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Student Research Report

Carbon Emissions Assessment for UBC Food Services

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In response to the climate emergency, UBC has developed the UBC Climate Action Plan 2030 (CAP 2030) with a target to reduce greenhouse gas emissions from food systems by 50% by 2030. Our research aims to identify the top 3-5 food product categories with the highest carbon emissions and provide recommendations to reduce carbon emissions. We begin by cleaning and visualizing data from all UBCFS food purchases in 2022. Our results show that "Grocery", "Dairy", and "Beverage" product classes are the top three emitters, while "Meat" contributes a relatively small portion of carbon emission. We then develop several regression models, and our results demonstrate that food products in the "Meat", "Dairy" and "Processed" product classes are the top contributors to carbon emissions. Weight of food purchased is an important factor determining the carbon intensity, which causes the difference between our data visualization and regression analysis results. Finally, we recommend purchasing alternative food products with a lower carbon footprint and we suggest several ways forward for future, more detailed analysis. Our findings offer a starting point for a more nuanced approach to reducing the carbon footprint of food systems, which is vital to achieving UBC's goal of net-zero operational emissions by 2035.

Climate change has evolved beyond being merely an environmental issue and is now a significant threat to global economic and social stability. According to the United Nations Intergovernmental Panel on Climate Change (IPCC), the Earth's temperature has increased by 1°C above pre-industrial levels, and current projections indicate that it may rise by up to 1.5-2°C in the coming decades, leading to catastrophic consequences for ecosystems and human societies (IPCC, 2022). Consequently, it is crucial to identify and address the sources of greenhouse gas emissions, including food systems, which account for a substantial portion of carbon emissions.

Our report examines the carbon emissions associated with food products purchased by UBC Food Services, aiming to identify the key contributors to carbon emissions and provide recommendations to reduce emissions related to food purchases at UBC. By applying our coding method and regression models, we uncover surprising insights that challenge our initial assumptions about the role of animal-based products in overall total carbon emissions at UBC. Our findings offer a starting point for a more nuanced approach to reducing the carbon footprint of food systems, which is vital to achieving UBC's goal of net-zero operational emissions by 2035, as laid out in the Climate Action Plan 2030 (CAP 2030).

The most important stages of our analysis involve cleaning, coding, and augmenting the dataset. We first clean the raw data that is already coded with the first-level code of "Product class", and then assign each food product a second-level "Subtype 1" code and a third-level "Subtype 2" code by using our three-level coding method. We then calculate the total carbon emissions for UBCFS from food purchases from January 1 to December 31, 2022, based on the carbon emissions values we find for each "Subtype 2" category. Next, we create summary statistics tables and visualizations to conduct a preliminary analysis to find key relationships. We surprisingly find that the "Meat" product class accounts for only 6.5% of total emissions. In contrast, the "Grocery," "Dairy," and "Beverage" classes contribute significantly more.

We conduct a further analysis of key relationships and patterns by employing four regression models with different explanatory variables. Our first three models are simple linear regression models, and the last model is a multivariate regression model. Our findings from the regression models largely correlate with the patterns we see in the visualizations from our preliminary analysis, except that the role of "Meat" is more significant than what is initially apparent in the preliminary analysis. Based on our findings, we recommend replacing more carbon-intensive food products with less carbon-intensive alternatives, such as replacing canola oil with less carbon-intensive rapeseed oil and substituting dairy cheese products with vegan cheese or other protein-rich alternatives. However, achieving a 50% reduction in emissions from food systems at UBC may prove challenging, given the continued growth in the campus population and UBCFS's business. Therefore, we suggest several ways forward for future analysis and recommend a more nuanced approach focusing on efficiency and food waste reduction.

The remainder of the paper is organized as follows. Section I reviews the background of the project and related literature. Section II provides a description of the dataset and key variables, as well as summary statistics and key relationships. Section III describes our regression model. Section IV presents our results and corresponding interpretation, along with robustness checks and limitations. Section V discusses our recommendations and potential further research, and Section VI provides a conclusion for our paper.

I. BACKGROUND

A. Community Partners

This project is a part of the ECON 490 Community Engaged Learning section, and we have partnered with the Social Ecological Economic Development Studies (SEEDS) Sustainability Program at UBC to deliver this analysis for our community partner, UBC Food Services (UBCFS). SEEDS creates interdisciplinary partnerships between students, faculty, staff and community partners with the goal of advancing sustainability ideas, policies and practices at UBC. Their projects are situated within the context of UBC's sustainability, climate and wellbeing commitments as outlined in the Strategic Plan, as well as the United Nations' Sustainable Development Goals (SDGs) and their alignment with the university's strategic priorities.

B. Project Background and Context

In December 2019, the University of British Columbia (UBC)'s Board of Governors endorsed the university's Declaration on the Climate Emergency and committed to align the university's work with the United Nations Sustainable Development Goals (UN SDGs). These commitments followed a student-led movement to recognize the climate crisis as a fundamental threat to our world, including an open letter signed by over 1600 students, staff, faculty and campus organization and the participation of over 5000 UBC community members in the 2019 Global Climate Strike. The 2019 Declaration on the Climate Emergency recognized UBC's responsibility as a public institution to combat climate change and advance a "sustainable and just society across British Columbia, Canada and the world" (Office of the President, 2019).

In the intervening years, the university has assembled its climate emergency response through a number of reports and strategic plans, most notably in the UBC Vancouver Campus' Climate Action Plan 2030 (Camus and Community Planning, 2021). The vision established in the Climate Action Plan lays out targets and actions that will accelerate and deepen GHG reductions in pursuit of a 2030 GHG reduction target of 85% on operational emissions (2007 baseline year) and 45 % on extended emissions (2010 baseline year), as well as UBC's target for net-zero operational emissions in 2035. Operational emissions in this context include buildings, energy and fleet, while extended emissions include commuting, business air travel, and waste and materials – and food, the focus of this project. UBC Vancouver currently pays overall carbon costs of around $3 million per year because of the BC Carbon Tax and other public sector offset requirements, and UBC's expected future carbon liability would accumulate to approximately $100 million over the next 20 years if no further actions are taken to reduce carbon emissions. Taking bold action now is key to reducing UBC's greenhouse gas emissions and avoiding risks to the institution's reputation, as well as considerable energy and carbon liabilities (C+CP, 2021).

Under the extended impact emissions umbrella, CAP 2030 lays out a bold target to reduce GHG emissions from food systems by 50% before 2030 (C+CP, 2021). Various short and medium term actions were also articulated, including developing and implementing "mandatory campus-wide Climate-Friendly Food System Procurement Guidelines applicable to all food providers" and developing a "Food System Resilience and Climate Action Strategy that holistically advances climate-friendly foods at UBC including climate mitigation and adaptation" (C+CP, 2021). These targets were informed by the understanding that

UBC's campus food system accounts for over 29,000 tonnes of carbon emissions per year, the equivalent of consuming 65,522 barrels of oil. Food is the second highest emissions category in extended impact emissions areas at UBC. UBC is not unique in this respect – food systems are well-established as a significant driver of greenhouse gas emissions. Food systems contribute between 21 - 50 % of total global GHG emissions, including carbon dioxide, methane, and nitrogen dioxide that directly impact climate change (C+CP, 2021). Approximately 71 % of food systems-related global GHG emissions are associated with the land-based sector, including agriculture, associated land use and land use change activities. The production process, including agriculture, fishing, aquaculture, and emissions from the production of inputs such as fertilizers, contribute to the largest share of emissions among the life-cycle stages of the food system that contributed substantially to GHG emissions (Crippa et al., 2021). High consumption of meat, seafood and certain cereals leads to intensive agriculture and unsustainable harvesting, resulting in increased climate breakdown. The production of food also has a major impact on habitat destruction and land use change, which leads to biodiversity loss (United Nations Environment Programme, 2022). Land clearing for grazing and feed crops, in addition to the increased use of fertilizer and pesticide, are the main factors that cause environmental degradation and species extinction (Benton et al., 2021).[1]

C. Related Literature

There is a growing body of literature that investigates the environmental impacts of different types of food and their production methods. In terms of carbon emissions and other environmental impacts, some types of food have been identified as having a larger impact than others.

Meat and dairy production is a major contributor to greenhouse gas (GHG) emissions and other environmental impacts. According to a study published in the journal Science in 2018, beef production has the highest environmental impact across all metrics, followed by other animal-based products such as pork and chicken (Springmann et al., 2018). Meat and dairy production also requires large amounts of land, water, and other resources, which can lead to deforestation, water scarcity, and soil degradation (Poore & Nemecek, 2018). Processed foods, such as snacks and soft drinks, often contain high amounts of sugar, salt, and fats, which can contribute to health problems such as obesity and heart disease. In addition, the production of processed foods can result in significant GHG emissions and other environmental impacts, due to the use of energy-intensive processing methods and transportation (Sáez-Almendros et al., 2013). While having a lower carbon footprint than many other food categories, fruits and vegetables can also

[1]The "Community Partner" and "Project Background and Context" sections are adapted from the initial SEEDS charter draft shared with our group by Laure Dupuy (Applied Research Coordinator, Climate Action Food Systems at SEEDS).

still contribute to carbon emissions, mainly due to transportation and the intensive use of pesticides and fertilizers (Jones, 2018). The expansion of fruit and vegetable production can also lead to deforestation and other forms of land use change. The production and transportation of seafood products, particularly farmed fish and shrimp, can contribute significantly to carbon emissions. Additionally, overfishing and unsustainable aquaculture practices can have negative impacts on marine ecosystems and thereby contribute to climate change (Costello et al., 2016).

D. Research Question

This project will analyze food purchases made by UBC Food Services from January-December 2022 and provide recommendations for reducing the greenhouse gas emissions associated with UBC Food Services' food purchases. Our overarching research question asks: how can UBC Food Services reduce its carbon emissions from food?

Our project works to understand this question by studying the following research questions: What are the top 3-5 food product categories with the most carbon emissions? Within those categories, what are the 1-2 biggest emitters? What are the biggest factors (size, weight, product type, etc.) contributing to the carbon intensity of various food products in UBC Food Services' supply chains? Crucially, our report will also include a set of recommendations that seek to answer the question: What actionable steps can UBCFS take before 2030 in order to reduce their carbon emissions associated with food systems?

II. DATA

The following section contains our data description and summary, including a list of variables present in our datasets with their descriptions, as well as other properties of the dataset and transformations that we have performed thus far. We also include a table of summary statistics and discuss our plan to clean, augment and restrict our data.

There are 20 categorical and quantitative variables in the dataset. Categorical variables include "SHIP TO", "Customer name", "Item #", "Item description", "Product class description", "Sub type 1", "Sub type 2", "UM sold", "Price by UM", "Brand name", "Vendor name", and "MFG NO.". Quantitative variables contain "Pack", "Size", "QTY", "Total QTY", "Carbon emissions per kg (kg CO2e/kg)", "Gross weight", "Total carbon emissions" and "Sales amount".

The following categorical variables were used extensively in our analysis:

- "Customer name": The names of the different UBC Food Services outlets (including first-year residence dining halls such as Gather at Place Vanier and other outlets like Ike Cafe in the IKB building) that ordered food products through UBC Food Services.

- “Item description”: Short description of the product.
- “Product class description”: The product class of each food product, such as “Beverage” and “Dairy”.
- “Sub type 1”: Food sub type subdivided by the food category in “Product class description”. The second level of our coding analysis.
- “Sub type 2”: More detailed sub types subdivided according to ”Sub type 1”. The third level of our coding analysis.

These categorical variables appeared in our dataset but were not used in our analysis:

- “Ship to”: The customer identification number associated with the food product in that observation. This variable has a one-to-one relation with the variable “Customer name”. In other words, each customer has a unique customer ID, and each customer ID corresponds to a unique customer.
- “Item #”: The item ID, which has a one-to-one relation with “ITEM DESCRIPTION”
- “UM sold”: UM means unit of measurement. This column indicates the units used to define the quantity of that food product. For example, CS (case), BX (box), EA (each).
- “Price by UM”: This column indicates what units are used in the unit measure price (e.g. CS, EA etc.).
- “Brand name”: The brand name of the product, such as “Coca Cola”.
- “Vendor name”: The food supplier company. For example, Coca Cola’s vendor name is “Coca Cola Bottling Co.”
- “MFG NO.”: The manufacturing code. This column may also contain information like the date of manufacture and the particular version of the product.

The following quantitative variables were used extensively in our analysis.

- “Gross weight”: The total weight of the product ordered. For example, for the product “Soft drink Coca Cola Zero can,” the value under the “WEIGHT” column is 151.68 kg. This value represents the total combined weight of all 32 cases (each case contains 12 cans of 355ml).

- “Total carbon emissions”: The total carbon emissions is the product of the carbon emissions per kilogram and the gross weight of a given food product product. The units for total carbon emissions is expressed in terms of carbon dioxide equivalents and kilograms, or ”kg CO2e”.
- “Carbon emissions per kg”: The carbon emissions per kilogram for each food product in the dataset. This data represents how much carbon dioxide one kilogram of the corresponding food product emits. The units for carbon emissions per kg are thus expressed as ”kg CO2e/kg”.

These quantitative variables appeared in our dataset but were not used in our analysis:

- “Pack”: The number of products in 1 UM sold. For example, for the product “Soft drink Coca Cola Zero can,” the value under the column “Pack” is listed as “12”, which means that this product is packaged in packs of 12. The value “CS” under the “UM SOLD” column means that there are 12 cans per case.
- “Size”: The unit size. For example, for the product “Soft drink Coca Cola Zero can,” the value under the “SIZE” column is listed as “355ml,” which means that each can is 355ml.
- “QTY”: The number of UM sold. For example, for the product “Soft drink Coca Cola Zero can,” the value under the “QTY” column is “32”, which means the order consisted of 32 cases.
- “Total QTY”: The total number of products sold.
- “Sales amount”: The total price paid for the order of that food product.

In this paper, we use the measure carbon dioxide equivalent (CO2e) in order to quantify carbon emissions, as seen in the variables ”Total carbon emissions” and ”Carbon emissions per kg.” Although discussions on climate issues tend to focus on carbon dioxide (CO2), there are many other greenhouse gases that contribute to climate change, including methane and nitrous oxide. Carbon dioxide equivalent (CO2e) quantifies all these greenhouse gases into a single metric. This metric is used to compare emissions from various greenhouse gases by their Global Warming Potential (GWP), or the amount of warming a certain greenhouse gas causes over a given period of time, and CO2e converts the GWP of other gases to the equivalent amount of carbon dioxide (Rabo, 2020). Throughout this paper, we will use the phrase ”carbon emissions” to refer not only to emissions from carbon dioxide but the emissions caused by all greenhouse gases.

A. *Dataset properties*

UBC Food Services provided us with two datasets. The first dataset, ”UBC - Feed BC 2021-2022,” records the food budget and revenue of UBC Food Services.

All the quantitative variables in this dataset are in dollar amounts, representing either revenue or expenditure. We did not use this dataset in our analysis.

The primary dataset that we worked with is called "GFS velocity report 2022." This dataset provides information on the food supply chain, including all orders made by UBCFS in 2022. The file contains three spreadsheets: "UBC DVEL JAN 1 - OCT 30, 2022," "UBC SVEL JAN 1 - OCT 30, 2022," and "UBC OCT 30 - DEC 31, 2022." The first and third sheets are similar, with the only difference being that the DVEL sheet contains only a column titled "Weight", while the third sheet includes both gross weight and net weight. The second SVEL sheet has a different structure compared to the other two. It provides summarized information by grouping the observations by product class and items and sums up the quantity within each group. For example, while the DVEL sheet provides clear information about customer names and their individual ordered quantity for "Beverage systems" and "Coffee decaf pike place filter pak", the SVEL sheet only indicates the total quantity of this product ordered, without customer information and quantity.

We mainly used data from "UBC DVEL JAN 1 - OCT 30, 2022," and "UBC OCT 30 - DEC 31, 2022," as we could obtain all the information contained in the SVEL sheet from the DVEL sheet and we needed customer information in our analysis. We combined these two sheets into one large dataset, which consists of all food orders made by UBCFS between January 1, 2022, and December 31, 2022. This allowed us to obtain specific order details and estimate carbon emissions, as well as explore possible strategies for reducing the carbon emissions associated with UBCFS's food purchases.

B. Cleaning and coding the data

In our data pre-processing, we took several steps to ensure the accuracy and reliability of our analysis. First, we removed observations under the non-food product categories ("Chemicals", "Disposables", " Table Top", "Clean Power", and "Service Fee") in the "Product class description" (hereafter referred to as "Product class") column. We also removed some unnecessary columns, such as "material number". We also added a column for greenhouse gas emissions per kilogram to create a more focused and relevant dataset. We merged the two sheets from the original dataset named "UBC DVEL JAN 1 - OCT 30 2022" and "UBC OCT 30 - DEC 31 2022" into one large sheet to make our analysis easier. We cleaned the "Customer name" column to ensure consistency across the dataset since some of the customers have different names in the two original sheets.

A crucial step of our process was to code each observation and then augment the dataset by assigning carbon emissions values. We decided to use three coding levels, including the "Product class" category that was already present in the original dataset. We further coded each observation into a "Sub type 1" and "Sub type 2" category based on the type of product. Table 1 in the Appendix shows the full list of all sub type 1s and sub type 2 categories that we created.

The "n" column shows the count of observations coded into the corresponding sub type 2 category. We changed the "Product class" category of some products – for example, we found later that we were not able to find distinct emissions values for frozen products versus their non-frozen counterparts, so we treated all the frozen products as if they were not frozen and re-classified them. We also created a new product class called "Processed" in order to deal with food products that were ready made meals or other processed foods that did not fit in other product classes.

In the second stage of our data augmentation process, we researched and calculated carbon emissions values for each "Sub type 2" category using a combination of academic sources and an online database (carboncloud.com). Many of our academic sources were a review of life-cycle analyses or assessments (LCAs), a standardized methodology used to evaluate the environmental impact of a product throughout its life cycle, which can include manufacturing, distribution, use and final disposal (Golsteijn, 2022). We discuss the reliability of the Carbon Cloud database in Section V. For each sub type 2 category, we attempted to find a carbon emissions value through an academic source first, then used the CarbonCloud database if we could not find a value through academic sources. For those observations where we could not find carbon emissions data, we removed the corresponding observations from our dataset and analysis. We removed 58 observations for this reason. Observations with negative or zero values for "Weight" or "Sales Amount" were also removed from our dataset and analysis, as a zero or negative value means the customer attempted to order the product and was shorted (zero value) or a credit was applied (negative value). We removed 128 observations due to their negative or zero values, in total removing 186 observations and leaving our final dataset with 4797 observations. By following these steps, we were able to create a reliable and accurate dataset for our analysis.

C. Summary statistics and key relationships

We used summary statistics and visualizations in order to uncover patterns and key relationships in our data. This preliminary analysis helped to inform our regression models and in-depth analysis that will be covered in Section III. Overall, UBC Food Services ordered 686,729.16 kilograms of food products from January 1 to December 31, 2022 and those food products generated 1,563,667.92 of carbon emissions. The total emissions generated by UBC Food Services' food orders is equivalent to driving 348 gas-powered cars for one year (EPA calculator). Table 1 shows summary statistics for key quantitative variables from our dataset, including carbon emissions per kilogram, total carbon emissions, gross weight, and sales amount.

Figure 1 shows the breakdown of total carbon emissions by product class. Interestingly, the "Meat" product class is only 6.5% of total carbon emissions, while "Dairy" makes up about 20% of carbon emissions. The largest product class by total carbon emissions is "Grocery" at 44.9%. Figure 2 shows that both the bev-

TABLE 1—SUMMARY STATISTICS OF KEY VARIABLES

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Carbon Emission per KG	0.11	1	2	2.68	3.65	30
Gross Weight (kg)	0.12	11.44	31.5	143.16	104.91	8474.56
TOTAL CO2E BY WT (kg CO2e)	0.18	21.12	58.5	325.97	207.9	35298.9
Sales Amount	0	NULL	NULL	0	NULL	NULL

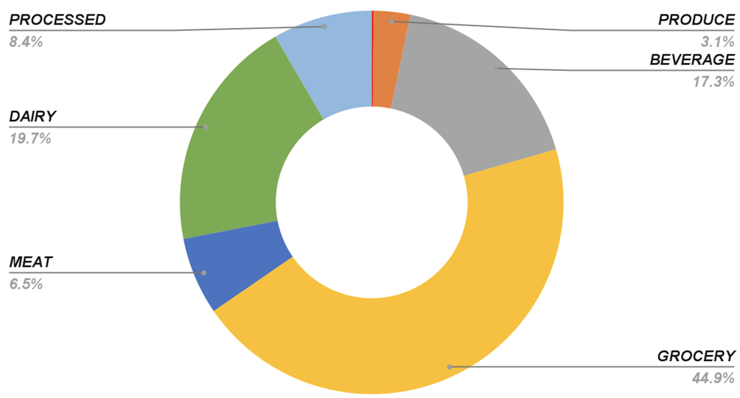

FIGURE 1. PROPORTION OF TOTAL CARBON EMISSIONS BY PRODUCT CLASS

erage (25.8%) and produce (6.6%) product classes are a higher proportion of total weight of all food products than total carbon emissions, where they are 17.3% and 3.1% respectively.

Figures 3 and 4 show the proportion of total weight and total carbon emissions of food purchases from each unique customer. The three first-year residence dining halls are the largest proportions in both figures, with Open Kitchen at Orchard Residence at 24.5%, Gather at Place Vanier Residence at 19.6% and Feast at Totem Residence at 20.9% for total carbon emissions, with similar proportions for total weight.

Figure 5 shows the total carbon emissions for each of the top 20 subtype 1 products. The subtype 1 category of "Oils" is the largest contributor of total carbon emissions, contributing around 190,000 overall. "Grains" contribute about 150,000 total carbon emission. Products in the "Beverage" category such as "Juices" and "Soft drinks" are in the top 10 list, while "Assorted Snacks" is the last contributor in the top 20 sub type 1. We can see a further breakdown of which sub type 2 products in the sub type 1 categories contribute the most carbon emissions with Figure 6, which shows the total carbon emissions for each of the top 20 sub type 2 products. "Canola oil" contributes the largest portion of the total carbon emissions, followed by soup, eggs, and cheese. "Fruit juice" is the major contributor to carbon emissions among the sub type 1 category

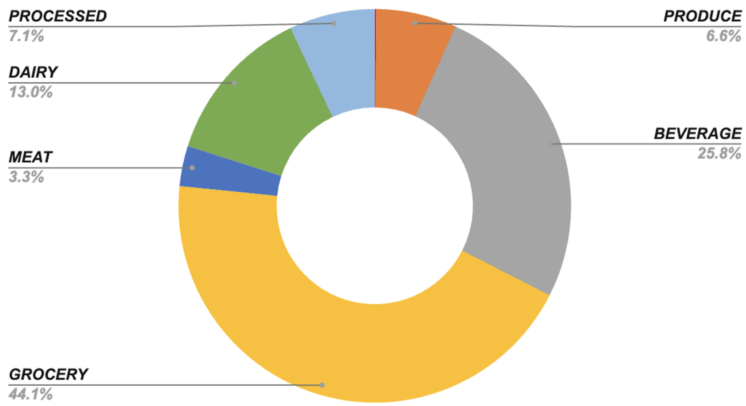

Figure 2. Proportion of total weight by product class

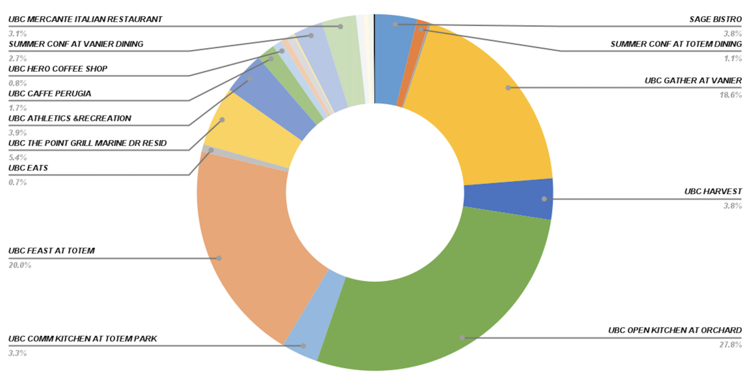

Figure 3. Proportion of total weight of food purchases from each unique customer

of "Juices", and Coca-Cola is the major contributor among the subtype 1 "Soft Drinks". "Rice", "Potato", "Pasta", and "Bread" are the four major contributors among the sub type 1 category of "Grains" on the top 20 list.

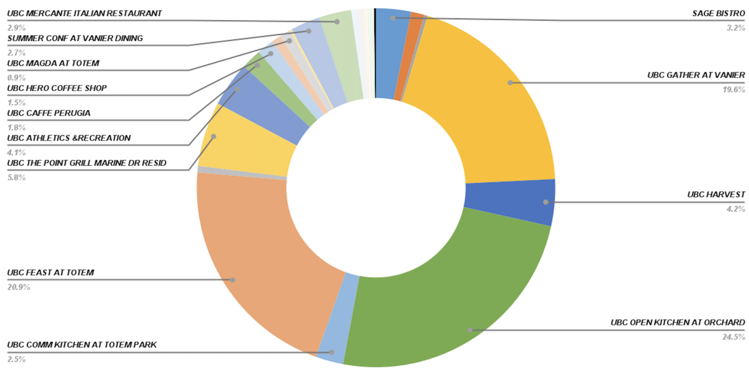

Figure 4. Proportion of total carbon emissions from each unique customer

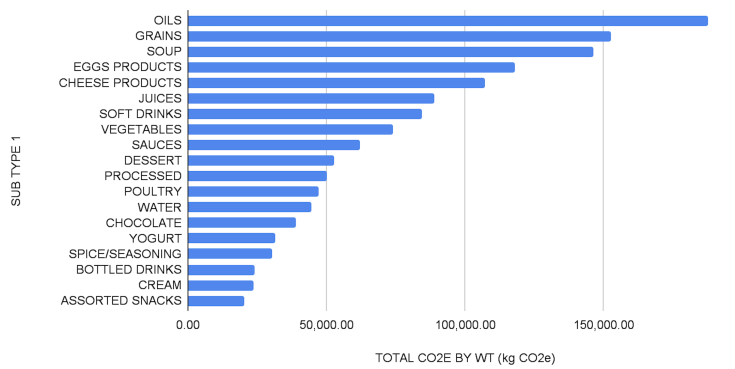

Figure 5. Total carbon emissions for top 20 subtype 1 products

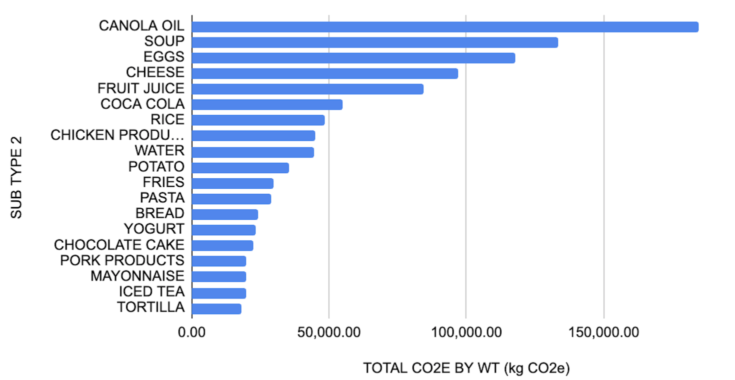

Figure 6. Total carbon emission for top 20 subtype 2 products

III. MODEL

In order to gain deeper insight into the patterns of our data and answer our research questions, we chose to use four regression models. Three of these models were simple linear regression models, while the final model was a multivariate regression model. We chose to use regression models because they would help us to understand the change in the dependent variable that is associated with the change in the explanatory variable(s). For each regression model, we had a set of two regression equations: one equation with the "Total carbon emissions" as the dependent variable and one equation with "Carbon emissions per kilogram" as the dependent variable, both with the same explanatory variable(s).

We chose to perform two regressions for each set of explanatory variables in order to better understand the relationship between weight and carbon emissions in our data. We were unable to use "Gross weight" as an explanatory variable in our dataset because it would have caused multi-collinearity issues, given that "Total carbon emissions" for each observation was calculated by multiplying "Gross weight" by "Carbon emissions per kg" for that observation. We circumvented this issue but while still gaining insight into the role that the weight of the food products ordered plays in total carbon emissions by customer, product class or sub type with the two different dependent variables in each regression model.

All of the explanatory variables used in the models are categorical variables, so each regression was performed with dummy variables corresponding to the unique values for the corresponding categorical variables. We chose these variables as our explanatory variables in order to gain a deeper understanding of the relationship between these explanatory variables and total carbon emissions or carbon emissions per kilogram. However, when determining our specification, the choice of which variables to *not* include in our regression models was as important as the choice of which variables *to* include. A variable like "Total QTY" or "Sales amount" would not have been meaningful in our regression models. For example, quantity was not useful because it is not in a standard unit like kilograms. Variables like "Brand name" or "Vendor name" may have been meaningful if we had been able to find more carbon emissions values that were specific to each individual product and its unique supply chain, a limitation that will be discussed later in the paper. Thus, our regression models and their specifications were carefully chosen to provide meaningful insight into the patterns of our data given our limitations.

Since all our predictor variables are categorical variables, we were deliberate about setting the baseline of the regression model so that we would know how to interpret and compare the coefficients of all the dummy variables. In comparison with setting a random level to be our baseline, setting the baseline level to be 0 is more sensible because we do not need to compare carbon emissions to understand the coefficients. For example, if our baseline was "Meat" and we were looking at the coefficient estimate for "Produce", the correct interpretation would be to compare the carbon emissions of "Produce" against "Meat", whereas setting the baseline to 0 means that the coefficient reveals directly how much carbon emissions “Produce” contributes. Since the default setting in R is not a zero-value baseline, we adjusted our R script to show all the levels of the regression. We also removed the intercepts in the regressions as they are trivial and do not illustrate meaningful information.

Each model is specified as follows:

$$Y_1 = \text{Total carbon emissions}$$
$$Y_2 = \text{Carbon emissions per kilogram}$$

A. Model A

$$Y_i = \beta_1(\text{CUSTOMER NAME}_i) + \epsilon \tag{1}$$

Model A is used to determine the relationship between each unique customer and total carbon emissions. ”Customer name” is a categorical variable that represents each unique customer. This model allows us to understand which customers have the most significant effects on total carbon emissions and carbon emissions per kilogram.

B. Model B

$$Y_i = \beta_1(\text{PRODUCT CLASS}_i) + \epsilon \tag{2}$$

Model B is used to determine the relationship between the product class of a food product and total carbon emissions. ”Product class” is a categorical variable that represents each product class type. This model allows us to understand which product classes have the most significant effects on total carbon emissions and carbon emissions per kilogram.

C. Model C

$$Y_i = \beta_1(\text{SUB TYPE } 1_i) + \epsilon \tag{3}$$

Model C is performed on a subset of the data with the product class “Meat” and is used to determine the relationship between ”Sub type 1” and total carbon emissions for food products in the “Meat” product class. ”Sub type 1” is a categorical variable that represents each sub type 1 category. We chose to limit this regression model to a subset of the data in order to better understand the patterns in the “Meat” product class subset, given that the “Meat” product class had the most statistically significant coefficient after running the Model B regression. This model allows us to understand which "Sub type 1" products in the "Meat" product class have the most significant effects on total carbon emissions and carbon emissions per kilogram.

D. Model D

$$Y_i = \beta_1(\text{CUSTOMER NAME}_i) + \beta_2(\text{PRODUCT CLASS}_i) + \epsilon \tag{4}$$

Model D is used to determine the effects of "Customer name" and "Product class" on the dependent variable and to what extent these explanatory variables can be used to understand variations in total carbon emissions or carbon emissions per kilogram. We included this final regression model to allow us to examine the relationship between the dependent variable and both the "Customer name" and "Product class" variables simultaneously while controlling for the other variable. We set the baseline level for Customer Name to "Chan Centre for the Performing Arts" because the Chan Centre ordered such a low amount of food that its total carbon emissions is functionally zero. The baseline level for "Product class" is set to zero. The separate regression models A and B allow us to understand the impact of each explanatory variable on the dependent variable independently, but it does not capture any potential interaction effects between the two variables.

For Model D, we used a partial F-test to determine if there is a significant difference between the full model (Model D) and the nested versions of the same model, which are Model A and Model B. We first compared Model D and Model B with an ANOVA analysis. The null hypothesis is that all the coefficients of the customer name are zero and the alternative hypothesis is that at least one coefficient of the customer name is non-zero. In Table 2, we see that the p-value is far less than 0.05, so we reject the null hypothesis at 5% significance level and we can conclude that at least one customer name is statistically significant. This means adding "Customer name" as the explanatory variable to our regression does improve the fitness of the model.

Table 2—ANOVA test for comparing Model D and Model B

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
4764	6306357450.00				
4790	6577409610.12	-26	-271052160.12	7.88	0.0000

Similarly, we would like to know if there is a significant difference between Model A and Model D. The null hypothesis is that all the coefficients of the product class are zero and the alternative hypothesis is that at least one coefficient of the product class is non-zero. Since the p-value is less than 0.05, we reject the null hypothesis and claim that at least one product class is statistically significant at 5% significance level, which means adding "Product class" as an explanatory variable also improves the fitness of the model.

Table 3—Anova test for comparing Model D and Model A

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
4764	6306357450.00				
4770	6373966687.81	-6	-67609237.81	8.51	0.0000

Now, we have shown that both product class variable and customer name variable are good enough for building the full regression, we also would like to find out whether there is a multicollinearity problem in our model. In order to test that, we use 'vif(fitall)' in R. By comparing GVIF$\hat{(}1/(2*\text{Df}))$, there seems to be no concerns of multicollinearity in our full model.

IV. RESULTS

A. Model A

$$Y_1 = \beta_1(\text{CUSTOMER NAME}_i) + \epsilon \tag{5}$$

Table 4 shows the results of the first regression in Model A. Six customers had highly statistically significant coefficient estimates, at the p-value <0.001 level: UBC Athletics & Recreation, Feast at Totem, Gather at Vanier, Open Kitchen at Orchard Residence, The Point Grill and Mercante Italian Restaurant. When looking at a table showing the total carbon emissions per customer, these six customers were all in the top 10 of total carbon emissions. All but Mercante make up the top five customers with the most carbon emissions. Open Kitchen also has the largest coefficient estimate at 805.53. Notably, the three first-year residences (Open Kitchen at Orchard, Feast at Totem, and Gather at Vanier) had the highest coefficient estimates. The customers with coefficient estimates significant at the p-value <0.01 level of significance were UBC Harvest and UBC Comm Kitchen at Totem Park. These two customers were also in the top 10 of total carbon emissions. Sage Bistro and Summer Conference at Vanier Dining, two customers who were also in the top 10 of total carbon emissions, had coefficient estimates significant at the p-value <0.01 level. Overall, the only ten customers with any level of significance in this regression were the same as the top 10 customers with the most total carbon emissions.

Table 4—Model A Regression 1 Results

	Estimate	Std. Error	t value	Pr(>|t|)
SAGE BISTRO	108.8065	49.3355	2.21	0.0275
SUMMER CONF AT TOTEM DINING	93.4165	86.6434	1.08	0.2810
SUMMER CONF AT VANIER DINING	200.2775	80.1519	2.50	0.0125
UBC ATHLETICS &RECREATION	304.6349	81.9444	3.72	0.0002
UBC BENTO SUSHI	212.0090	211.0499	1.00	0.3152
UBC CAFFE PERUGIA	103.9673	73.1098	1.42	0.1551
UBC CHAN CTR PERFORM ARTS	23.0500	1155.9677	0.02	0.9841
UBC COMM KITCHEN AT TOTEM PARK	259.9179	81.5357	3.19	0.0014
UBC CONFERENCES & ACCOM	357.5780	298.4696	1.20	0.2310
UBC EATS	101.2905	113.9009	0.89	0.3739
UBC FEAST AT TOTEM	484.4900	45.4458	10.66	0.0000
UBC FOOD HUB	56.4859	151.7860	0.37	0.7098
UBC FOOOOD	134.4672	272.4642	0.49	0.6217
UBC FOOOOD 2.0 AT IRC	101.6690	252.2528	0.40	0.6869
UBC GATHER AT VANIER	510.9951	48.4182	10.55	0.0000
UBC HARVEST	204.8338	68.2346	3.00	0.0027
UBC HERO COFFEE SHOP	134.9735	116.7704	1.16	0.2478
UBC HUBBARDS CAFE	159.1761	157.3073	1.01	0.3116
UBC IKE CAFE IRVING K BARBER LEARN CTR	75.8060	123.9327	0.61	0.5408
UBC LAW COFFEE CART	46.8831	178.3697	0.26	0.7927
UBC MAGDA AT TOTEM	170.1659	150.4942	1.13	0.2582
UBC MERCANTE ITALIAN RESTAURANT	314.8393	92.8496	3.39	0.0007
UBC OPEN KITCHEN AT ORCHARD RESIDENCE	805.5349	49.7449	16.19	0.0000
UBC STIR IT UP	53.9205	144.4960	0.37	0.7090
UBC STUD HSG&HOSP SRV H/O	26.9200	1155.9677	0.02	0.9814
UBC STUDENT HOUSING &HOSP SERVICES	184.4340	516.9645	0.36	0.7213
UBC THE POINT GRILL MARINE DR RESID DINING	237.0959	61.1803	3.88	0.0001

$$Y_2 = \beta_1(\text{CUSTOMER NAME}_i) + \epsilon \tag{6}$$

Table 5 shows the results of the Model A regression with Y = Carbon emissions per kilogram. This regression is less useful. Almost all customers had coefficient estimates with had some level of significance, with most at a p-value <0.001 level of significance. The only two customers without some level of significance were “UBC STUD HSG&HOSP SRV H/O” and “UBC CHAN CTR PERFORM ARTS.” These two were also the two customers with the lowest total carbon emissions. The difference between the results of the regression of total carbon emissions on customer name versus carbon emissions per kg on customer name seem to show that weight likely plays a large role in the carbon intensity of a particular customer.

TABLE 5—MODEL A REGRESSION 2 RESULTS

	Estimate	Std. Error	t value	Pr(>|t|)
SAGE BISTRO	108.8065	49.3355	2.21	0.0275
SUMMER CONF AT TOTEM DINING	93.4165	86.6434	1.08	0.2810
SUMMER CONF AT VANIER DINING	200.2775	80.1519	2.50	0.0125
UBC ATHLETICS &RECREATION	304.6349	81.9444	3.72	0.0002
UBC BENTO SUSHI	212.0090	211.0499	1.00	0.3152
UBC CAFFE PERUGIA	103.9673	73.1098	1.42	0.1551
UBC CHAN CTR PERFORM ARTS	23.0500	1155.9677	0.02	0.9841
UBC COMM KITCHEN AT TOTEM PARK	259.9179	81.5357	3.19	0.0014
UBC CONFERENCES & ACCOM	357.5780	298.4696	1.20	0.2310
UBC EATS	101.2905	113.9009	0.89	0.3739
UBC FEAST AT TOTEM	484.4900	45.4458	10.66	0.0000
UBC FOOD HUB	56.4859	151.7860	0.37	0.7098
UBC FOOOOD	134.4672	272.4642	0.49	0.6217
UBC FOOOOD 2.0 AT IRC	101.6690	252.2528	0.40	0.6869
UBC GATHER AT VANIER	510.9951	48.4182	10.55	0.0000
UBC HARVEST	204.8338	68.2346	3.00	0.0027
UBC HERO COFFEE SHOP	134.9735	116.7704	1.16	0.2478
UBC HUBBARDS CAFE	159.1761	157.3073	1.01	0.3116
UBC IKE CAFE IRVING K BARBER LEARN CTR	75.8060	123.9327	0.61	0.5408
UBC LAW COFFEE CART	46.8831	178.3697	0.26	0.7927
UBC MAGDA AT TOTEM	170.1659	150.4942	1.13	0.2582
UBC MERCANTE ITALIAN RESTAURANT	314.8393	92.8496	3.39	0.0007
UBC OPEN KITCHEN AT ORCHARD RESIDENCE	805.5349	49.7449	16.19	0.0000
UBC STIR IT UP	53.9205	144.4960	0.37	0.7090
UBC STUD HSG&HOSP SRV H/O	26.9200	1155.9677	0.02	0.9814
UBC STUDENT HOUSING &HOSP SERVICES	184.4340	516.9645	0.36	0.7213
UBC THE POINT GRILL MARINE DR RESID DINING	237.0959	61.1803	3.88	0.0001

B. Model B

$$Y_1 = \beta_1(\text{PRODUCT CLASS}_i) + \epsilon \quad (7)$$

The results show that all the product classes except for "Produce" and "Seafood" have a statistically significant effect on total carbon emissions. The coefficients of the regression model represent the estimated effect of each product class on total carbon emissions. "Meat" has the highest coefficient estimate of 612.29, indicating that meat has the largest effect on total carbon emissions. The top three product classes contributing to total carbon emissions are "Meat", "Dairy" and "Processed". The adjusted R-squared value of 0.07674 suggests that 7.67% of the variability in total carbon emissions can be explained by the product class variable. The F-statistic value of 57.96 indicates that the regression model is significant overall. The residual standard error of 1172 indicates that the average difference between the observed values and the predicted values is 1172 kg CO2e.

The formula used for the regression model to analyze the relationship between carbon emissions per kg of food and the product class is:

TABLE 6—MODEL B REGRESSION 1 RESULTS

	Estimate	Std. Error	t value	Pr(>|t|)
BEVERAGE	283.6252	37.9390	7.48	0.0000
DAIRY	481.6184	46.3564	10.39	0.0000
GROCERY	285.0701	23.6213	12.07	0.0000
MEAT	612.2944	90.6779	6.75	0.0000
"Processed"	464.4035	69.7807	6.66	0.0000
PRODUCE	176.2831	71.1828	2.48	0.0133
SEAFOOD	121.3335	244.3407	0.50	0.6195

$$Y_2 = \beta_1(\text{PRODUCT CLASS}_i) + \epsilon \tag{8}$$

TABLE 7—MODEL B REGRESSION 2 RESULTS

	Estimate	Std. Error	t value	Pr(>|t|)
BEVERAGE	1.6916	0.0976	17.34	0.0000
DAIRY	4.2482	0.1192	35.64	0.0000
GROCERY	2.5596	0.0607	42.14	0.0000
MEAT	5.0725	0.2332	21.75	0.0000
PROCESSED	3.5391	0.1794	19.72	0.0000
PRODUCE	0.9091	0.1830	4.97	0.0000
SEAFOOD	5.3683	0.6283	8.54	0.0000

The regression output shows that the coefficients of all the product classes are statistically significant, with p-value <0.0001 level of significance.

The coefficient estimates for each product class indicate how much the carbon emissions per kilogram of food increases on average for each unit increase in the product class variable. "Meat" has the highest coefficient estimate of 5.07246, indicating that meat still has the largest effect on carbon emissions per kg of food. The top three product classes contributing to carbon emissions per kg are still "Meat", "Dairy" and "Processed". "Seafood" and "Produce" are significant in the second regression (Y = Carbon emissions per kilogram) but not in the first one (Y = Total carbon emissions). The difference in weight of food could be a contributing factor to the different results in the two regressions. If the total weight of seafood and produce products consumed is relatively small compared to other product classes, then its impact on total carbon emissions may be diluted, making it statistically insignificant. However, when we look at carbon emissions per kilogram of food, the weight of the food is constant for each product class, which could make seafood and produce more significant.

C. Model C

After the regression of total carbon emissions on product class, we found that the product class "Meat" may be the most significant contributor to carbon emissions, with an estimate of 612.29 — the highest among the seven product classes. As a result, it is sensible to dive deeper, and further analyze which sub types within the meat category are largely associated with greenhouse gases.

$$Y_1 = \beta_1(\text{SUB TYPE } 1_i) + \epsilon \tag{9}$$

Similar to above, we first explore the relationship between total carbon emissions and sub types, such as "Pork", "Poultry", through regression analysis. From the summary table, we can see that "Meat", "Mixed meats" and "Poultry" are significant, since their p-values are all smaller than significance level equals to 0.01. The most influential sub type is "Beef" as it has the highest coefficient 3073.2. This number illustrates that if the food product is beef related, it has 3073.2 units of impact on total carbon emissions.

Table 8—Model C regression 1 results

	Estimate	Std. Error	t value	Pr(>|t|)
BEEF	3073.1700	781.8324	3.93	0.0001
MIXED MEATS	1584.1890	494.4743	3.20	0.0016
PLANT-BASED MEAT	156.9708	223.3807	0.70	0.4832
PORK	299.5118	192.4738	1.56	0.1216
POULTRY	1227.8747	253.6599	4.84	0.0000

$$Y_2 = \beta_1(\text{SUB TYPE } 1_i) + \epsilon \tag{10}$$

We next investigate how sub types of meat class relate to carbon emissions per kilogram of food. Using the results from the regression summary table, we see that all five sub types are significant in this case. Besides the three sub types we mentioned above, "Plant-based meat" and "Pork" become important here. However, the most remarkable contributor is still "Beef" with the highest coefficient 26.82.

The difference in results between the first regression and the second can be attributed to the weight effect. The weight of beef is 485.34 kg, a relative low weight compared with other meat categories, but it is still one of the most significant contributor to carbon emissions. There are many plant-based meat products

TABLE 9—MODEL C REGRESSION 2 RESULTS

	Estimate	Std. Error	t value	Pr(>|t|)
BEEF	26.8200	0.3945	67.99	0.0000
MIXED MEATS	9.7000	0.2495	38.88	0.0000
PLANT-BASED MEAT	1.5714	0.1127	13.94	0.0000
PORK	6.0000	0.0971	61.78	0.0000
POULTRY	4.4689	0.1280	34.92	0.0000

being ordered, 4837.47 kg, but it is not significantly associated with carbon emissions. Since we expect that the weight purchased for each product may not change under normal circumstances, we can focus on the result of total carbon emissions.

TABLE 10—WEIGHT FOR MEAT PRODUCTS

	BEEF	MIXED MEATS	PLANT-BASED MEAT	PORK	POULTRY
WEIGHT(kg)	485.34	1588.68	4837.47	3294.63	12527.88

D. *Model D*

$$Y_1 = \beta_1(\text{CUSTOMER NAME}_i) + \beta_2(\text{PRODUCT CLASS}_i) + \epsilon \tag{11}$$

None of the coefficient estimates in this regression were found to be statistically significant.

The adjusted R-squared value of 0.4786 is in Model D, versus the adjusted R-squared value of 0.1015 in Model A and 0.07674 in Model B. The higher adjusted R-squared value in Model D indicates that the model is a better fit for the data, and that a larger proportion of the variability in the dependent variable can be explained by including both explanatory variables in the model.

$$Y_2 = \beta_1(\text{CUSTOMER NAME}_i) + \beta_2(\text{PRODUCT CLASS}_i) + \epsilon \tag{12}$$

In the second regression where Y = Carbon emissions per kilogram, the coefficient estimates on the "Seafood" and "Meat" product classes are still significant at the p-value <0.01 level, while the coefficient estimates on "Dairy" and "Processed" are significant at the p-value <0.05 level. The largest coefficient estimate is for "Seafood" at 8.38 kg of carbon emissions. We interpret this estimate to mean that the effect of being in the "Seafood" product class for a food product is 8.38 kg of carbon emissions, holding the "Customer name" constant. Comparing Model B, where we only take into account one factor, and Model D, the more

TABLE 11—MODEL D REGRESSION 1 RESULTS

	Estimate	Std. Error	t value	Pr(>|t|)
BEVERAGE	23.0500	1150.5445	0.02	0.9840
DAIRY	137.8656	1152.3111	0.12	0.9048
GROCERY	-105.4245	1151.6248	-0.09	0.9271
MEAT	307.5611	1154.8722	0.27	0.7900
PROCESSED	151.1997	1153.5681	0.13	0.8957
PRODUCE	-184.5271	1153.5573	-0.16	0.8729
SEAFOOD	-138.6391	1176.3112	-0.12	0.9062
SAGE BISTRO	116.0453	1152.3740	0.10	0.9198
SUMMER CONF AT TOTEM DINING	135.5847	1154.6315	0.12	0.9065
SUMMER CONF AT VANIER DINING	216.1150	1154.1878	0.19	0.8515
UBC ATHLETICS &RECREATION	303.1296	1153.7345	0.26	0.7928
UBC BENTO SUSHI	214.6539	1169.6056	0.18	0.8544
UBC CAFFE PERUGIA	98.9646	1153.3861	0.09	0.9316
UBC COMM KITCHEN AT TOTEM PARK	269.6073	1154.3565	0.23	0.8153
UBC CONFERENCES & ACCOM	370.6091	1188.5629	0.31	0.7552
UBC EATS	78.9093	1157.0020	0.07	0.9456
UBC FEAST AT TOTEM	513.9839	1152.2664	0.45	0.6556
UBC FOOD HUB	96.9063	1161.3481	0.08	0.9335
UBC FOOOOD	147.3320	1182.9691	0.12	0.9009
UBC FOOOOD 2.0 AT IRC	105.5214	1178.6425	0.09	0.9287
UBC GATHER AT VANIER	544.1286	1152.3609	0.47	0.6368
UBC HARVEST	223.2198	1153.0631	0.19	0.8465
UBC HERO COFFEE SHOP	132.5636	1156.4900	0.11	0.9087
UBC HUBBARDS CAFE	145.6427	1161.1547	0.13	0.9002
UBC IKE CAFE IRVING K BARBER LEARN CTR	96.5423	1157.3882	0.08	0.9335
UBC LAW COFFEE CART	39.1277	1164.1760	0.03	0.9732
UBC MAGDA AT TOTEM	159.7140	1160.2787	0.14	0.8905
UBC MERCANTE ITALIAN RESTAURANT	335.9521	1154.6650	0.29	0.7711
UBC OPEN KITCHEN AT ORCHARD RESIDENCE	861.7581	1152.4340	0.75	0.4546
UBC STIR IT UP	83.8054	1159.6783	0.07	0.9424
UBC STUD HSG&HOSP SRV H/O	132.3445	1627.8797	0.08	0.9352
UBC STUDENT HOUSING &HOSP SERVICES	189.8107	1260.7049	0.15	0.8803
UBC THE POINT GRILL MARINE DR RESID DINING	276.2146	1152.9359	0.24	0.8107

comprehensive model, we can see that meat is significant in both of our analyses, indicating we should focus on this product class in our recommendations.

Table 12—Model D regression 2 results

	Estimate	Std. Error	t value	Pr(>|t|)
BEVERAGE	4.6000	2.9963	1.54	0.1248
DAIRY	7.3447	3.0009	2.45	0.0144
GROCERY	5.6721	2.9991	1.89	0.0587
MEAT	8.1122	3.0076	2.70	0.0070
PROCESSED	6.5617	3.0042	2.18	0.0290
PRODUCE	4.0306	3.0042	1.34	0.1798
SEAFOOD	8.3804	3.0634	2.74	0.0062
SAGE BISTRO	-2.7621	3.0011	-0.92	0.3574
SUMMER CONF AT TOTEM DINING	-3.6631	3.0070	-1.22	0.2232
SUMMER CONF AT VANIER DINING	-3.1997	3.0058	-1.06	0.2871
UBC ATHLETICS &RECREATION	-2.2252	3.0046	-0.74	0.4590
UBC BENTO SUSHI	-2.9704	3.0460	-0.98	0.3295
UBC CAFFE PERUGIA	-2.7525	3.0037	-0.92	0.3595
UBC COMM KITCHEN AT TOTEM PARK	-3.1481	3.0063	-1.05	0.2951
UBC CONFERENCES & ACCOM	-0.3748	3.0953	-0.12	0.9036
UBC EATS	-3.0165	3.0131	-1.00	0.3168
UBC FEAST AT TOTEM	-3.1279	3.0008	-1.04	0.2973
UBC FOOD HUB	-4.0101	3.0245	-1.33	0.1849
UBC FOOOOD	-3.9707	3.0808	-1.29	0.1975
UBC FOOOOD 2.0 AT IRC	-4.2973	3.0695	-1.40	0.1616
UBC GATHER AT VANIER	-3.3182	3.0011	-1.11	0.2689
UBC HARVEST	-3.0254	3.0029	-1.01	0.3137
UBC HERO COFFEE SHOP	-3.1010	3.0118	-1.03	0.3032
UBC HUBBARDS CAFE	-3.0202	3.0240	-1.00	0.3180
UBC IKE CAFE IRVING K BARBER LEARN CTR	-3.1929	3.0141	-1.06	0.2895
UBC LAW COFFEE CART	-2.9657	3.0318	-0.98	0.3280
UBC MAGDA AT TOTEM	-3.0329	3.0217	-1.00	0.3156
UBC MERCANTE ITALIAN RESTAURANT	-2.3261	3.0071	-0.77	0.4392
UBC OPEN KITCHEN AT ORCHARD RESIDENCE	-3.3139	3.0012	-1.10	0.2696
UBC STIR IT UP	-2.9392	3.0201	-0.97	0.3305
UBC STUD HSG&HOSP SRV H/O	-3.8521	4.2394	-0.91	0.3636
UBC STUDENT HOUSING &HOSP SERVICES	1.1022	3.2832	0.34	0.7371
UBC THE POINT GRILL MARINE DR RESID DINING	-3.1450	3.0026	-1.05	0.2950

V. DISCUSSION

We plotted a graph of total carbon emissions against the gross weight of food products (aggregated by sub type 2 category) to see if there were any unexpected points. Figure 7 demonstrates a positive correlation between total CO2 emission and gross weight, which aligns with our intuition. The distribution of points on this graph shows a diagonal-funnel shape, which means some points at the boundaries of the funnel may be worthy of discussion. “Oils” clearly contributes the most total carbon emissions, despite the fact that its weight is not the highest. This means that ”Oils” per kilogram contribute significantly to carbon emission. When comparing water, soft drinks and juices, we see that water has higher total weight but lower total carbon emission than soft drinks and juices, meaning that water is a more environmentally-friendly drink than other drinks. In the figure, the products that lie in the bottom right quadrant all have higher weights but lower total carbon emissions, and these can be useful to our research goal, since higher weight purchases mean that they are an important part of UBC Food Services’ business but low in carbon emissions. “Vegetables” is clearly a positive example — it may be a good idea for UBCFS to introduce more vegetable-rich food to students.

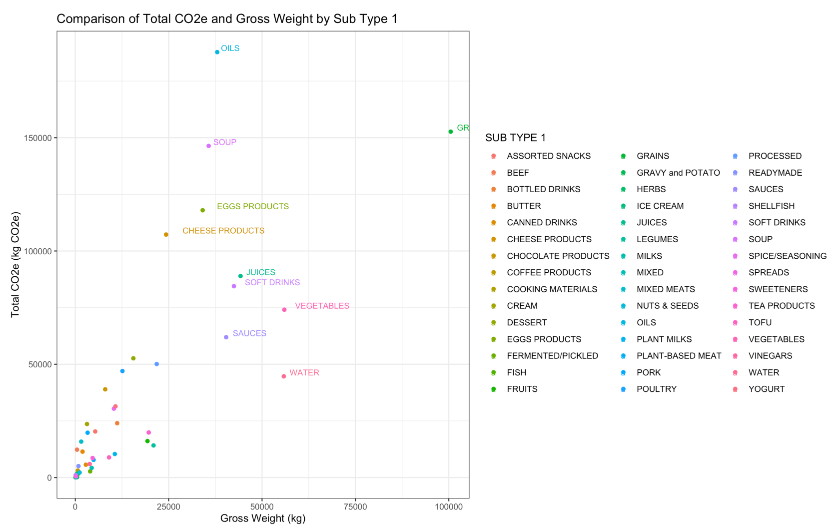

FIGURE 7. COMPARISON OF TOTAL CO2E AND GROSS WEIGHT BY SUBTYPE 1

A. Robustness checks

A primary concern in the robustness of our analysis is the reliability of the carbon emissions data we used, particularly the values from the online database

"CarbonCloud." We found CarbonCloud to be a trustworthy and dependable source for verifying food product carbon emissions for several reasons. CarbonCloud employs rigorous and scientifically grounded methodologies to measure and verify carbon emissions as an independent third-party provider of carbon footprinting services. The company adheres to globally recognized standards such as ISO 14064-1 and the Greenhouse Gas Protocol, ensuring the accuracy and reliability of the results. The database undergoes periodic audits by third-party accreditation bodies to maintain the highest quality assurance standards.

Furthermore, CarbonCloud has a comprehensive and robust database of over 10,000 products and corresponding carbon emissions data. The database is regularly updated and includes information on raw materials, manufacturing processes, and transportation. The comprehensive database guarantees that CarbonCloud's carbon emissions data is highly reliable and accurate. CarbonCloud strongly emphasizes transparency in its methodology and data sources, providing in-depth reports that detail the employed methodology, the assumptions made, and the data sources utilized for each product's carbon footprint assessment.

The reputation of CarbonCloud is well-established and widely respected by various stakeholders. It has successfully collaborated with numerous multinational corporations, including IKEA. Additionally, CarbonCloud has been recognized for its efforts and achievements by prominent international organizations such as the Carbon Trust. These certifications and partnerships testify to CarbonCloud's commitment to sustainability and its ability to deliver results that meet the highest industry standards. Therefore, we found CarbonCloud to be a reliable source for verifying product carbon emissions due to its adherence to rigorous and scientifically grounded methodologies and recognition from various organizations. We can have confidence in the robustness of our results because of our confidence in the robustness of the CarbonCloud database and the carbon emissions values we used from it in our dataset.

Given the reliability of our carbon emissions data, our analysis yielded a surprising result – that the "Meat" product class was a relatively low proportion of total carbon emissions compared to other product classes. We surmise that the low proportion of total carbon emissions from the "Meat" product class is due to the fact that there were relatively few food products in the "Meat category" purchased by UBC Food Services in 2022. However, we could have underestimated the carbon emissions values for "Meat" products and thereby skewed the proportion of total carbon emissions attributed to "Meat" class products too low.

To check the robustness of our findings, we conducted a test by doubling the carbon emissions of all the products in the "Meat" regression and then rerunning the Model A regressions. We observed that the same customers remained statistically significant in this regression as in the initial Model A regression, and the doubling of the carbon emissions did not have a significant impact on the regression results. Figure 8 also illustrates that while the proportion of total carbon emissions attributed to the "Meat" product class nearly doubled, its relative proportion compared to the other product classes remained essentially the same as depicted in Figure 1. This finding suggests that even if we had significantly underestimated the carbon emission values for subtypes in the "Meat" class, our results would not have changed significantly.

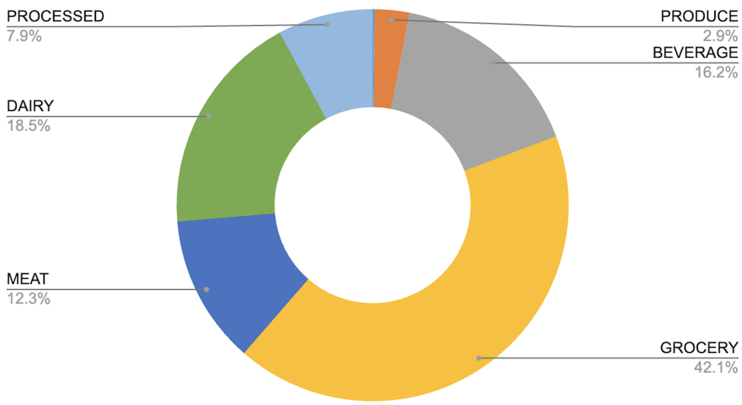

Figure 8. Robustness check: Proportion of total carbon emissions by product class

B. *Limitations*

There were a number of limitations that we had to contend with while conceptualizing and performing our analysis.

First, the carbon emissions values that we used to augment our dataset were generalized estimates found through LCAs and an online database, so these values were not specific to the brands and vendors from which UBC Food Services orders their food products. This lack of specificity meant that we could not perform analysis based on supply chain stages like production or transportation and we also could not include variables like "Vendor name" or "Brand name" in our regression models. As well, we were not able to distinguish between frozen and non-frozen products in our carbon emissions estimates, which meant that we also could not analyze the differential effect of freezing and transporting a food product may have been. We used the coding methodology to reduce the number of carbon emissions values that we had to find, which meant that each carbon emissions value is assigned to the sub type 2 value and not to the unique food product. In an ideal world, we would be able to measure and determine specific greenhouse gas emissions associated with each unique product in order to perform this analysis, but our time and resource constraints limited our ability to extensively research the carbon emissions values.

The lack of specificity in our carbon emissions values also meant that we had difficulty specifying our regression models because we were not able to use many of the variables in our dataset. Many of the variables were not relevant to our analysis, and others that were, like "weight" or "quantity" could not be included because they would have caused multi-collinearity issues. Our regression analysis was therefore limited to three explanatory variables, though we were able to discover more patterns by performing regression analysis on different subsets of the data.

VI. RECOMMENDATIONS

A. *Alternative products*

For many of the top 20 sub type 1 and sub type 2 categories by total carbon emissions, there are potential alternative products that could be purchased in order to reduce overall carbon emissions.

The "Oils" sub type 1 category had the largest total carbon emissions of all sub type 1 categories, at 187,788.64 kg CO2e. The "Canola oil" sub type 2 category was the majority of that "Oils" sub type 1 category, at 184,788.55 kg CO2e. The total carbon emissions of food products in the "Oils" category could be reduced by switching from canola oil, which was 5 kg CO2e per kg to a less carbon intensive oil like rapeseed oil. Rapeseed oil has been found to be the least carbon intensive vegetable oil in multiple academic studies, and a 2022 study by Alcock et al. found that per kilogram of refined oil, rapeseed oil produces about 2.49 kg of carbon dioxide equivalent.

The sub type 1 and sub type 2 catogories for Cheese products also have high total carbon emissions. Based on a 2013 study by Verge et al., we assigned cheese products a carbon emissions value of 4.2 kg COe per kg. The total weight for "Cheese products" is 23080.36kg, and the total carbon emissions produced by "Cheese products" is 96937.52 kg CO2e. Dairy cheese products could be replaced by vegan cheese products or by similarly protein-rich products such as meat or legumes. Though we were unable to find a carbon emissions value for vegan cheese, the main ingredients in vegan cheese tend to be ingredients like almonds, cashew and coconut, which all have a per kilogram carbon emissions value much lower than 4.2 (Owens, 2022). Cheese products could theoretically be replaced by protein-rich plant based products like those in our "Legumes" category. To show the potential effect of reducing the purchase of cheese products and replacing them with alternatives, we calculated the mean carbon emissions values of all the "Subtype 2" categories that fall under the "Subtype 1" category of "Legumes," which have a mean value of 0.6 CO2e/kg. By replacing all "Cheese products" with "Legumes," we would achieve a reduction of 83,089.3 kg CO2e.

Chicken and pork products could be replaced by plant-based alternatives. "Chicken products" emit 3.65 kg CO2e per kg and "Pork products" emit 6 kg CO2e per kg. The total CO2e produced by "Chicken products" is 45073.16 kg CO2e, and the total CO2e produced by "Pork products" is 19767.78 kg CO2e. The total CO2e from "Chicken products" and "Pork products" is 64840.94 kg CO2e. By replacing all chicken and pork products with tofu, which emits 0.98 CO2e/kg, the total carbon emissions would be reduced to 15361.86 kg CO2e, a reduction of 49479.0784 kg CO2e.

Overall, although the "Meat" product category accounts for only 6.5% of total carbon emissions, we recommend that UBCFS further reduce the amount of animal-based products it orders. The combined total carbon emission of food products in the "Dairy", "Meat", and "Seafood" product classes amounts to almost one-fifth of UBCFS's total carbon emissions. In all our regression analyses, we found that the "Meat" and "Dairy" product classes were consistently statistically significant, likely due to the relatively high carbon emissions per kilogram of products in those classes. Therefore, we believe that continuing to reduce the purchase of animal-based products will still have a significant impact on total carbon emissions.

B. Future research and analysis

Due to limitations in time and resources, the scope of our analysis was also limited. Nevertheless, our analysis has provided insights into general patterns and key relationships in the dataset, illuminating a path forward for future research and analysis that would be useful to help UBC Food Services where its carbon emissions are coming from and how they can reduce the carbon emissions associated with food purchases. One further analysis that could be undertaken in future study is to follow the same general method of our analysis but with 3-5 years' worth of UBC Food Services food product purchasing data. Having this data over time would allow future researchers to perform a time-series analysis and gain a more complete picture of UBC Food Services' purchasing patterns over time. A more robust dataset could also potentially allow for predictive analysis to help UBC Food Services model its purchases and how different actions could affect its carbon emissions in the future. Another direction for further analysis could be researching specific vendors and suppliers to figure out ways to get carbon emissions numbers that are more specific to each individual product and its unique supply chain. For example, future researchers could reach out to vendors to see if they have their own internal carbon emissions measurements or they could do more research into the carbon emissions produced at each production stage for a given sub type. This potential research could potentially provide an analysis of how the location of a vendor could impact carbon emissions in UBCFS's food purchases.

In order to successfully determine how to effectively and efficiently reduce carbon emissions related to food systems at UBC, we recommend that UBCFS undertake a more comprehensive and robust research project equipped with adequate time and resources. However, it may be that a re-evaluation on the feasibility of the UBC Climate Action Plan's goal to reduce food systems-related carbon emissions 50% by 2030 is in order. Given the findings of this paper and the continuing expansion of UBC's campus population – as well as its food offerings –

we believe that the 50% reduction goal may not be feasible. There is no way to get around the fact that UBC needs to feed people, and the number of people that this campus needs to feed will only grow from now until 2030. With this in mind, it may make more sense to apply a more nuanced framework to approach reducing carbon emissions associated with food systems at UBC, rather than only focusing on the absolute amount of carbon emissions, as we did in this paper. For example, UBCFS could approach this problem from the perspective of efficiency and do a comprehensive analysis of food waste and efficacy that asks: if we are going to feed this amount of people and purchase food products that are going to contribute to carbon emissions, how can we make sure that as little of that food as possible is going to waste?

VII. CONCLUSION

In response to the climate emergency, our research aimed to evaluate the carbon emissions of food products purchased by UBCFS and provide recommendations to help reduce emissions related to food systems at UBC, in service of the UBC Climate Plan's goals. To answer our research questions, we analyzed data on all UBC Food Services food purchases from January 1 to December 31, 2022. In our summary statistics and preliminary analysis of key relationships, we discovered that the "Grocery" product class contributes to the largest portion of total carbon emissions, followed by the "Dairy" and "Beverage" classes. Surprisingly, we found that the "Meat" accounted for only 6.5% of total emissions from food products purchased. Through our four regression models, we identified that food products in the "Meat", "Dairy" and "Processed" product classes are the top contributors to carbon emissions from UBC food purchases. We also found that weight plays an important role in determining carbon intensity, which could explain the discrepancy between the results of the data visualization and the regression analysis. Based on our findings, we recommended purchasing alternative food products to reduce carbon emissions, such as replacing canola oil with less carbon-intensive rapeseed oil and switching from dairy cheese products to vegan cheese or similarly protein-rich products like meat or legumes. However, our data analysis revealed that given the continued growth in the campus population, achieving the 50% reduction goal for emissions from food systems laid out in the Climate Action Plan may not be feasible. Despite the limitations of the results, our research has provided insights into general patterns and significant relationships in the dataset, illuminating a path forward for future research, such as a time-series analysis of purchasing data spanning three to five years to model the future effects of various actions. Our findings offer a starting point for a more nuanced approach to reducing the carbon footprint of food systems, which is vital to achieving UBC's goal of net-zero operational emissions by 2035.

References

About us [CarbonCloud]. (n.d.). Retrieved April 23, 2023, from https://carboncloud.com/about-us/

Alcock, T. D., Salt, D. E., Wilson, P., & Ramsden, S. J. (2022). More sustainable vegetable oil: Balancing productivity with carbon storage opportunities. *Science of The Total Environment*, *829*, 154539. https://doi.org/10.1016/j.scitotenv.2022.154539

Bartzas, G., Vamvuka, D., & Komnitsas, K. (2017). Comparative life cycle assessment of pistachio, almond and apple production. *Information Processing in Agriculture*, *4*(3), 188–198. https://doi.org/10.1016/j.inpa.2017.04.001

Benton, T. G., Bieg, C., Harwatt, H., Pudasaini, R., & Wellesley, L. (2021). *Food system impacts on biodiversity loss*. Chatham House.

CarbonCloud verification methodology [CarbonCloud]. (n.d.). Retrieved April 23, 2023, from https://carboncloud.com/carboncloud-verification-methodology/

Clune, S., Crossin, E., & Verghese, K. (2017). Systematic review of greenhouse gas emissions for different fresh food categories. *Journal of Cleaner Production*, *140*, 766–783. https://doi.org/10.1016/j.jclepro.2016.04.082

Costello, C., Ovando, D., Hilborn, R., Gaines, S. D., Deschenes, O., & Lester, S. E. (2012). Status and solutions for the world's unassessed fisheries [Publisher: American Association for the Advancement of Science]. *Science*, *338*(6106), 517–520. Retrieved April 23, 2023, from https://www.jstor.org/stable/41703799

Crippa, M., Solazzo, E., Guizzardi, D., Monforti-Ferrario, F., Tubiello, F. N., & Leip, A. (2021). Food systems are responsible for a third of global anthropogenic GHG emissions [Number: 3 Publisher: Nature Publishing Group]. *Nature Food*, *2*(3), 198–209. https://doi.org/10.1038/s43016-021-00225-9

Declaration on the climate emergency [Office of the president]. (2019, December 5). Retrieved April 23, 2023, from https://president.ubc.ca/homepage-feature/2019/12/05/climate-emergency-declaration/

de Vries, M., & de Boer, I. J. M. (2010). Comparing environmental impacts for livestock products: A review of life cycle assessments. *Livestock Science*, *128*(1), 1–11. https://doi.org/10.1016/j.livsci.2009.11.007

EPA, U. (2015, August 28). *Greenhouse gas equivalencies calculator*. Retrieved April 23, 2023, from https://www.epa.gov/energy/greenhouse-gas-equivalencies-calculator

Force, U. C. E. T. (2021, January). *Final report and recommendations*. University of British Columbia. Retrieved April 23, 2023, from https://bm-climate-emergency-2020.sites.olt.ubc.ca/files/2021/02/4_2021.02_Climate-Emergency-Engagement.pdf

Golsteijn, L. G. (2020, July 17). *Life cycle assessment (LCA) explained* [PRé sustainability]. Retrieved April 23, 2023, from https://pre-sustainability.com/articles/life-cycle-assessment-lca-basics/

Hannah, R. (2022, January 19). *Dairy vs. plant-based milk: What are the environmental impacts?* [Our world in data]. Retrieved April 23, 2023, from https://ourworldindata.org/environmental-impact-milks

Home - CarbonCloud [CarbonCloud]. (n.d.). Retrieved April 23, 2023, from https://carboncloud.com/

IPCC (Ed.). (2022). Framing and context. In *Global warming of 1.5°c: IPCC special report on impacts of global warming of 1.5°c above pre-industrial levels in context of strengthening response to climate change, sustainable development, and efforts to eradicate poverty* (pp. 49–92). Cambridge University Press. https://doi.org/10.1017/9781009157940.003

Jones, C. (2018, February 14). *Wonky fruit and veg: The carbon footprint of food* [Circular ecology]. Retrieved April 23, 2023, from https://circularecology.com/news/carbon-footprint-of-food

Mejia, A., Harwatt, H., Jaceldo-Siegl, K., Sranacharoenpong, K., Soret, S., & Sabaté, J. (2018). Greenhouse gas emissions generated by tofu production: A case study. *Journal of Hunger & Environmental Nutrition*, *13*(1), 131–142. https://doi.org/10.1080/19320248.2017.1315323

Owens. (2020, February 12). *Vegan cheese* [Ethical consumer]. Retrieved April 23, 2023, from https://www.ethicalconsumer.org/food-drink/shopping-guide/vegan-cheese

Planning, U. C.

bibinitperiod C. (2021, December). *UBC climate action plan 2030*. Retrieved April 23, 2023, from https://planning.ubc.ca/sites/default/files/2021-12/UBCV_CAP2030_FINAL.pdf

Poore, J., & Nemecek, T. (2018). Reducing food's environmental impacts through producers and consumers. *Science*, *360*(6392), 987–992. https://doi.org/10.1126/science.aaq0216

Rabo, O. (n.d.). *What is CO2e and how is it calculated?* Retrieved April 23, 2023, from https://www.coolerfuture.com/blog/co2e

Roy, P., Nei, D., Orikasa, T., Xu, Q., Okadome, H., Nakamura, N., & Shiina, T. (2009). A review of life cycle assessment (LCA) on some food products. *Journal of Food Engineering*, *90*(1), 1–10. https://doi.org/10.1016/j.jfoodeng.2008.06.016

Sáez-Almendros, S., Obrador, B., Bach-Faig, A., & Serra-Majem, L. (2013). Environmental footprints of mediterranean versus western dietary patterns: Beyond the health benefits of the mediterranean diet. *Environmental Health*, *12*(1), 118. https://doi.org/10.1186/1476-069X-12-118

Springmann, M., Clark, M., Mason-D'Croz, D., Wiebe, K., Bodirsky, B. L., Lassaletta, L., de Vries, W., Vermeulen, S. J., Herrero, M., Carlson, K. M., Jonell, M., Troell, M., DeClerck, F., Gordon, L. J., Zurayk, R., Scarborough, P., Rayner, M., Loken, B., Fanzo, J., ... Willett, W. (2018). Options for keeping the food system within environmental limits [Number:

7728 Publisher: Nature Publishing Group]. *Nature*, *562*(7728), 519–525. https://doi.org/10.1038/s41586-018-0594-0

UN Environment Programme, U. N. (2022, January 28). *Annual report 2021* [Section: publications]. Retrieved April 23, 2023, from http://www.unep.org/resources/annual-report-2021

Vasilaki, V., Katsou, E., Ponsá, S., & Colón, J. (2016). Water and carbon footprint of selected dairy products: A case study in catalonia. *Journal of Cleaner Production*, *139*. https://doi.org/10.1016/j.jclepro.2016.08.032

Vergé, X. P. C., Maxime, D., Dyer, J. A., Desjardins, R. L., Arcand, Y., & Vanderzaag, A. (2013). Carbon footprint of canadian dairy products: Calculations and issues [Publisher: Elsevier]. *Journal of Dairy Science*, *96*(9), 6091–6104. https://doi.org/10.3168/jds.2013-6563

Wexler. (2020, February 13). *Plant vs dairy – comparing their climate impacts* [Ethical consumer]. Retrieved April 23, 2023, from https://www.ethicalconsumer.org/food-drink/plant-vs-dairy-comparing-their-climate-impacts

Wróbel-Jedrzejewska, M., & Polak, E. (2022). Determination of carbon footprint in the processing of frozen vegetables using an online energy measurement system. *Journal of Food Engineering*, *322*, 110974. https://doi.org/10.1016/j.jfoodeng.2022.110974

Appendix

Table A1—: Count of observations and carbon emissions per kilogram for each "Sub type 2" category

PRODUCT CLASS	SUB TYPE 1	SUB TYPE 2	n	Carbon emissions per kg
BEVERAGE	BOTTLED DRINKS	PROTEIN SHAKE	35	2.2
BEVERAGE	BOTTLED DRINKS	SPORTS DRINK	29	2.0
BEVERAGE	CANNED DRINKS	ENERGY DRINK	56	2.0
BEVERAGE	COFFEE PRODUCTS	COFFEE	7	4.6
BEVERAGE	JUICES	APPLE CIDER	1	2.0
BEVERAGE	JUICES	CAESAR COCKTAIL	2	1.4
BEVERAGE	JUICES	FRUIT JUICE	196	2.0
BEVERAGE	JUICES	LEMONADE	25	2.0
BEVERAGE	JUICES	LEMONADE MIX	4	10.0
BEVERAGE	SOFT DRINKS	COCA COLA	151	2.0
BEVERAGE	SOFT DRINKS	FRESCA	7	2.0
BEVERAGE	SOFT DRINKS	GINGER ALE	36	2.0
BEVERAGE	SOFT DRINKS	ROOT BEER	19	2.0
BEVERAGE	SOFT DRINKS	SODA	6	2.0
BEVERAGE	SOFT DRINKS	SPRITE	42	2.0
BEVERAGE	SOFT DRINKS	TONIC WATER	3	0.8
BEVERAGE	TEA PRODUCTS	ICED TEA	93	1.0
BEVERAGE	TEA PRODUCTS	ICED TEA MIX	4	10.0
BEVERAGE	WATER	WATER	238	0.8
DAIRY	BUTTER	BUTTER	23	5.9
DAIRY	CHEESE PRODUCTS	CHEESE	275	4.2
DAIRY	CHEESE PRODUCTS	CREAM CHEESE	29	12.0
DAIRY	CHEESE PRODUCTS	cheese	5	
DAIRY	CREAM	COFFEE CREAMER	8	20.0
DAIRY	CREAM	CREAM	1	1.7
DAIRY	CREAM	HALF AND HALF CREAM	10	8.0
DAIRY	CREAM	SOUR CREAM	15	2.0
DAIRY	CREAM	WHIPPED CREAM	26	8.0
DAIRY	EGGS PRODUCTS	EGGS	68	3.46
DAIRY	ICE CREAM	GELATO	4	4.0
DAIRY	ICE CREAM	ICE CREAM	2	4.0
DAIRY	MILKS	CONDENSED MILK	1	2.0
DAIRY	MILKS	COW MILK	29	0.93
DAIRY	MILKS	EVAPORATED MILK	1	2.0
DAIRY	MILKS	EVAPORATED MILK	1	2.0
DAIRY	MILKS	EVAPORATED MILK	1	2.0
DAIRY	MILKS	EVAPORATED MILK	1	2.0
DAIRY	PLANT MILKS	ALMOND MILK	19	0.7
DAIRY	PLANT MILKS	COCONUT MILK	16	0.6
DAIRY	PLANT MILKS	COFFEE CREAMER	3	20.0
DAIRY	PLANT MILKS	OAT MILK	38	0.9
DAIRY	PLANT MILKS	PLANT-BASED BUTTER	1	3.3
DAIRY	PLANT MILKS	SOY MILK	13	0.98
DAIRY	YOGURT	GREEK YOGURT	15	2.92
DAIRY	YOGURT	VEGAN YOGURT	9	2.92
DAIRY	YOGURT	YOGURT	28	2.92
GROCERY	ASSORTED SNACKS	CHOCOLATE	1	3.0
GROCERY	ASSORTED SNACKS	CHOCOLATE BAR	2	3.0
GROCERY	ASSORTED SNACKS	CHOCOLATE BARS	1	5.0

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Table A1 Continued from previous page

PRODUCT CLASS	SUB TYPE 1	SUB TYPE 2	n	Carbon emissions per kg
GROCERY	ASSORTED SNACKS	COOKIE	30	4.0
GROCERY	ASSORTED SNACKS	COTTON CANDY	1	2.0
GROCERY	ASSORTED SNACKS	CRACKERS	15	2.0
GROCERY	ASSORTED SNACKS	JELLO POWDER	14	0.545
GROCERY	ASSORTED SNACKS	POTATO CHIPS	86	4.0
GROCERY	ASSORTED SNACKS	PRETZEL	1	4.0
GROCERY	ASSORTED SNACKS	PROTEIN BARS	15	3.0
GROCERY	ASSORTED SNACKS	SPRINKLES	1	1.0
GROCERY	ASSORTED SNACKS	TORTILLA CHIPS	9	4.0
GROCERY	CHOCOLATE PRODUCTS	CHOCOLATE	15	3.0
GROCERY	CHOCOLATE PRODUCTS	CHOCOLATE BARS	16	5.0
GROCERY	CHOCOLATE PRODUCTS	CHOCOLATE CHIPs	1	
GROCERY	CHOCOLATE PRODUCTS	CHOCOLATE WAFER	1	1.0
GROCERY	CHOCOLATE PRODUCTS	HOT CHOCOLATE MIX	16	10.0
GROCERY	CHOCOLATE PRODUCTS	NUTELLA	8	6.0
GROCERY	COOKING MATERIALS	BAKING POWDER	1	1.0
GROCERY	COOKING MATERIALS	BAKING PoWDER	1	
GROCERY	COOKING MATERIALS	YEAST	4	1.0
GROCERY	DESSERT	CHEESECAKE	4	4.0
GROCERY	DESSERT	CHOCOLATE CAKE	18	4.0
GROCERY	DESSERT	CHURRO	2	3.5
GROCERY	DESSERT	CREAM PUFF	1	4.4
GROCERY	DESSERT	FRUIT CAKE	11	2.0
GROCERY	DESSERT	PUDDING	2	2.0
GROCERY	FERMENTED/PICKLED	KIMCHI	7	2.0
GROCERY	FERMENTED/PICKLED	PICKLE	8	0.14
GROCERY	FRUITS	BANANA	5	0.72
GROCERY	FRUITS	CAPER	13	2.0
GROCERY	FRUITS	CHERRY	4	0.78
GROCERY	FRUITS	COCONUT FLAKES	2	1.0
GROCERY	FRUITS	COCONUT MILK	8	0.6
GROCERY	FRUITS	CRANBERRY	8	0.48
GROCERY	FRUITS	DRIED APRICOT	4	4.0
GROCERY	FRUITS	DRIED APRICOT	4	4.0
GROCERY	FRUITS	DRIED APRICOT	4	4.0
GROCERY	FRUITS	DRIED APRICOT	4	4.0
GROCERY	FRUITS	OLIVE	38	0.63
GROCERY	FRUITS	ORANGE	5	0.11
GROCERY	FRUITS	PEAR	2	0.27
GROCERY	FRUITS	PINEAPPLE	3	0.5
GROCERY	FRUITS	PUMPKIN	5	0.14
GROCERY	FRUITS	PUMPKIN	5	0.25
GROCERY	FRUITS	PUMPKIN	5	0.14
GROCERY	FRUITS	PUMPKIN	5	0.25
GROCERY	FRUITS	RAISIN	1	1.6
GROCERY	FRUITS	TOMATO	1	0.45
GROCERY	GRAINS	BARLEY PEARL	1	6.0
GROCERY	GRAINS	BREAD	171	1.83
GROCERY	GRAINS	CEREAL	15	2.0
GROCERY	GRAINS	CORN	4	0.35
GROCERY	GRAINS	CORN	4	0.16
GROCERY	GRAINS	CORN	4	0.35
GROCERY	GRAINS	CORN	4	0.16
GROCERY	GRAINS	CORN STARCH	35	1.0
GROCERY	GRAINS	COUSCOUS	1	1.24
GROCERY	GRAINS	CRACKERS	5	2.0
GROCERY	GRAINS	FLOURS	19	0.114
GROCERY	GRAINS	Flours	13	

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Table A1 Continued from previous page

PRODUCT CLASS	SUB TYPE 1	SUB TYPE 2	n	Carbon emissions per kg
GROCERY	GRAINS	GRAVY	5	4.0
GROCERY	GRAINS	MINI DANISH	6	2.0
GROCERY	GRAINS	NOODLE	6	3.6
GROCERY	GRAINS	OATS	12	0.55
GROCERY	GRAINS	PANCAKE	19	2.0
GROCERY	GRAINS	PASTA	170	1.1
GROCERY	GRAINS	PASTRY	30	1.0
GROCERY	GRAINS	PASTRY TART	3	1.0
GROCERY	GRAINS	PIE	1	2.9
GROCERY	GRAINS	POTATO STARCH	4	1.6
GROCERY	GRAINS	PRETZEL	1	4.0
GROCERY	GRAINS	QUINOA	18	1.48
GROCERY	GRAINS	RICE	89	1.92
GROCERY	GRAINS	RICE NOODLE	6	5.0
GROCERY	GRAINS	TEMPURA BATTER	1	2.0
GROCERY	GRAINS	TORTILLA	22	4.0
GROCERY	GRAINS	WHEAT FLOUR	20	0.61
GROCERY	GRAINS	bread	8	
GROCERY	GRAVY and POTATO	FLOURS and POTATO	9	
GROCERY	HERBS	BASIL	1	0.6
GROCERY	HERBS	HERB	9	2.1
GROCERY	LEGUMES	BEAN	20	0.305
GROCERY	LEGUMES	BLACK BEAN	19	1.0
GROCERY	LEGUMES	CHICKPEA	22	0.47
GROCERY	LEGUMES	HUMMUS	12	1.0
GROCERY	LEGUMES	KIDNEY BEAN	6	1.0
GROCERY	LEGUMES	LENTIL	9	0.48
GROCERY	LEGUMES	PEA	1	0.6
GROCERY	LEGUMES	PINTO BEAN	5	1.0
GROCERY	LEGUMES	SOY BEAN	7	0.43
GROCERY	NUTS & SEEDS	ALMOND	8	2.119
GROCERY	NUTS & SEEDS	CASHEW	1	3.3
GROCERY	NUTS & SEEDS	HAZELNUT	1	1.8
GROCERY	NUTS & SEEDS	PEANUT	2	
GROCERY	NUTS & SEEDS	PEANUT BUTTER	9	2.0
GROCERY	NUTS & SEEDS	PECAN	6	1.61
GROCERY	NUTS & SEEDS	PINE NUT	2	4.0
GROCERY	NUTS & SEEDS	PISTACHIO	3	2.119
GROCERY	NUTS & SEEDS	PUMPKIN SEED	13	2.0
GROCERY	NUTS & SEEDS	SESAME SEED	13	2.4
GROCERY	NUTS & SEEDS	SUNFLOWER SEED	8	1.5
GROCERY	NUTS & SEEDS	WALNUT	8	0.54
GROCERY	OILS	CANOLA OIL	55	5.0
GROCERY	OILS	COOKING SPRAY	8	5.0
GROCERY	OILS	OLIVE OIL	26	2.5
GROCERY	OILS	SESAME OIL	5	5.0
GROCERY	PLANT MILKS	COCONUT MILK	1	0.6
GROCERY	POULTRY	CHICKEN PRODUCTS	2	3.65
GROCERY	PROCESSED	CHOCOLATE PUDDING	1	5.0
GROCERY	PROCESSED	COOKIE	1	4.0
GROCERY	PROCESSED	FRENCH FRIED ONION	1	3.0
GROCERY	PROCESSED	GRAHAM CRACKER	2	4.0
GROCERY	PROCESSED	GRAHAM CRACKER	2	4.0
GROCERY	PROCESSED	GRAHAM CRACKER	2	4.0
GROCERY	PROCESSED	GRAHAM CRACKER	2	4.0
GROCERY	PROCESSED	PIZZA	10	4.0
GROCERY	SAUCES	ALFREDO	7	1.0
GROCERY	SAUCES	BBQ SAUCE	24	1.0

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Table A1 Continued from previous page

PRODUCT CLASS	SUB TYPE 1	SUB TYPE 2	n	Carbon emissions per kg
GROCERY	SAUCES	BEAN	1	0.305
GROCERY	SAUCES	CARAMEL	2	1.0
GROCERY	SAUCES	CHEESE	3	4.2
GROCERY	SAUCES	CHILI PEPPER	13	2.0
GROCERY	SAUCES	CHOCOLATE	1	3.0
GROCERY	SAUCES	CHUTNEY	17	1.7
GROCERY	SAUCES	CRANBERRY SAUCE	1	1.0
GROCERY	SAUCES	CURRY	3	3.0
GROCERY	SAUCES	GRAVY	4	4.0
GROCERY	SAUCES	HOISIN SAUCE	10	1.0
GROCERY	SAUCES	HOT SAUCE	44	1.82
GROCERY	SAUCES	KETCHUP	25	1.5
GROCERY	SAUCES	MAYONNAISE	42	2.5
GROCERY	SAUCES	MUSTARD	42	1.1
GROCERY	SAUCES	PESTO	20	1.0
GROCERY	SAUCES	PIZZA SAUCE	1	1.0
GROCERY	SAUCES	PLUM SAUCE	4	1.0
GROCERY	SAUCES	RELISH	15	2.0
GROCERY	SAUCES	RICE WINE	14	1.3
GROCERY	SAUCES	SALAD DRESSING	52	3.0
GROCERY	SAUCES	SALSA	4	1.0
GROCERY	SAUCES	SAUERKRAUT	3	2.0
GROCERY	SAUCES	SOY SAUCE	17	1.2
GROCERY	SAUCES	SWEET CHILI	13	1.0
GROCERY	SAUCES	TERIYAKI SAUCE	4	1.0
GROCERY	SAUCES	TOMATO SAUCE	26	0.6
GROCERY	SAUCES	TZATZIKI SAUCE	5	1.0
GROCERY	SAUCES	WORCESTERSHIRE SAUCE	5	1.0
GROCERY	SOUP	BEEF STOCK	8	5.0
GROCERY	SOUP	BEEF STOCK	8	5.0
GROCERY	SOUP	BEEF STOCK	8	5.0
GROCERY	SOUP	BEEF STOCK	8	5.0
GROCERY	SOUP	CHICKEN STOCK	18	5.0
GROCERY	SOUP	SOUP	63	5.0
GROCERY	SOUP	TOMATO	13	0.45
GROCERY	SOUP	VEGETABLE STOCK	25	3.5
GROCERY	SPICE/SEASONING	ANISE	1	1.2
GROCERY	SPICE/SEASONING	BLACK PEPPER	21	9.5
GROCERY	SPICE/SEASONING	CHILI POWDER	22	30.0
GROCERY	SPICE/SEASONING	CINNAMON	7	0.69
GROCERY	SPICE/SEASONING	CINNAMON	7	1.2
GROCERY	SPICE/SEASONING	CINNAMON	7	0.69
GROCERY	SPICE/SEASONING	CINNAMON	7	1.2
GROCERY	SPICE/SEASONING	COCOA POWDER	2	1.1
GROCERY	SPICE/SEASONING	CORIANDER	1	0.6
GROCERY	SPICE/SEASONING	CUMIN	13	1.7
GROCERY	SPICE/SEASONING	CURRY POWDER	3	30.0
GROCERY	SPICE/SEASONING	GARLIC	1	0.41
GROCERY	SPICE/SEASONING	GARLIC POWDER	3	2.2
GROCERY	SPICE/SEASONING	GINGER	1	0.88
GROCERY	SPICE/SEASONING	HERB	2	2.1
GROCERY	SPICE/SEASONING	MUSTARD	1	1.1
GROCERY	SPICE/SEASONING	ONION	1	0.216
GROCERY	SPICE/SEASONING	ONION	1	0.17
GROCERY	SPICE/SEASONING	ONION	1	0.216
GROCERY	SPICE/SEASONING	ONION	1	0.17
GROCERY	SPICE/SEASONING	ONION POWDER	2	4.0

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Table A1 Continued from previous page

PRODUCT CLASS	SUB TYPE 1	SUB TYPE 2	n	Carbon emissions per kg
GROCERY	SPICE/SEASONING	PAPRIKA	7	30.0
GROCERY	SPICE/SEASONING	PEPPER	26	1.6
GROCERY	SPICE/SEASONING	SAGE AND MARJORAM AND ROSEMARY	2	3.1
GROCERY	SPICE/SEASONING	SALT	40	2.0
GROCERY	SPICE/SEASONING	SALT AND COFFEE AND GARLIC	1	3.89
GROCERY	SPICE/SEASONING	SALT AND PEPPER	6	1.43
GROCERY	SPICE/SEASONING	SUGAR	65	3.2
GROCERY	SPICE/SEASONING	VANILLA EXTRACT	9	4.1
GROCERY	SPICE/SEASONING	WHITE PEPPER	1	9.0
GROCERY	SPREADS	JAM	2	2.0
GROCERY	SPREADS	MARGARINE	5	6.0
GROCERY	SPREADS	STRAWBERRY JAM	8	2.0
GROCERY	SWEETENERS	CORN SYRUP	2	2.0
GROCERY	SWEETENERS	HONEY	17	1.4
GROCERY	SWEETENERS	MAPLE SYRUP	20	2.0
GROCERY	SWEETENERS	MOLASSES	4	0.32
GROCERY	VEGETABLES	ARTICHOKE	16	1.0
GROCERY	VEGETABLES	ASPARAGUS	1	0.9
GROCERY	VEGETABLES	CORN	5	0.35
GROCERY	VEGETABLES	CORN	5	0.16
GROCERY	VEGETABLES	CORN	5	0.35
GROCERY	VEGETABLES	CORN	5	0.16
GROCERY	VEGETABLES	GARLIC	7	0.41
GROCERY	VEGETABLES	GINGER	1	0.88
GROCERY	VEGETABLES	HORSERADISH	2	1.0
GROCERY	VEGETABLES	ONION	1	0.216
GROCERY	VEGETABLES	ONION	1	0.17
GROCERY	VEGETABLES	ONION	1	0.216
GROCERY	VEGETABLES	ONION	1	0.17
GROCERY	VEGETABLES	PEA	1	0.6
GROCERY	VEGETABLES	PEPPER	15	1.6
GROCERY	VEGETABLES	PICKLE	5	0.14
GROCERY	VEGETABLES	POTATO	25	
GROCERY	VEGETABLES	PUMPKIN	1	0.14
GROCERY	VEGETABLES	PUMPKIN	1	0.25
GROCERY	VEGETABLES	PUMPKIN	1	0.14
GROCERY	VEGETABLES	PUMPKIN	1	0.25
GROCERY	VEGETABLES	Potato	8	4.0
GROCERY	VEGETABLES	SAUERKRAUT	2	2.0
GROCERY	VEGETABLES	TOMATO	64	0.45
GROCERY	VEGETABLES	VEGETABLE MIX	1	0.6
GROCERY	VINEGARS	APPLE CIDER VINEGAR	11	1.0
GROCERY	VINEGARS	BALSAMIC VINEGAR	20	5.0
GROCERY	VINEGARS	RED WINE VINEGAR	12	0.61
GROCERY	VINEGARS	RICE VINEGAR	11	1.0
GROCERY	VINEGARS	SHERRY WINE VINEGAR	2	1.0
GROCERY	VINEGARS	WHITE VINEGAR	23	1.0
MEAT	BEEF	BEEF PRODUCTS	4	26.82
MEAT	MIXED MEATS	MEATBALL	1	7.0
MEAT	MIXED MEATS	WIENER	9	10.0
MEAT	MIXED MEATS	WIENER	9	10.0
MEAT	MIXED MEATS	WIENER	9	10.0
MEAT	MIXED MEATS	WIENER	9	10.0
MEAT	PLANT-BASED MEAT	FALAFEL	14	1.0

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Table A1 Continued from previous page

PRODUCT CLASS	SUB TYPE 1	SUB TYPE 2	n	Carbon emissions per kg
MEAT	PLANT-BASED MEAT	VEGAN MEAT	35	1.8
MEAT	PORK	PORK PRODUCTS	66	6.0
MEAT	POULTRY	CHICKEN PRODUCTS	28	3.65
MEAT	POULTRY	DUCK	1	3.09
MEAT	POULTRY	TURKEY	9	7.17
PROCESSED	CHOCOLATE PRODUCTS	CHOCOLATE	12	3.0
PROCESSED	CHOCOLATE PRODUCTS	Chocolate bars	9	
PROCESSED	CHOCOLATE PRODUCTS	Chocolate chips	40	
PROCESSED	DESSERT	CHEESECAKE	11	4.0
PROCESSED	DESSERT	CHOCOLATE CAKE	28	4.0
PROCESSED	DESSERT	CHURRO	3	3.5
PROCESSED	DESSERT	COOKIE DOUGH	17	3.5
PROCESSED	DESSERT	CREAM PUFF	1	4.4
PROCESSED	DESSERT	EGG AND SUGAR AND FLOUR	26	2.258
PROCESSED	DESSERT	FRUIT CAKE	21	2.0
PROCESSED	DESSERT	OATMEAL RAISIN COOKIE	5	4.0
PROCESSED	DESSERT	PIE	15	2.9
PROCESSED	DESSERT	PUDDING	3	2.0
PROCESSED	DESSERT	WHITE CHOCOLATE MACADAMIA COOKIE	1	4.0
PROCESSED	FRUITS	CHERRY	1	0.78
PROCESSED	PROCESSED	CORN DOG	1	4.0
PROCESSED	PROCESSED	FRIES	15	1.3
PROCESSED	PROCESSED	GUACAMOLE	1	1.0
PROCESSED	PROCESSED	ONION RING	5	7.0
PROCESSED	PROCESSED	PEROGY	10	4.0
PROCESSED	PROCESSED	PIE	10	2.9
PROCESSED	PROCESSED	PIZZA	4	4.0
PROCESSED	PROCESSED	SAMOSA	1	4.0
PROCESSED	READYMADE	BEEF CHILI	4	9.4
PROCESSED	READYMADE	CHANA MASALA	2	4.0
PROCESSED	READYMADE	MACARONI AND CHEESE	1	4.0
PROCESSED	READYMADE	Onion ring	4	
PROCESSED	READYMADE	SAMOSA	1	4.0
PROCESSED	READYMADE	SPRING ROLL	2	0.545
PROCESSED	READYMADE	VEGAN CHILI	2	4.0
PROCESSED	READYMADE	VEGETABLE DUMPLING	2	5.4
PROCESSED	VEGETABLES	FRIES	24	1.3
PRODUCE	FRUITS	APPLE	5	0.29
PRODUCE	FRUITS	AVOCADO	14	1.3
PRODUCE	FRUITS	BANANA	1	0.72
PRODUCE	FRUITS	BERRIES	7	3.0
PRODUCE	FRUITS	BLUEBERRY	3	0.92
PRODUCE	FRUITS	BREAD	1	1.83
PRODUCE	FRUITS	CRANBERRY	10	0.48
PRODUCE	FRUITS	DRIED APRICOT	1	4.0
PRODUCE	FRUITS	DRIED APRICOT	1	4.0
PRODUCE	FRUITS	DRIED APRICOT	1	4.0
PRODUCE	FRUITS	DRIED APRICOT	1	4.0
PRODUCE	FRUITS	GRAPEFRUIT	1	0.2
PRODUCE	FRUITS	LEMON	1	0.2
PRODUCE	FRUITS	LEMON JUICE	19	1.0
PRODUCE	FRUITS	LIME JUICE	17	1.0
PRODUCE	FRUITS	MANGO	6	0.5

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PRODUCT CLASS	SUB TYPE 1	SUB TYPE 2	n	Carbon emissions per kg
PRODUCE	FRUITS	PEACH	5	0.2
PRODUCE	FRUITS	PINEAPPLE	6	0.5
PRODUCE	FRUITS	RASPBERRY	6	0.84
PRODUCE	FRUITS	RASPBERRY	6	0.84
PRODUCE	FRUITS	RASPBERRY	6	0.84
PRODUCE	FRUITS	RASPBERRY	6	0.84
PRODUCE	FRUITS	STRAWBERRY	3	0.3
PRODUCE	FRUITS	TOMATO	4	0.45
PRODUCE	GRAINS	RICE	1	1.92
PRODUCE	HERBS	BASIL	1	0.6
PRODUCE	HERBS	CILANTRO	1	0.2
PRODUCE	HERBS	LEMONGRASS	1	1.5
PRODUCE	HERBS	PARSLEY	1	0.15
PRODUCE	MIXED	APPLE	2	0.29
PRODUCE	MIXED	BROCCOLI	2	0.207
PRODUCE	MIXED	CHICKPEA	4	0.47
PRODUCE	TOFU	FRUIT JUICE	1	2.0
PRODUCE	TOFU	TOFU	24	0.982
PRODUCE	VEGETABLES	ARUGULA	2	1.6
PRODUCE	VEGETABLES	BAMBOO SHOOT	1	0.9
PRODUCE	VEGETABLES	BEAN	19	0.305
PRODUCE	VEGETABLES	BROCCOLI	5	0.207
PRODUCE	VEGETABLES	CAULIFLOWER	2	0.31
PRODUCE	VEGETABLES	CHILI PEPPER	1	2.0
PRODUCE	VEGETABLES	CORN	17	0.35
PRODUCE	VEGETABLES	CORN	17	0.16
PRODUCE	VEGETABLES	CORN	17	0.35
PRODUCE	VEGETABLES	CORN	17	0.16
PRODUCE	VEGETABLES	GARLIC	5	0.41
PRODUCE	VEGETABLES	GINGER	1	0.88
PRODUCE	VEGETABLES	GREEN ONION	3	0.5
PRODUCE	VEGETABLES	LETTUCE	2	0.92
PRODUCE	VEGETABLES	ONION	9	0.216
PRODUCE	VEGETABLES	ONION	9	0.17
PRODUCE	VEGETABLES	ONION	9	0.216
PRODUCE	VEGETABLES	ONION	9	0.17
PRODUCE	VEGETABLES	PEA	11	0.6
PRODUCE	VEGETABLES	POTATO	14	
PRODUCE	VEGETABLES	SOY BEAN	2	0.43
PRODUCE	VEGETABLES	SPINACH	17	0.54
PRODUCE	VEGETABLES	SPINACH	17	0.54
PRODUCE	VEGETABLES	SPINACH	17	0.54
PRODUCE	VEGETABLES	SPINACH	17	0.54
PRODUCE	VEGETABLES	VEGETABLE MIX	12	0.6
SEAFOOD	FISH	CANNED TUNA	10	2.15
SEAFOOD	FISH	COD	1	3.51
SEAFOOD	PLANT-BASED MEAT	VEGAN MEAT	4	1.8
SEAFOOD	SHELLFISH	CLAM	2	20.0
SEAFOOD	SHELLFISH	MUSSEL	3	9.51
SEAFOOD	SHELLFISH	SHRIMP	2	7.8
SEAFOOD	SHELLFISH	SQUID	1	7.13

Table A2—Total Carbon Emissions by Product Class

PRODUCT CLASS	Total carbon emissions
BEVERAGE	270578.49
DAIRY	307754.15
GROCERY	701557.08
MEAT	102253.17
PROCESSED	130961.68
PRODUCE	47772.68
SEAFOOD	2790.67

Table A3—Total Carbon Emissions by Sub Type 1

SUB TYPE 1	Total carbon emissions
ASSORTED SNACKS	20316.61
BEEF	12292.68
BOTTLED DRINKS	23978.17
BUTTER	11421.76
CANNED DRINKS	5645.22
CHEESE PRODUCTS	107253.64
CHOCOLATE PRODUCTS	38931.77
COFFEE PRODUCTS	3045.15
COOKING MATERIALS	181.52
CREAM	23604.80
DESSERT	52625.74
EGGS PRODUCTS	117979.39
FERMENTED/PICKLED	2701.24
FISH	1650.80
FRUITS	16093.66
GRAINS	152686.25
GRAVY and POTATO	155.36
HERBS	53.96
ICE CREAM	1616.40
JUICES	88919.14
LEGUMES	14155.45
MILKS	4225.49
MIXED	103.53
MIXED MEATS	15841.89
NUTS & SEEDS	2201.40
OILS	187788.64
PLANT MILKS	10371.65
PLANT-BASED MEAT	7794.53
PORK	19767.78
POULTRY	46995.41
PROCESSED	50101.76
READYMADE	5028.66
SAUCES	61938.93
SHELLFISH	1036.91
SOFT DRINKS	84463.64
SOUP	146382.92
SPICE/SEASONING	30397.17
SPREADS	457.98
SWEETENERS	8605.95
TEA PRODUCTS	19870.74
TOFU	8879.66
VEGETABLES	74083.62
VINEGARS	5962.30
WATER	44656.43
YOGURT	31402.24

Table A4—Total Carbon Emissions by Customer

CUSTOMER NAME	Total carbon emissions
UBC OPEN KITCHEN AT ORCHARD RESIDENCE	434988.81
UBC FEAST AT TOTEM	313464.93
UBC GATHER AT VANIER	291267.13
UBC THE POINT GRILL MARINE DR RESID DINING	84643.23
UBC ATHLETICS &RECREATION	60622.31
SAGE BISTRO	59734.70
UBC HARVEST	58787.26
UBC COMM KITCHEN AT TOTEM PARK	52243.48
UBC MERCANTE ITALIAN RESTAURANT	48800.05
SUMMER CONF AT VANIER DINING	41657.72
UBC CAFFE PERUGIA	25991.80
SUMMER CONF AT TOTEM DINING	16628.12
UBC HERO COFFEE SHOP	13227.39
UBC EATS	10432.89
UBC MAGDA AT TOTEM	10039.77
UBC HUBBARDS CAFE	8595.52
UBC IKE CAFE IRVING K BARBER LEARN CTR	6595.10
UBC BENTO SUSHI	6360.27
UBC CONFERENCES & ACCOM	5363.67
UBC STIR IT UP	3450.91
UBC FOOD HUB	3276.19
UBC FOOOOD	2420.40
UBC FOOOOD 2.0 AT IRC	2135.06
UBC LAW COFFEE CART	1969.09
UBC STUDENT HOUSING &HOSP SERVICES	922.17
UBC STUD HSG&HOSP SRV H/O	26.92
UBC CHAN CTR PERFORM ARTS	23.05