scope
Contemporary Research Topics

work-based learning 4:
Technology

November 2022

https://doi.org/10.34074/scop.6004006

REDUCING CAMPUS CARBON FOOTPRINTS

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Published by Otago Polytechnic Press. Otago Polytechnic Ltd is a subsidiary of
Te Pükenga, New Zealand Institute of Skills and Technology.

Article

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ABSTRACT

Organisations are now focussing on strategy with more sustainable operations, now that pandemic uncertainties and lockdowns are less unpredictable. To balance strategy and risk, business intelligence and data-driven, decision support is needed. This article considers tertiary campus emissions based on a yearly summary report, where emissions are measured and monitored for mitigation. The data problem is framed, so that linear regression, clustering and a basic semantic analysis can lead to further insights. The discussion and rationalisation lead to future-based conclusions. Temporal emissions analysis is recommended for similar organisations. The article also finds that even in the tertiary education sector, unique circumstances may lead to a shift in focus, anomalies or unique strategies to reduce operational emissions immediately and in the longer term.

INTRODUCTION

The purpose of this article is to analyse a quantitative data set that can serve as a tool to help reduce organisational greenhouse gas (GHG) emissions. The report focusses on critically framing the data problem generally, from the perspective of a tertiary campus. The data are used to consider issues, and the application of data driven techniques is evaluated and used to justify insights, conclusions and recommendations.

Greenhouse gases can lead to global warming and have serious and existential consequences. Thus, the global response is to limit GHG emissions and global warming to 1.5°C, with the aim of constraining modulation in land, air, and water ecosystems. If the '1.5 degree threshold' is breached, sea levels will rise, and life-threating heatwaves and other natural disasters are likely to result (Aydos et al., 2020). Socially responsible businesses are becoming more proactive in emissions mitigation efforts, and finding innovative ways to operate more sustainably. Failure to act will increase the potential risk within organisations and may lead to sanctions, levies, or other negative repercussions. This article offers recommendations, for organisations, that are particularly useful in any tertiary campus towards the goal of reducing emissions.

This article frames the data problem with a methodology that supports data description, linear regression, clustering and semantics, with discussion, rationalisations and conclusions.

FRAMING THE DATA PROBLEM

Greenhouse gases are typically compound gases released into the atmosphere that have an ability to trap longwave radiation or heat in the atmosphere, which causes 'Global Warming' as a consequential result (Jonas et al., 2019). The Intergovernmental Panel on Climate Change (2018) signalled considerable additional damage of 2°C warming over 1.5°C, highlighting the short time left to avoid exceeding the lower threshold. Crossing the 1.5°C limit will accelerate the climate change disaster (Aydos et al., 2020). Therefore, it is a responsibility of businesses globally to reduce their emissions. This can be viewed as a genuine opportunity; failing to take action now creates more risk for organisations and may lead to fines and sanctions.

The data used to frame the problem is the 2021 emissions report of the University of Otago in Aotearoa New Zealand, including the years 2019 and 2020 (University of Otago, 2021). It contains many data graphs and highlights the 'Total Emissions' by tonnes of Carbon Dioxide emitted (tCO_2e) and 'Proportion of Total Inventory.' Summarised data are given for 2019 and 2020 in Table 1.

The data are grouped by Scope 1, Scope 2 and Scope 3 for 2019 and 2020 emission sources. An emissions inventory is a way of accounting for the air pollutants discharged into the atmosphere (World Health Organisation, n.d.). When sources of emissions are divided into the three main scopes, they can be viewed from different operational levels; the sources are categorised by the GHG Protocol (GHGP) (Standard, 2011), the premier guide for carbon accounting and are as follows:

- Scope 1 are direct emissions come from owned or controlled sources by the reporting company.
- Scope 2 are indirect emissions come from the generation of purchased electricity, steam, heating, and cooling used by the reporting company.
- Scope 3 are indirect emissions that occur in a company's value chain, outside of the reporting company's walls.

Three data perspectives have been used to frame emissions considerations and focus different abstract challenges as well as actionable opportunities. By articulating the viewpoints by scope, it is possible to conceptualise various emissions risks. Aligning emissions mitigation with business strategy requires understanding the sustainability expectations of the wider community, and suggesting actionable recommendations that include potential opportunities within future commitments (Spradlin, 2012).

In this study, three considerations were explored via data.

1. ***The impact of direct and indirect greenhouse gas emissions***

   By identifying the amount of emissions generated by the sources owned/controlled by the university and the indirect sources (from purchased electricity, heat, and steam consumed), the management can measure the total amount of CO_2 generated each year, against the total cost spent on maintaining/running those sources for the same length of time. Priority should be given to reducing the impact of top emission sources in these two categories. As the sources in these two scopes are owned/controlled, the management can analyse the current impact, then try using different or other sustainable practices in the future, to see the amount of emission reduction and the cost for implementing the changes accordingly. This will enable the campus to measure the success of newly implemented greenhouse gas reduction practices towards cutting down on direct and indirect GHG emissions.

Emission Source	Category	2019 Emissions Reported (tCO_2e)	2019 Emissions Rebaselined (tCO_2e)	2020 Emissions	% Difference (Rebaselined 2019 to 2020)	Proportion of Total 2020 Inventory
SCOPE 1						
Stationary Combustion	Biomass	66	69	64	-7%	0%
Stationary Combustion	Coal	1,559	1,559	1,384	-11%	5%
Stationary Combustion	Diesel	78	78	58	-26%	0%
Stationary Combustion	LPG	1,276	1,276	1,116	-12%	4%
Mobile Combustion	Road Vehicles	226	228	168	-26%	1%
Mobile Combustion	Marine	17	18	21	+14%	0%
Fugitive Emissions	Refrigerants	106	106	109	+3%	0%
Total Scope 1		**3,328**	**3,334**	**2,920**	**-12%**	**10%**
SCOPE 2						
Electricity	Electricity	4,628	5,082	5,427	+7%	18%
Steam & MTHW	Coal	5,257	6,176	1,226	-80%	4%
Steam & MTHW	Biomass	273	273	417	+53%	1%
Steam & MTHW	Natural Gas (Wellington)	NA	260	181	-31%	1%
Total Scope 2		**10,158**	**11,791**	**7,251**	**-39%**	**24%**
SCOPE 3						
Transmission & Distribution Losses	Electricity	350	385	467	+21%	2%
Steam & MTHW Losses	Coal	263	309	61	-80%	0%
Steam & MTHW Losses	Biomass	14	14	21	+53%	0%
Steam & MTHW Losses	Natural Gas (Wellington)	NA	30	11	-63%	0%
Business Travel	Air Travel (All Categories)	11,894	11,982	1,699	-86%	6%
Business Travel	Accommodation	269	338	115	-66%	0%
Business Travel	Taxis & Shuttles	82	64	36	-43%	0%
Business Travel	Private Mileage	142	142	71	-50%	0%
Student Travel	Air Travel (All Categories)	NA	11,244	9,143	-19%	30%
Employee Commuting	Public Transport	47	69	76	-10%	0%
Employee Commuting	Private Vehicles	1,434	1,548	1,320	-15%	4%
Student Commuting	Public Transport	NA	187	147	-21%	0%
Student Commuting	Private Vehicles	NA	957	755	-21%	2%

Table 1. Campus greenhouse gas emissions inventory by scope.

2. *The impact of business travel on greenhouse gas emissions*

Business travel alone has eight different sources of emissions. Thus, efforts must be made to measure the total impact of business travel on the overall carbon footprint. Doing so could be a potential sustainability and a financial breakthrough for the organisation. With the impact of business travel so high, management must make efforts to improvise, adopt and overcome the emission activities with new technologies. Adopting technological advancements to replace business travel in terms of interacting with audiences could potentially be highly cost-efficient as well as environmentally friendly.

3. *The impact of working remotely from home*

Pandemic lockdowns accelerated online ways to work. The practicality of remote work for emissions reduction (excluding business travel) was considered. Employees now working from home during the COVID-19 global pandemic compelled organisations to think of working from home as the new normal. It reduced office operational costs as well as commuting-based emissions. Management must figure out which employees are working from home, which energy sources are consumed, how often they are consumed and how much emissions are caused as a result annually. This type of analysis could be a game changer in terms of overcoming costs associated with office maintenance and reducing the overall emissions by a considerable margin.

METHODOLOGY

The University of Otago data was already summarised. The original 2019 data was focussed on the University's main campus in Dunedin and the services that were administered there. The 're-baselined' 2019 figures in the report were the ones that we utilised; some null entries became populated, as data for all of the campuses were included (in line with the 2020 data), making comparisons more relevant.

The data in 2019 (re-baselined as 2019r) and 2020 were compared using a number of analytical techniques (data description, simple linear regression and clustering). The three considerations were reflected on, in light of our findings. A simple semantics analysis was included using a text inquiry; the intent was to explore emissions mitigation from the standpoint of a Scott and Jaffe Change Model.

The three impact considerations were then reflected upon in the context of the University report (University of Otago, 2021) as a whole, to yield insights. Conclusions and recommendations are given.

DATA DESCRIPTION

The descriptive statistics in Table 2 are for 2019r and 2020 with only the subtotals removed. An improvement is noted (lower mean, standard deviation and maximum) in 2020; this is to be expected, and was seen globally due to the initial COVID-19 lockdowns in 2020 (Aktar et al., 2021). The real management question is, when delivery on campus resumes, will emissions mitigation strategies be reactivated?

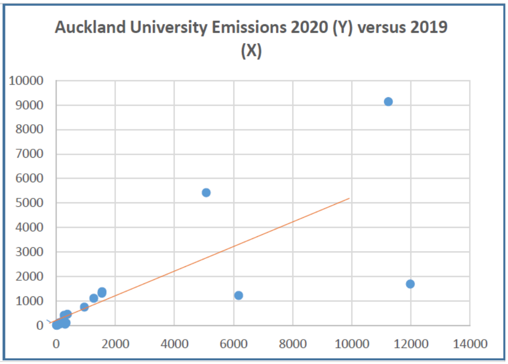
The greatest emissions, with the highest proportion of inventory is emitted by 'Business Travel (Long Haul International)' and the lowest amount of emission with the lowest proportion of inventory is emitted by 'Waste from Operations (Recycling and other).'

2019 REBASELINED		2020	
Mean	**1766.416667**	**Mean**	**1003.875**
Standard Error	695.600116	Standard Error	424.0236155
Median	266.5	Median	157.5
Mode	69	Mode	21
Standard Deviation	**3407.730699**	**Standard Deviation**	**2077.282994**
Sample Variance	11612628.51	Sample Variance	4315104.636
Kurtosis	4.758522407	Kurtosis	11.06630629
Skewness	2.363097947	Skewness	3.252523859
Range	11968	Range	9132
Minimum	14	Minimum	11
Maximum	**11982**	**Maximum**	**9143**
Sum	42394	Sum	24093
Count	24	Count	24
Largest(1)	11982	Largest(1)	9143
Smallest(1)	14	Smallest(1)	11
Confidence Level 95%	1438.958474	Confidence Level 95%	877.1596792

Table 2. Descriptive statistics for 2019r and 2020.

LINEAR REGRESSION

Regression analysis is a crucial technique to that allows you to study the affiliation between two more variables on a particular topic or area of interest, in terms of closely monitoring the impact of each variable on each other (Freund et al., 2006). In order to consider any relationship between 2019r and 2020 in the selected dataset, a simple linear regression technique was adopted. Table 3 has the summary output of the regression.



REGRESSION STATISTICS	
Multiple R	0.750531921
R Square	0.563298164
Adj. R Square	0.542502828
Observations	23

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	55386649.35	5.5E+0.7	27.08773	3.7032E-05
Residual	21	42938985.09	2044714		
Total	22	98325634.43			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95%	Upper 95%
Intercept	201.9854384	339.2938998	0.59531	0.557997	-503.61485	907.58573	-503.61485	907.58573
SLOPE	0.457964204	0.087992413	5.20459	3.7E-05	0.27497396	0.6409544	0.274974	0.6409544

Table 3. Polytechnic 2020 emissions (2019r as x variable).

The correlation statistics show good linear relationships between the two years and a highly significant model, being:

$$2020 = 0.458\ (2019_r) + 202 \qquad (1)$$

The slope indicates an emissions reduction in 2020, but this is likely due largely to COVID-19 lockdowns. The large values (from left to right on the scatter plot) are Scope 2 Electricity and then Coal with Scope 3 Student Air Travel and then Business Air Travel (all categories) respectively. In terms of using the regression analysis for predictive modelling, it is likely that the data should be pre-processed by categorising emission types further, as well as exploring scopes (Cherrington et al., 2020).

The scatterplot serves as a stark visual representation of the data, possibly more important than the predictive model (Tufte, 1985). Increasingly, data scientists are finding innovative ways to visualise data alongside results and to 'tell the data story' for impact and to compel action, especially climate action (Ojo & Heravi, 2018).

DATA CLUSTERING

The clustering technique used to analyse the University of Otago data set is k-means clustering, as in Table 4.

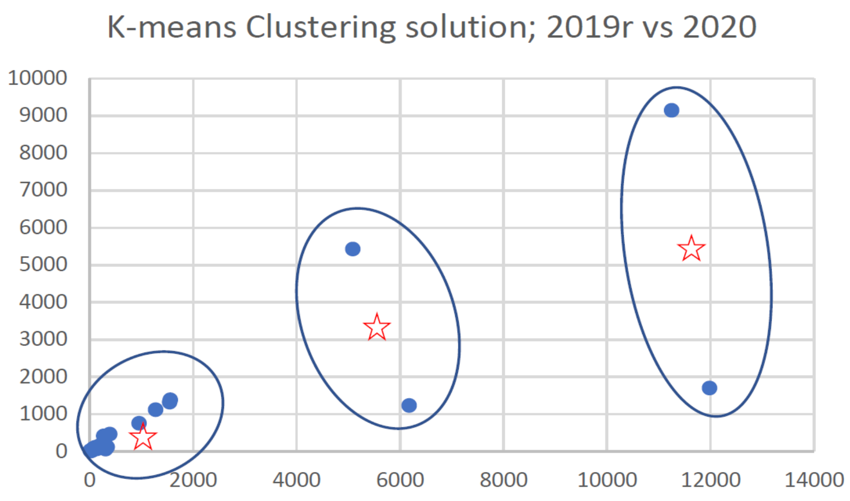


Table 4. Data clustering for 2020 versus 2019r

K-means clustering is an unsupervised learning algorithm, dividing the unlabelled dataset into different groups by analysing similarities (Pace & Cherrington, 2020); 'k' denotes how many predetermined clusters must be created in the iterative analysis. Here, k=3, which means three clusters will be created for the selected data set. This is reasonable, given the scatterplot. Obviously, the low emissions will become one cluster, but will the algorithm deal with the four high emission totals by grouping by Scope 2 and Scope 3? Indeed, that is the result, as in Table 4 with 'centroids' labelled for each cluster. Centroid 1 is [994.5,329.9], Centroid 2 is [5629,3326.5], and Centroid 3 is [11613,5421]. These are useful for comparison.

SEMANTIC ANALYSIS

For organisations engaged in climate action, a cultural shift is taking place. Analytical tools, text and semantic analyses are becoming commonplace in organisations and are often used to gauge stakeholder opinion and even to change policy (Madanian et al., 2021).

The report was sampled for descriptive text, grouping emotive text such as 'difficult', 'tackle', 'interest' and 'ensuring.' Such text may be categorised as belonging in the 'deny', 'resist', 'explore' and 'commit' quadrants of a Scott and Jaffe Change model, respectively. The 2 x 2 categorisation can be thought of as a tool to gauge organisational focus for change management. A deeper semantic exploration can attempt to quantify the emotive content of text, or explore stakeholder comments, so as to "listen for the future" of the organisation (Kiesling, 2022) or lead to better alignment and investment (Zaffron & Logan, 2011) including more innovative leadership (Cherrington et al., 2021).

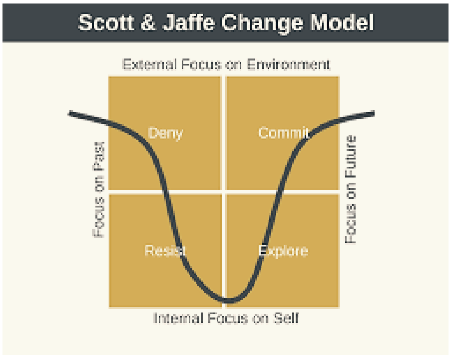


Figure 1. Scott and Jaffe change model link with semantic analysis.

Analysis of eligible text put eight per cent in a 'deny' category, 18 per cent in 'resist', 42 per cent in 'explore' and 32 per cent in 'commit' quadrants, respectively. This shows a strong future focus for the University of Otago on emissions mitigation, as well as some tendency to internal focus with respect to emissions reduction.

DISCUSSION AND RATIONALISATIONS

The k-means clustering easily determined which emission sources were the least contributors to emissions in 2019r and 2020, which sources were the moderate contributors and which sources were the high contributors. Clustering can support feature selection pre-processing (Cherrington et al., 2019a) as well as revealing data outliers (Cherrington et al., 2019b). This could be seen in Table 1 as well, but the visual display of quantitative information adds to the storytelling of motivated action and even transformational leadership (Cherrington et al., 2021).

The determinations and assumptions that underpin emission sources and scopes is critical for any organisation seeking to measure, monitor and mitigate their emissions (Cherrington et al., 2020).

The emissions groups within Clusters 1, 2, and 3, rated as lowest, moderate and highest, could be contended with differently. There are many groups in Cluster 1 whose sum makes an impact; actioning these emissions may be 'low hanging fruit', creating 'short-term wins' to shift the culture of an organisation (Kotter, 2012). Failure to consider such opportunities has been identified as a cultural barrier to change (Cherrington, 2020a; Cherrington, 2020c).

Clustering and descriptive statistics highlighted that emission sources that were identified as 'Direct & Indirect GHG Emissions' had a combined contribution of 38.6 per cent of the overall carbon dioxide (CO_2) emissions, while the emissions from 'Business Travel' alone singlehandedly contributed 35.5 per cent of overall CO_2 emissions in year 2019r.

Sources from 'other indirect GHG emissions' (excluding business travel) contributed to overall CO_2 emissions in year 2019r by 25.9 per cent. It is clear, all the sources that relate to 'business travel' are the highest contributors to the overall carbon footprint, while the sources of 'direct & indirect GHG emissions' combined are the second highest contributors to overall GHG emissions. The majority of emission sources relating to business travel and emissions from steam, purchased electricity and heat consumed by the University of Otago were well above the mean value of 1165.37 tCO_2e.

CONCLUSIONS AND FUTURE WORK

In conclusion, 'Business Travel' is the biggest single emission source and is a considerable area of concern for mitigating future emissions impacts. However, adopting digital/online interaction platforms like Microsoft Teams or Zoom for audience interactions while restricting short air travels could significantly reduce the overall carbon footprint by approximately 70–80 per cent. 'Direct & Indirect GHG Emissions' collectively contributed to 38.6 per cent of overall CO_2 emissions, thereby it must be a focus for emissions mitigation.

Initiatives such as the usage of energy-efficient lighting and sustainable space heating control practices create quick wins in terms of emissions reduction. Furthermore, as 'Other Indirect Emissions (Excluding Business Travel)' contribute a just over a quarter of overall carbon emissions, it is projected that working from home could almost halve travel emissions.

A temporal emissions analysis can be used to create more effective policy on business travel, but most organisations will have unique circumstances that lead to shifts in focus for unique strategies to reduce operational emissions.

The data analytic techniques and approaches used here are simple and reductive, yet they help visualise the data. The analysis helps managers make short-term and long-term strategic decisions towards promoting sustainable practices to radically reduce the impact of business operations on emissions which lead to global warming.

Future work will delve into emissions data for other tertiary campuses, especially from societal perspectives (Naviza et al., 2021). A temporal exploration will support better understanding of the evolving emissions landscape in the sector and will support more focussed strategies for campuses via data-driven decisions. A firm intention of Scopes 2 and 3 emissions analyses is also needed for most organisations going forward to meet net zero targets nationally and towards global goals.

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