAPE stands for Mean Absolute Percentage Error, MASE stands for Mean Absolute Scaled Error, ACF1 stands for Autocorrection of errors at lag 1. This are the measures used to calculate the error between the prediction and actual values. In this case we paid special attention to RMSE value which represent the square root of the average of squared differences between prediction and actual observation. This is because this value is also known as the estimated white noise standard deviation in ARIMA analysis (JJ, 2016, Mar 23). The

smaller the RMSE value is, the greater the model predict actual observation. As we seem in the figure, **RMSE = 0.029,** it is small enough to conclude that the forecasting model is valid.
Figure 7. Accuracy Measure result of Forecasting Model for Monthly Electricity Usage (2008-2015)

This current ARIMA forecasting model was constructed based on the assumption that the underlying patterns in this time series will continue to stay the same. However, from our

```
                        ME       RMSE        MAE         MPE      MAPE
Training set -0.002457787 0.02878184 0.02286803 -0.04145907 0.3652924
                  MASE        ACF1
Training set 0.8045098 -0.04863321
```

knowledge, there is quite amount of construction going on in campus, such as new Senior apartment, new Eisner center and new Whistler Center. Since the construction might cause a considerable amount of energy usage, the underlying patterns in the present data can be affected, so it could be a limitation that makes the production model inaccurate. From the client meeting with Mr. King, he suggested us to project electricity consumption for year 2019 based on actual consumption in year 2015 with **8%** increase by the new Senior apartment, **4%** increase by new Eisner center and **1%** increase new Whistler Center. By following Mr. King's suggestion, we further adjusted our ARIMA model by taking into the consideration on campus consumptions. We manually added the expiated monthly data for year 2019 in the data set and performed the same model again.



Black Line: Past & Current Electricity Usage **Blue Line: Forecasting Usage from 2020 to 2030**
Red Line: Forecasting Confidence Interval (One Standard Deviation)

Figure 8. Accuracy Measure result of Forecasting Model for Monthly Electricity Usage (2008-2015, 2019)

Figure 8 is the adjusted ARIMA model with the assumption on year 2019's data. As shown in the figure, the line in black are the existing data in the data set, including actual data from year 2008 to 2015 and the expected data for year 2019. The blue line represents the forecasted electricity usage from 2020 to 2030. And the area in between the red line is the expected error range with one standard deviation. It means we expected the error of the prediction is limited in this given range. The model suggests with the given updated underlying patterns, we would perceive Denison community's monthly electricity usage after 2015 stay within the range 1500000 to 2200000 kWh. This model suggests the average monthly usage will be around 1700000 kWh as time continues. Compared with the previous forecasting model, we perceived a raise in the expected electricity consumptions and a more stable pattern instead of downwards trend as before.

We also ran the accuracy measure to validate our forecasting model. As shown in Figure 10, RMSE = 0.030, which is small enough to say our forecasting model is valid.

```
                        ME       RMSE        MAE          MPE      MAPE
Training set -0.0004508911 0.03010214 0.02417085 -0.009570533 0.3858611
                  MASE        ACF1
Training set 0.7199619 -0.04986439
```

Figure 9. Accuracy Measure result of Forecasting Model for Monthly Electricity Usage (2008-2015, 2019)

<u>Limitation & Recommendation:</u>

As mentioned before, predicting 300 months with only 96 months as observation is an ambitious task. The minimum request for a forecasting period is to have more observations than parameter. In other words, if we want to project 300 months, we are recommended to have more than 300 months' observations. One suggestion from us is cut down the forecasting period and updating the data with any new information. Instead of forecasts for a long period, concentrating on a short-term is usually a good idea to forecast with a reasonable accuracy. Generally, the more data we have, the more confidence in predictability of the change. Also adding new information to the model can quickly adjust the pattern and so the model can perform with a better accuracy. With the knowledge of electricity consumption would increase due to the constructions of the new buildings. As we know, in 2007, Denison installed a 6.44 kW solar array on the roof of the Library. And in the winter of 2017 Denison turned on, a 2-megawatt array that includes more than 6000 solar panels and produces enough electricity to offset 15 percent of the college's annual usage as well as reduce its carbon footprint by nearly 10 percent. To reduce the e CO_2 emissions that brought by electricity, we suggest Denison to continue to apply more solar panel in the future years. And also, spread the awareness of saving electricity in Denison Community.

Food Purchasing Data from Bon Appetit

The data that we have been provided from Bon Appetit are two excel files that contain Bon Appetit's purchasing data for February and September of 2017. We were provided data from February and September because these two months represent one of the lowest and one of the highest purchasing months, especially for local products.

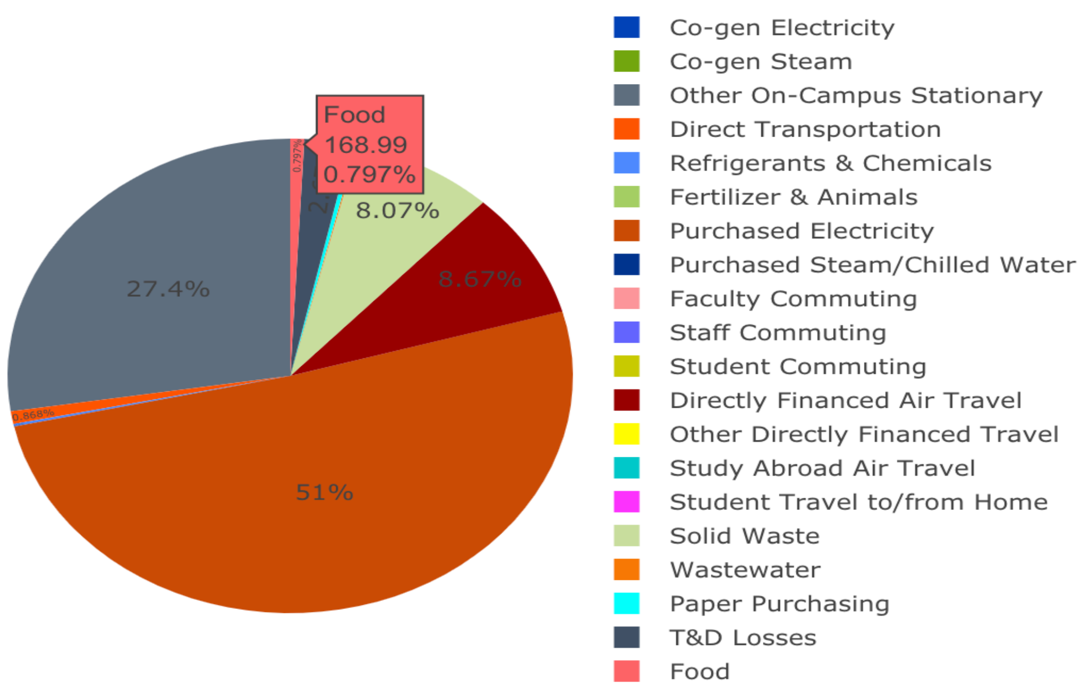
The data was then manipulated in Rstudio to create a separate and smaller dataset that had the estimated average amount of pounds of meat (Turkey, Chicken, Beef and Pork) that were purchased in a month and the estimated amount of meat purchased in a school year (or 8 months). In order to get the amount of pounds of meat that were purchased by Denison regular expressions were used to pull the pounds in a case purchased and the number of cases purchased amounts out of the Manufacturer Product Description.

The estimated amount of emissions for a year's worth of meat purchasing: **168.99 MT** $\mathbf{e}CO_2$

The estimated amount of emissions from a year's worth of total purchasing: **422.475 MT** $\mathbf{e}CO_2$

- $\mathbf{(168.99 \times 2.5)}$(other foods besides meats make up roughly 5 times more of the data than meat but they only have about half the emissions of meat)**.**

The estimated total purchasing makes up**. 797% of overall campus emissions** (SIMAP)**.** This amount seems pretty insignificant in the term of carbon emissions in scopes on Denison's campus, but this is likely not right total amount of emissions from food purchasing that Denison



has because the data that was provided by Bon Appetit is not well organized or easily analyzed. This .797% is also just taking into account the amount of meat purchased not the whole amount of goods purchased by Bon Appetit. Even with the data missing all of the other produce besides meat it still comes in as the 5th highest contributor to carbon emissions on campus.

igure 11. Pie chart showing eC02 emissions of different categories of campus contributors. SIMAP visual

The estimated amount of emissions in a single day from meat purchasing: **.7041 MT e**CO_2 **or 7041250 kg e**CO_2**.**

This means that everytime Denison has a meatless Monday they remove 7041250 kg eCO_2 from their carbon footprint. This does not seem like alot but over the course of an entire year it reduces Denison's carbon emissions by **24.15 MT e**CO_2

- ($.7041 \times 34.3$ (number of weeks in 8 months so assume that number of Mondays))

<u>Limitations and Recommendations:</u>

We would recommend that as Denison debates renewing their contract with Bon Appetit for next year, Denison should consider adding into the contract that they require Bon Appetit put in their datasets the total amount of any product purchased per each month. Bon Appetit would only ever need to provide datasets for September and February because the average of these two months is an understood industry average for measuring emissions data. With a single added column that contains the total amount of any given product in a month the Office of Sustainability would be able to just remove any missing values from the data set then import it into SIMAP and SIMAP would calculate the eCO_2 emissions.

Conclusion:

We believe we have made provided our client Jeremy King with the information and data he was most interested in. We have:

- Completed emission analysis of commuter data
- Created an updateable database for commuter data
- Came up with possible suggestions for improving Bon Appetit's data collection of food produce
- Identified insignificant sources of emissions that need not be prioritized
- Produced a forecasting model that will help predict total emissions in the future.
- Complete analysis of flights data in order to obtain the total emissions caused by it
- Updatable database for scope 3 emissions, mainly commuter data
- Identifying significant and insignificant emission sources on campus

- Created infographics to connect with a larger portion of campus

Deliverables and Supporting material

The final products and the supporting material that we will be providing to our client are:

- Commuter analysis
    - Folder name: Commuter Final
    - Main files included (not mentioning helper files):
        - commuter_README.txt: Read me file that provides information regarding each file present in the folder, and instructions on how to use them (if necessary)
        - Commuter.rmd: Commuter analysis that helped us obtain longitudinal and latitudinal values to help create a visual of commute as well as will help in analysis of emissions
        - Commuter.html: Contains the same things as the commuter.rmd file, but is easier to access, as it opens in the web browser. Helpful if one wants to show the analysis to someone not familiar with the R software.
        - Commuter_final.csv: An updatable csv file that calculates the total commute distance between faculty residence and Denison University.

- Electricity analysis
    - Folder name: Electricity Final
    - Main files included (not mentioning helper files):
        - Electricity_README.text:Read me file that provides information regarding each file present in the folder, and instructions on how to use them (if necessary)
        - ElectricityCom.csv : A tidy/normalized version of the monthly electricity data which comes from the Consumables FY 15-16 9-2-16.xlsx file that will help us import the data into R for further analysis.
        - ForecastE.rmd : the R-Markdown file that consists of the ARIMA foracsting model and all its visuals.
        - ForecastE.html : This file contains the same things as the ForecastE.rmd file, but is easier to access since no pre-requisite software required to open it, as it opens in the web browser. This will help if one wants to show the analysis to someone not familiar with the R software.
        - ForecastEW.html : This file contains the same code as the ForecastE.rmd file with different data import. It is easier to access since no pre-requisite software required to open it, as it opens in the web browser. This will help if one wants to show the analysis to someone not familiar with the R software.

- Scope 1 Analysis
  - Folder name: Scope 1 Final
  - Main files included (not mentioning helper file):
    - scope 1_README.text: Read me file that provides information regarding each file present in the folder, and instructions on how to use them (if necessary)
    - Scope1.csv: a clean format of data that come from the S_eCO_2_Sum.csv file that has been used to import data into R for further analysis.
    - RegressionScope1.Rmd: R-Markdown file that consists of all the linear regression model for identify scope 1 main contributor
    - RegressionScope1.html: This file contains the same things as the RegressionScope1.rmd file but is easier to access since no pre-requisite software required to open it, as it opens in the web browser. This will help if one wants to show the analysis to someone not familiar with the R software.

- Bon Appetit Analysis:
  - Folder Name: Bon_Appetit_Final
  - Main File:
    - February 2017 data for analytics class.csv: the original file given by Piper Fernmway, Director of Bon Appetit at Denison University, which consists of the purchasing history of Bon Appetit for the month of February 2017.
    - September 2017 data for analytics class.csv: the original file given by Piper Fernmway, Director of Bon Appetit at Denison University, which consists of the purchasing history of Bon Appetit for the month of September 2017.
    - Bon_Ap_analysis.rmd: the R-Markdown file that consists of all the analysis done to obtain the total amount of each meat (Beef, Pork, Turkey, Chicken) purchased during the months of February and September of 2017.
- Infographics:
  - 3 separate infographics about emissions at Denison meant to communicate with the campus
    - Flights / Commuter
    - Electricity
    - Bon Appetit

Personnel

Author Contributions:

Danish Siddiquie:

- Responsible for cleaning commuter and flights data, and creating an updatable database for client to analyze commuter distances if new staff/faculty are added in database
- Analyzed total emissions contributed by commute of faculty/staff.
- Analyzed total emissions contributed by flights taken by staff
- Came up with recommendations for reducing Scope 3 emissions on campus
- Helped create infographics to spread awareness regarding campus sustainability

Lin Ma:

- Responsible for clean and normalize the scope 1 data set
- Performed the linear regressions model and statistical test for scope 1 data set and located the dominant contributor
- Normalized the electricity usage data for future analysis
- Performed the ARIMA time series forecasting model for electricity consumption
- Came up with recommendations for create a better model in the future as well as reducing electricity's eCO_2 emissions
- Created the infographic for campus electricity

Madeline Ness:

- Responsible for cleaning the Bon Appetit purchasing Data from February 2017 and September 2017
- Created code in R that can be used to find estimates of average monthly meat consumption on campus and yearly meat consumption on campus
- Analyzed the carbon footprint of the meat used by Bon Appetit in a year using SIMAP
- Created recommendations to consider while Bon Appetit is in a contract year
- Created infographics for flight data and food data

People who have contributed to the project:

Piper Fernway, Director of Bon Appetit at Denison: Provided us with Food data from Bon Appetit.

Art Chanko and Bob Jude: Provided us with data regarding future electricity consumption by Eisner center, new apartment buildings, and Whisler center. # I assume the data comes directly from Jeremy King's email

Ethics Statement and Data Management:

The members of Carbon Consulting are committed to providing the highest ethical standard of data management. We will be working with human data, and thus will comply with all protocol and codes expected by the NIH Institutional Review Board. Because this research will be conducted with data sourced from Denison University we will adhere to BPEDS. All of the data that we will be sourced from secure locations that require at least dual authentication. Once the data is converted to csv files for analysis in R, SQL, Excel, and Tablea it will be stored within a Team Drive within Denison University provided Google Drive or on our personal laptops. We will keep all of the data we use only for the duration of the project, after which we will remove the data from our Team Drive and delete it from our laptops. In summary, we will maintain the security of the data that we use and will maintain no bias towards the outcome of the analysis.

Literature review

To provide the best product(s)/solutions to the client, we had to research an ample amount and obtain an in-depth knowledge on carbon emissions and sustainability. We first researched basic carbon emissions factors to get accustomed to how different variables contribute to overall emissions. We explored different ways emissions analysis is done, looking at different tools and software that will help through our analysis. Most of this research came from our previous DA classes of cleaning and analyzing multiple data sets. Moreover, emission specific analysis research was done by Madeline Ness, who looked at scholarly articles and papers to gain an in-depth knowledge in the area. Primary papers and information which Madeline reviewed were:

- "U.S. Energy Information Administration - EIA - Independent Statistics and Analysis." Carbon Dioxide Emission Coefficients. Accessed September 24, 2018. https://www.eia.gov/environment/emissions/co2_vol_mass.php.
- "Emissions & Generation Resource Integrated Database (eGRID)." EPA. July 26, 2018. Accessed September 24, 2018. Https
- Dowdey, Sarah. "How Carbon Footprints Work." HowStuffWorks Science. June 28, 2018. Accessed September 24, 2018. https://science.howstuffworks.com/environmental/green-science/carbon-footprint1.htm.

We then further researched into the idea of carbon neutrality, and the specific ways to approach and tackle the problem. This was vital in our overall research since it propelled us in the right direction while coming up with possible solutions and recommendations for our client to reduce carbon emissions on campus. Primary papers and information which Madeline reviewed were:

- 25+ Ways to Reduce Your Carbon Footprint, (n.d.) Retrieved from https://cotap.org/reduce-carbon-footprint/#home
- Martin L.J (2006), *Carbon Natural-What Does It Mean?* http://www.eejitsguides.com/environment/carbon-neutral.html

Finally, Danish Siddiquie researched on the advantages of Carbon trading and offsets, if Denison needs to buy credits as a last resort to reach carbon neutrality by 2030. The team researched the economic and environmental advantages and disadvantages of carbon trading and offsets, trying to find the best balance that would be perfectly right for Denison to implement. Primary papers and information which we reviewed were:

- CALDER, A. (2009). CARBON AND CARBON TRADING. In *Compliance for Green IT: A Pocket Guide* (pp. 53-70). Ely, Cambridgeshire: IT Governance Publishing
- Stillman, J. (2008, May 1). What is Carbon Credit? CBS *News*. Retrieved from https://www.cbsnews.com/news/what-is-carbon-credit/
- Dhanda, K., & Murphy, P. (2011). The New Wild West Is Green: Carbon Offset Markets, Transactions, and Providers. *Academy of Management Perspectives, 25*(4), 37-49

A comprehensive list of all the citations can be found in the references section at the end of the report

Tools/Software Used:

- R in Rstudio
  - We are using R to create graphics as well as perform statistical analysis on the data, such as creating linear regression models and ARIMA model.
  - We are also using R to clean and calculate emission data for Bon Appetit.
- Piktochart
  - To create infographics for posters, with the intention spread awareness of campus sustainability on campus
- Excel
  - To store csv files that will be used in R for analysis
  - To create updatable databases (deliverables), since our client primarily uses excel for most data storage, and also since it is the most universal software used for data storing, making it easier to share data with other stakeholders
- Google Drive
  - To share files within group members, as well as with Dr. Supp. Google drive was primarily used to work on reports and analysis, since it provides the option of multiple people working together on a file in real time.

- Email
    - To share files of R. To also communicate with clients and stakeholders. Client would send required datasets through email.

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- Are Severe Rain storms, Snow storms, Drought, and Tornadoes Linked to Global Warming? (June 17, 2011) Retrieved from https://www.ucsusa.org/global-warming/science-and-impacts/impacts/global-warming-rain-snow-tornadoes.html#.W6AoCf5KiCQ

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