University of British Columbia

Social Ecological Economic Development Studies (SEEDS) Sustainability Program

Student Research Report

Policy Recommendations of Carbon Footprints Reduction for AMS Supply Chain

Replacing Products with High Agricultural Emissions

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Abstract

The UBC AMS is a large community that offers a variety of services to UBC students and employees. While it caters for the whole campus, a huge amount of carbon emissions are also generated in the supply chain. We are concerned about this because greenhouse gasses may have an influence on climate changes and the environment. Among all the stages in the supply chain, agricultural production is the one that has been found to be the major source of emissions. Hence, to help AMS build a eco-friendlier supply chain, we consider replacing products that are high in agricultural emissions by their alternatives. To do so, we conducted an audit on AMS' products and calculated their total carbon footprints. We then regressed the total carbon footprints on food types, controlling for distances, weights, and packaging materials. This would allow us to estimate the agricultural impact of each product. Based on the results, we found coffee and dairy are two types that have high agricultural emissions. Consequently, we recommended replacing those by tea and vegan milk, respectively. Moreover, we have also proposed a supplementary plan to further reduce the emission, that is, replacing white chocolate with dark chocolate. For each of the three pairs mentioned above, we stimulated the reductions in overall emissions when substituting different proportions of the high-emission types (i.e. 15%, 20%, and 25% for coffee and dairy; 30%, 40%, 50% for white chocolate), so that AMS can choose the plan that best suits their needs. Although there are still some limitations such as insufficient data and omitted variables, our findings are robust to different assumptions and specifications. We hope that while AMS is balancing between the demand and supply of their foods, our research can shed some light on possible ways to lower their emissions.

1. Introduction

1.1 Context and Motivations

Environmental protection has always been a crucial issue that draws wide social attention. According to the research conducted by Susan Solomon (2009), the increasing carbon emissions have caused several irreversible climate changes including atmospheric warming, precipitation changes, and sea-level rise. The carbon emissions associated with agricultural production are causing a lot of concern. Consequently, with the notice of environmental changes, the consumers begin to make changes in their choice of products and consumption afterward (Migliore, 2021). Therefore, the research area of this project focuses on green economics, which aims at sustainable development without degrading the environment.

In 2021, AMS has announced an ambitious program of achieving net zero carbon emissions by the year of 2025 (Vallenas et al., 2021). As a leading community who always strives for sustainability, it has also been putting tremendous efforts to cut its carbon emissions. In order to provide insights for AMS to achieve its goal of zero carbon emissions, we have been researching for possible recommendations to help lower their carbon emissions generated in the supply chain.

As reported by Hannah Ritchie and Max Rose (2020), admittedly, the distance of transportation impacts the footprints, but only to a mild degree. In fact, most of the carbon footprints come from agricultural production stages such as land-use changing, farming, and animal feeding. Therefore, the essential factor for reducing carbon emission would center around the choices of foods instead of the travel distances. Based on this research finding, we believe that substituting products with massive agricultural emissions would be an effective way of building a supply chain that is more environmentally-friendly.

After reading through some existing research, we have decided to pay specific attention to food categories including meat, vegetable, dairy, beverages and other intermediate products since they are found to have particularly high carbon emissions. According to Nijdam et al. (2012), for the category of meat, the carbon footprint of the most climate-friendly protein sources is up to a hundred times smaller than those of the most climate-unfriendly products. For vegetables, as discovered by Stoessel (2012), asparagus, lettuce, and cucumber appear to have relatively high agricultural carbon emissions, which inspires us to look for possible alternatives. Furthermore, based on the research conducted by Konstants (2018), for the intermediate products such as chocolate, the land-use change associated with its production has been found to have an impact of increasing total global warming potential by three to four times. This also draws our attention, and we hope that we are able to find feasible substitution plans that help alleviate such pressures on environmental issues.

Based on the secondary research that we collected, we believe that re-structuring the choices of foods would be a practical and convincing approach to improve the sustainability of AMS' supply chain. In particular, we are going to use agricultural carbon emission as a benchmark to identify products that need to be replaced and their alternatives. Aiming at improving the sustainability of AMS' supply chain and ultimately moving closer to a greener lifestyle, we hope that our project can bring a more positive impact to both AMS and UBC.

1.2 Research Questions

This project primarily focuses on the research topic of "how to reduce the carbon footprints of AMS' supply chain by replacing products that are high in agricultural emissions with their alternatives?" Therefore, in order to identify products to be substituted, we are interested in finding close estimates for each product's agricultural impacts. In particular, our project will be completed in four stages.

The first stage is to conduct secondary research to recover the total carbon footprints of each product provided by AMS. We will then divide the products into broad types, such as meat, vegetables, dairy, and so on. Estimating each type's agricultural emissions is the second step. In this stage, we will try out several regression models by adding different controls and determining the best model for explaining our data. The next step is to determine which goods have high emissions during agricultural production, and those products are the ones to be substituted. Finally, we will implement multiple substitution plans that allow different fractions of high-emission products to be replaced by lower-emission alternatives. The resulting reductions in total supply chain emission will be simulated, which enables us to compare the effectiveness of different plans. We believe the aforementioned four steps will guide us through the project, helping provide practical recommendations for AMS Nest to meet their sustainability objective.

1.3 Method

Our outcome variable is the total emissions of each of the products provided by AMS. It is calculated via $totalEmission \ = \ totalWeight \times Emission\_per\_kilogram$ (Equation(2)). The total weights are obtained directly from AMS; the per-kg emissions are the amount of carbon emissions released in the entire supply chain (including stages like agricultural production, processing, packaging, transportation, and retail), and they are obtained from previous research findings and other secondary sources (Poore, N., 2018; Our World in Data.,nd; Marié, À., 2022; Winans et al., 2019; Migdon, 2021). Prior to the implementation of the models, some necessary processing of the raw data was carried out, such as categorizing products into more general types and ensuring uniform scale of variable measurement.

To isolate the agricultural impact from the total emissions, we divide products into different types, and as a baseline model, we regress total emissions on those food types controlling for weights. Because transportation and packaging are also two tangible factors that are influential for total supply chain emissions (Our World in Data, 2022), in order to eliminate their confounding effects, they have also been subsequently added into the baseline model. Next, an exhaustive search algorithm (*regsubsets*) is applied in *R*, which would allow us to filter out variables that are "important" in the sense that they explain most of the variance in the total emissions. Thus, the resulting model serves as a confirmation that helps us better identify products with extensive agricultural emissions.

By establishing these simple regressions, we have made three major assumptions. First, we assume the total emissions are generated with normally distributed errors. Second, the errors have a constant variance, that is, they are homoscedastic. Third, the per-kg emissions are the same across all food types. We realize that these assumptions do not necessarily hold. Therefore, tests and diagnostic plots have been produced to check for the first two assumptions, and interaction terms have been added to check for the third one.

1.4 Empirical Challenges (Limitations)

While we develop the models, several issues are found. One of the issues we faced was the availability of data. For many of the products in the dataset, there is no information on how they were delivered (was it by plane, ship, or truck?), their places of origin, and the packaging materials. In order to control for the impact of transportation and packaging, we have to come up with hypothetical values for these attributes. More seriously, some food types only have a few records, which imposes large variances when fitting the regression lines.

Our second hurdle was the presence of potential omitted variable bias. Some contributors of the supply chain emissions, such as retail, processing, and food wastes are not included in our model. As a result, it is possible that the accuracy of our estimations will be influenced.

Thirdly, because we do not have data on students' demand, what we recommend may not necessarily meet the actual desires of AMS' products. To best address this issue, we propose multiple replacement plans with different fractions of high-emission products replaced, and we hope AMS can find the optimum one that is most applicable to their market conditions.

1.5 Key Results and Paper Structure

After fitting a series of regression models, we identify three products that are relatively high in agricultural emissions – coffee, dairy, and chocolate. According to the output of our candidate model Best Subset, the respective agricultural impacts of coffee, dairy and chocolate in their total emissions are 46780, 30413, and 25121 kg higher than that of the reference food type (chicken).

Admittedly, due to the limited sample size and the existence of omitted variables, the accuracy of the results may be potentially affected; and the market demand is not taken into account when proposing substitution plans. However, our findings are robust to different assumptions and specifications. There are two verifiable assumptions raised when we have done the robustness check, which include homoscedastic and normally distributed errors. To examine if the data has homoscedastic errors, both visual inspection and the Breusch-pagan test have been conducted, and the results suggest the validity of this assumption holds. Furthermore, a quantile-quantile plot has been applied to check the distribution of the error. The patterns in the plot are not consistent with a normal distribution, which would be one of the limitations that exist in our model, nonetheless this hypothesis is still appealing for any further analysis in the paper. Lastly, to relax the assumption of uniform per-kg emission in the basic regressions, interaction terms have been added. Based on the extended models, chocolate, coffee, and dairy that are identified for replacements still remain high in their estimated agricultural emission. Therefore, the credibility of our results has been guaranteed due to the robustness under different hypotheses and alternative specifications.

Based on the results, we provide three practical recommendations for AMS' supply chain, including replacing coffee with tea, dairy with vegan milk, and lastly white chocolate with dark chocolate as the supplementary recommendation. Under each recommendation, we consider different proportions of the products to be substituted. For white chocolate, it would be 30%, 40%, and 50% replacements; for dairy and coffee, it would be 15%, 20%, and 25% replacement. In particular, by replacing 50% white chocolate with dark chocolate, we could achieve 2.47% reduction of the total chocolate emissions. Similarly, with 25% replacement of coffee, an amount of 8933.28 kgCO2eq emissions can be effectively reduced; with 25% replacement of dairy, the emission reductions are up to 28083.08 kgCO2eq.

The remainder of this paper is organized according to the following structure. The Background Section (section 2) reviews relevant literature, which provides the context of our topic. The Data Section focuses primarily on the data source (section 3.1), data transformation (section 3.2), and the detailed description of our data (section 3.3). In the

Methodology Section, we mainly explain the basic models we used in this paper (section 4.2) and give a closer look at the selection of best models (section 4.3) as well as the inclusion of interactions (section 4.4). The Result Section (section 5) presents the results we have obtained based on the models and the replaceable products found. The Discussion Section includes the robustness check and alternative specification (section 6.1); on top of that, the recommendation (section 6.2), economic meaning (section 6.3), and limitations (section 6.4) are also addressed. Lastly, the Conclusion Section (section 7) will provide an overall summary of the key findings throughout the text and provide some additional suggestions.

2.Background

2.1 Context

During the 20th century, the concentration of greenhouse gasses in the atmosphere increased as a result of human activity. Humans are the main cause of changes in the composition of the Earth's atmosphere and therefore the driving force behind future climate change. The severity of damaging human-induced climate change depends not only on the magnitude of the change but also on the likelihood of irreversibility. Paper written by Solomen, Plattner, Knutti, and Friedlingstein (2018) has shown that climate change due to increased CO2 concentrations is essentially irreversible within one thousand years of the cessation of emissions. These rising carbon emissions are undoubtedly staggering, and of these, food emissions are responsible for more than a quarter of global greenhouse gas emissions according to the data presented in Konstantas' research (Konstantas et al., 2018). With the growing awareness of environmental protection people have, what would be the most effective way of reducing carbon emissions is an issue worth considering. Eating local food would be the most misleading piece of advice since greenhouse gas emissions from transport account for only a small proportion of emissions from food. In the study data, we can see that livestock and fisheries account for 31% of food emissions, crop production for 27%, land use for 24%, and the supply chain for 18%. Hence, choosing relatively low food choices could have a significant impact on carbon reduction. In addition, not just as an objective stated by United Nations Framework Convention on Climate Change (UNFCCC) is to stabilize greenhouse gas concentrations in the atmosphere at levels low enough to prevent 'dangerous anthropogenic interference with the climate system' (Solomon et al., 2009), the environmental protection and the healthy food selection use has also raised strong concern for consumers in everyday life. As a result, not only are consumers trying to determine the greenhouse gas emissions generated by various consumption categories to choose their preferred food category, but businesses are also trying to find new options for decarbonization to create a more sustainable food supply chain (Migliore, 2021). This paper will therefore be set in the context of the pursuit of sustainability and minimization of carbon emissions in university education institutions of UBC. Moever, AMS, the most dominant student-run institution in control, has made a corresponding claim, namely the ambition to achieve a net zero-carbon emissions plan for the campus by 2025 (Vallenas et al., 2021). In AMS Sustainable Action Plan (ASAP), AMS has also demonstrated its commitment to redefining the meaning of sustainability and integrating it into the priorities of the three core pillars of the mainstream sustainability strategy: environmental, social, and economic sustainability.

2.2 Related Literature

Before any reduction in carbon emissions in the AMS supply chain can be implemented, there is one further step that is needed - an audit of the products on the AMS product list to determine the total carbon footprint of each product. In this paper, the carbon emissions are identified in a slightly different way in the secondary source investigated for different products, including but not limited to meat, vegetables, dairy products, etc. However, one of the most popular methods, and the one used to measure carbon emissions for the majority of products in this paper, is Life Cycle Analysis (LCA). LCA, also known as life-cycle assessment, is a primary tool used to support decision-making for sustainable development, which quantifies the environmental impacts associated with a given product (Hill, 2013). The LCA process consists of four components: goal definition and scoping, inventory analysis, impact assessment, and interpretation (Brusseau, 2019). At each step of the way, LCA identifies the key materials and processes that are likely to have the greatest impact on the product's life cycle, including resource requirements and human health impacts. These assessments describe the full benefits and costs of a product or process, enabling decision-makers to select the most effective solution. LCA measures the full range of a product at a specific scale over a long period, which gives credibility to the result of data, but as Ayres (1995) mentioned in his article, the data required to accomplish this very first step are often not available from published sources. Therefore, the theoretical description of the process from published sources may not be consistent with actual practice, and this cannot be verified. However, despite this limitation, LCA is still a comprehensive method for assessing all direct and indirect environmental impacts across the full life cycle of a product system (Brusseau, 2019).

3. Data

3.1 Data Sources

Our dataset contains 39 observations and 11 variables. The types of all the variables are summarized below (Table 1).

Table 1. All variables in the dataset

Variable Name	**Data Type**
type	categorical (13 levels)
product	categorical (25 levels)
kg_per_case	numerical, non-negative real numbers

cases	numerical, non-negative integers
emission_per_kg	numerical, non-negative real numbers
packaging	categorical (3 levels)
origin	categorical (6 levels)
dist_ship	numerical, non-negative real numbers
dist_truck	numerical, non-negative real numbers
total_weight	numerical, non-negative real numbers
total_emission	numerical, non-negative real numbers

The list of products together with the quantities purchased are provided by the Nest. The per-unit carbon footprints of each product were obtained from websites including: *Our World in Data* (the main source), *CO2 everything* (oak milk), *HEALable* (tea), *theHill* (avocado), *swns digitals* (butter), *Novidon Sustainable starch solutions* (starch), and *research papers from Springer* (almond milk) (Poore, N., 2018; Our World in Data, 2022; Marie, A., 2022; Winans et al., 2019; Migdon, 2021).

To account for the emissions during transportation, distances between the origins of the products and the Nest were computed. Each product has a travel distance that consists of two parts, the ship distances and truck distances. The ship distances were obtained from *Ports.com* and truck distances were looked up on *Google Maps*. It is worth noting that because the detailed information of most products is not available, the places of origin were derived based on common sense.

To control for the emissions during packaging, a categorical variable "packaging" was added to indicate the wrapping materials of the products. Again, this information is also hypothetical due to our limited access to the products.

3.2 Data Transformations

The products have been classified into broader types. For each type in the original dataset, we have tried to search for its overall carbon emissions across the entire supply chain. However, such information is not available for all types. Therefore, products with missing weights and unknown per-unit carbon footprints have been omitted from our modified dataset.

Because carbon footprints are commonly measured per kilogram of food, for each product, we first converted the per-case weight into kg. In particular, the vegan milk comes in a pack of 12 1L cartons. This was converted into kg assuming that plant-based milk has a similar density to regular milk (1L=1.03kg, data from *Convert,nd*). Given that there are 600 tea bags in each case, the per-case weights of different types of tea were calculated by assuming that each tea bag weighs 2g (*Leaf Tea Company,nd*). After the conversion, the total weight of each product was obtained by multiplying the per-case kilograms with the number of cases.

To ensure that our outcome variable ("total_emissions") is measured on a uniform scale, the per-unit carbon footprints of each product were converted into kgCO2eq/kg. For instance, the carbon footprint of oat milk was found to be 0.22kgCO2eq/250ml (Marie, A. , 2022). Because 250ml milk approximately weighs 259g, the carbon footprint was then converted to 0.85kgCO2eq/kg (1000/259*0.22=0.85). The total carbon emissions of each product were obtained by multiplying the per-kg carbon footprints with the total weights.

In terms of the distances, there are three possible scenarios. If the product is domestically produced, then its *dist_ship=0*, and dist_truck is measured from its supplier to the Nest. If the product is imported and transported by truck only, it also has *dist_ship=0*, and dist_truck is measured from its place of origin to the supplier and then to the Nest. Lastly, if the product is imported via ship, its *dist_ship* is the distance between the place of origin and the Port of Metro Vancouver, and *dist_truck* is measured from the Port of Metro Vancouver to the supplier and the to the Nest.

3.3 Data Description

We consider *total_emission* as our outcome variable. It measures total emissions of each product in kgCO2 equivalent across the entire supply chain, which includes emissions in agriculture (land-use + farming +animal feed), processing, transportation, retail, and packaging. Potential explanatory variables include *type, total_weight, packaging, dist_ship,* and *dist_truck*.

Table 2 reports the summary statistics of all the quantitative variables in the dataset. That the values of *emission_per_kg* are distributed over a wide range, which verifies that each product varies in its impact on carbon emissions significantly. Moreover, the difference between the minimum and maximum *total_weight* is also quite large. Consequently, the *total_emission* of each food product, which is a product of *emission_per_kg* and *total_weight,* also demonstrates large variations.

Table 2. Summary statistics of quantitative variables

	MEAN	MIN	MAX	SD
kg_per_case	7.304	0.90	20.40	5.041
cases	251.692	8.00	1362.00	286.425
emission_per_kg	8.190	0.30	21.20	8.384
dist_ship	1317.057	0.00	13758.51	3767.088
dist_truck	993.274	14.10	4394.00	1719.646
total_weight	1621.051	9.60	9033.72	1899.477
total_emission	10479.834	18.24	85224.00	16649.048

Table 3 provides the summary statistics of the major qualitative variables in the dataset. The issue of insufficient data can be clearly seen from this table. Notice we only have a few data points associated with each type. What's even more problematic, for plant oil, pork, rice, starch and tofu, there is only one record. Similarly, there is only entry in the data with aluminum packaging. In order to further demonstrate the lack of data. We plotted the range of the total emissions available for each food type (Figure 3). Consistent with Table 3, for a number of the types (from egg to tofu), the distributions of their total emissions are as narrow as lines. This indicates that we only have limited data to assess the agricultural impact of each food type. As a result, there is likely to be high variance in the model fitting stage, especially for products that only have one related record. We are well aware of this issue, and will take extra care when analyzing model outputs.

Table 3. Summary statistics of qualitative variables

Variables	Levels	Frequencies	Proportions
TYPE	chicken	2	0.051
	chocolate	4	0.103
	coffee	3	0.077
	dairy	7	0.179
	egg	2	0.051
	plant oil	1	0.026
	pork	1	0.026
	rice	1	0.026
	starch	1	0.026
	tea	3	0.077
	tofu	1	0.026
	vegan milk	3	0.077
	vegetable	10	0.256
PACKAGING	aluminium	1	0.026
	paper	18	0.462
	plastic	20	0.513
ORIGIN	BC	23	0.59
	Brazil	3	0.077
	California	2	0.051
	Colorado	3	0.077
	Mexico	1	0.026
	Ontario	7	0.179

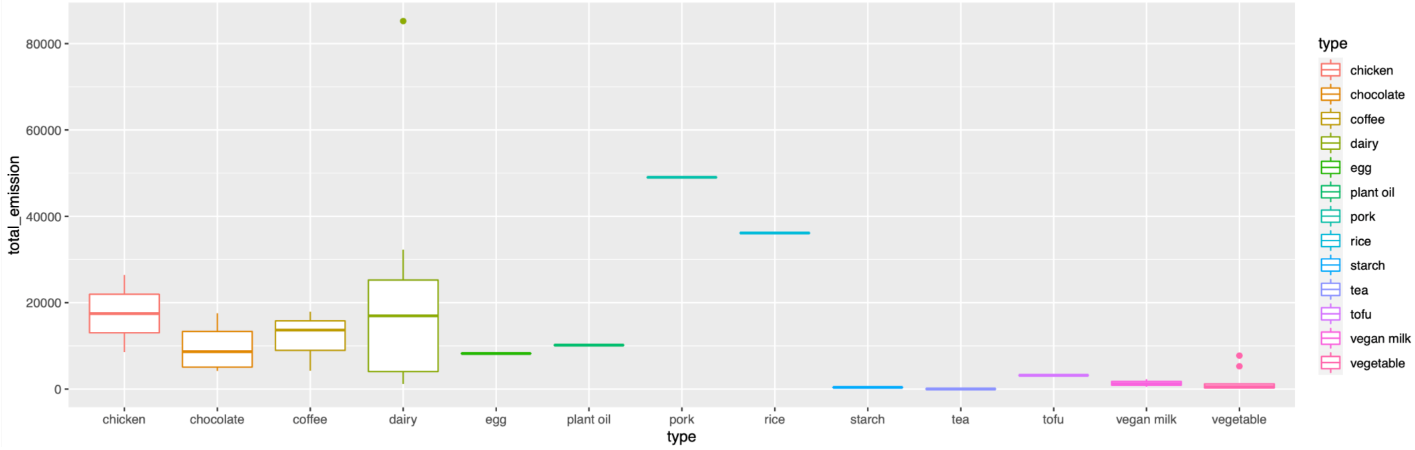

Figure 1. The distribution of each food type's total emissions

4. Methodology

4.1 Setup

The outcome variable is the amount of total supply chain carbon emissions of each food category. Since the dataset is a cross sectional dataset and there is no time difference, we think it is appropriate to use multivariable regression models to explore the impact of potential factors during the important stages in the supply chain. Specifically, the stages being investigated are agricultural production, transportation, and packaging. Before the regression estimation, total carbon emissions are calculated by the following equation.

$$(1)\ totalWeight = number\_of\_cases \times kilogram\_per\_case$$

$$(2)\ totalEmission = totalWeight \times Emission\_per\_kilogram$$

Notice that the footprint per kg covers the emissions across all stages of the supply chain, which include agricultural production, processing, packaging, transportation, and retail.

4.2 Basic Regressions

After obtaining the total emissions, we will investigate the correlations by establishing multivariable regression models with different specifications. In order to examine the rough impact associated with each supply chain stage, we will form a series of basic regression models by gradually adding in explanatory variables until we reach the "full model" (Equation (3)).

$$(3)\ totalE_i = \alpha_0 + \alpha_1 totalW_i + \beta_1 T1_i + ... + \beta_{12} T12_i + \gamma_1 P1_i + \gamma_2 P2_i +$$

$$\alpha_2 shipdist_i + \alpha_3 truckdist_i + e_i$$

The dependent variable is the total emissions ($totalE_i$) obtained from Equation (2). The independent variables are factors that have been found to be essential for the emissions in different supply chain stages (Our World in Data, 2022), including agricultural production, packaging, truck transportation, and ship transportation. In particular, $totalW_i$ is the total weight of each product calculated by Equation (1). $Truckdist_i$ and $shipdist_i$ are the truck distances and ship distances associated with product i. The categorical variable P_i represents the packaging material: taking "aluminum" as base level, $P1_i = 1$ if i is wrapped by paper, 0 otherwise; and $P2_i = 1$ if i is wrapped by plastic, 0 otherwise The categorical variable T_i represents the food types: taking "chicken" as the base level, $T1_i$=1 if i is chocolate, 0 otherwise; $T2_i$=1 if i is coffee, 0 otherwise, and so on.

The last term e_i is the error term that captures other possible factors that we may not be able to account for, for instance, the impact of retail, processing and food waste in the supply chain emissions. These variables are hard to trace and therefore, it would be difficult for us to collect their information. However, we are aware that by omitting these factors, we may create bias that deteriorates the accuracy of our estimation results.

By these basic regressions, we assume all food types have the same per-kg emission rate. Thus, after controlling the impacts of transportation (by adding $shipdist_i$ and $truckdist_i$) and packaging (by adding P_i), the coefficients β_1- β_{12} would be our initial estimates of each food type's agricultural impacts. For instance, β_1 could be interpreted as: compared to chicken, how much the agricultural processes involved in chocolate production have contributed to the total carbon emissions in the data. Thus, by comparing the β values, we are able to rank the products in terms of their agricultural emissions.

4.3 Select Best Subsets

Since we are interested in identifying products that are high in agricultural emissions and subsequently replacing them with their low emission counterparts, we would like to see which food types are particularly influential in the regression models.
To do so, we will apply an exhaustive search algorithm called *regsubsets* in *R* . Given a set of variables (the variable pool) , the algorithm will return "best" regression models of various sizes. Specifically, for each model size *s*, the algorithm will search for all possible subsets of size *s* from the variable pool. It will then choose the best one that minimizes the residual sum of squares. In our case, we will pass all the variables used in the full model (Equation (3)) into the algorithm as our variable pool. Among all the models prompted by *regsubsets*, we will choose the optimal model size that maximizes the adjusted R^2.

4.4 Incorporate Interactions

Knowing that our former assumption on the uniform per-kg emissions may be too rigid (Section 4.2), we will relax this by incorporating interaction terms into the basic models.

This also serves as a robustness check to test if our estimates are able to remain consistent under different specifications.

After comparing all the models that we previous get in Section 4.1 and 4.2, we will pick one or two that perform the best based on their adjusted R^2 values, and these models will be taken as our candidate models in which the interactions will be added. Specifically, two types of interactions will be considered, which include the interactions between total weights and the food types, as well as the interactions between total weights and the packaging materials. By adding the interactions, we now allow the per-kg agricultural emissions to vary across types, that is, different types can now have different agricultural emission rates. Since this specification is closer to real-life situations, it is the one that we will use to provide quantitative evaluations when proposing the substitution plans.

5. Results

5.1 Basic Regressions

As our baseline models, we first construct a series of simple regressions, assuming that all food types have exactly the same per-kg emissions. We gradually expand our simple regression by adding in new controls until it reaches the full size (Equation (3) in Section 4.2). The coefficients obtained are shown in the first three columns in Table 4.

Column (1) corresponds to the case where only one control is added, that is, the total weight of each product. We see that the total weight is estimated to have a significant correlation with the total emission. In particular, for a 1kg increase in the total weight, there is estimated to be a 9.688kg rise in the total carbon emissions regardless of the food types. Although there are variations among the sizes of the coefficients on food types, they are not significant enough for us to assert the agricultural impact that each type has on its total emissions. Hence, in order to better identify the agricultural emissions, more controls are required.

Column (2) shows the results when the packaging materials are incorporated into the model. Despite the insignificance of the packaging materials, the incorporation of them actually improves the model. Now, not only does the total weight continue to be significant, the majority of the food types also become significant. After the addition of the packaging materials, the effect of the total weight has been strengthened – the per-kg emission now increases from 9.688 to 13.165 kgCO2/kg. Among all the food types that have been identified as significant, the coefficient on rice is the lowest, which is about -62,537 kgCO2. This means, compared to chicken, the agricultural processes associated with rice production contribute 62,537 kg less carbon to its total emissions in the dataset. In contrast, the coefficient on coffee is the highest, which is about 44,773 kgCO2. This means, compared to chicken, the agricultural processes of coffee production contribute 44,773 kg more carbon to its total emissions. The estimates on plant oil, pork, tofu, and vegetables, however, are insignificant. Their large variance is probably due to the lack of records for each of these types in the dataset.

In order to build a more rigorous model, we have considered adding the distances as another set of controls (Column (3)). The results are generally consistent with the Basic 2 Model (Column (2)). Notice there is no significant evidence for the impact of packaging materials and the distances. This suggests that the effect of packaging and transportation may not be as remarkable as agricultural productions.

Notice the three basic models all have very large adjusted R^2 values. This further verifies that agriculture is the major contributor to the variations in the total emissions. Among all three basic regressions, Basic 2 (Column (2)) is the one that has the highest adjusted R^2. Hence, we will regard it as our first candidate model.

5.2 Best Subset

In order to filter out food types that are particularly influential in terms of their agricultural impacts, we pass the full model (Column (3)) into an exhaustive search algorithm in *R* called *regsubsets.* This algorithm will try all possible subsets of variables used in the full model, and we consider the one that maximizes the adjusted R^2 as the best subset. The model that got selected is the following:

$$\textit{(4)}\ totalE_i = \alpha_0 + \alpha_1 totalW_i + \beta_1 T1_i + \ldots + \beta_{11} T11_i + \gamma_1 P1_i + \gamma_2 P2_i + e_i$$

Compared to the full model, there are three things that the best subset model drops: type plant oil, ship distances, and truck distances. Again, these variables are excluded probably because they do not help much in explaining the variations in the total emissions. The fourth column in Table 4 displays the output of this best subset model. We see that the results are similar to the ones estimated from Basic Model 2 and 3 (Column (2) and (3)). This similarity observed across the models further demonstrates the consistency of our estimations. Notice the best subset model has the highest adjusted R^2, which makes it another appealing candidate model.

Table 4. Coefficient table for Basic Model 1-3 and Best Subset Model

	Dependent variable:			
	total_emission			
	Basic 1	Basic 2	Basic 3	Best Subset
	(1)	(2)	(3)	(4)
Constant	−10,287.280 p = 0.252	−31,259.960 p = 0.033**	−31,570.320 p = 0.038**	−33,277.070 p = 0.018**
total_weight	9.688 p = 0.00002***	13.165 p = 0.00000***	12.946 p = 0.00001***	13.185 p = 0.00000***
chocolate	14,997.320 p = 0.134	23,147.510 p = 0.013**	22,642.240 p = 0.019**	25,121.080 p = 0.004***
coffee	15,219.050 p = 0.140	44,773.440 p = 0.002***	47,742.170 p = 0.082*	46,780.480 p = 0.0004***
dairy	21,272.420 p = 0.021**	28,449.290 p = 0.002***	21,821.380 p = 0.081*	30,412.870 p = 0.0002***
egg	417.644 p = 0.968	25,991.410 p = 0.033**	25,016.240 p = 0.048**	27,975.450 p = 0.016**
plant_oil	−6,185.454 p = 0.622	−5,781.759 p = 0.586	−13,320.070 p = 0.374	
pork	−6,657.156 p = 0.644	−20,365.100 p = 0.122	−19,501.670 p = 0.154	−18,517.840 p = 0.138
rice	−41,098.060 p = 0.020**	−62,536.830 p = 0.0005***	−60,546.950 p = 0.002***	−60,734.230 p = 0.0004***
starch	7,047.971 p = 0.597	37,815.670 p = 0.015**	36,593.240 p = 0.022**	39,829.720 p = 0.008***
tea	10,143.980 p = 0.344	42,151.410 p = 0.004***	36,811.470 p = 0.023**	44,172.630 p = 0.002***
tofu	3,180.435 p = 0.806	9,453.481 p = 0.398	9,058.353 p = 0.433	11,416.200 p = 0.275
vegan_milk	−3,719.708 p = 0.699	22,837.220 p = 0.052*	22,094.160 p = 0.070*	24,826.940 p = 0.025**
veggie	−3,352.744 p = 0.685	14,364.450 p = 0.108	13,867.930 p = 0.135	16,339.180 p = 0.045**
paper		−11,098.730 p = 0.313	−9,545.980 p = 0.409	−11,103.200 p = 0.306
plastic		11,005.470 p = 0.269	11,889.920 p = 0.251	11,038.510 p = 0.260
dist_ship			−0.300 p = 0.864	
dist_truck			1.722 p = 0.455	
R^2	0.757	0.841	0.845	0.838
Adjusted R^2	0.631	0.737	0.720	0.744
Residual Std. Error	10,113.360 (df = 25)	8,543.877 (df = 23)	8,813.323 (df = 21)	8,419.291 (df = 24)
Note:				*p<0.1; **p<0.05; ***p<0.01

5.3 Identify Products to Be Replaced

Since our ultimate goal is to carry out proper substitution plans for AMS to reduce their supply chain emissions, after obtaining the two decent candidate models (Basic Model 2 & Best Subset), we would now like to use them to identify products that need to be replaced.

Figure 2 plots the coefficients on all food types that are estimated by our two candidate models. By comparing the sizes of these coefficients, we are able to rank their relative impact on agricultural emissions; thus, the products we aim to replace are the ones that are significantly high on the plot. The contrasting of the two models serves two purposes. First, it provides a direct visualization of the consistency of the estimation results; second, it ensures that the products identified are not outstanding by chance.

Because plant oil, pork, and tofu have been consistently estimated to be insignificant (Table 4), they will not be considered in our final recommendations (There is only one estimate for plant oil because it does not get selected in the Best Subset Model). After discarding these three types, we have found two major products that are extensive in agricultural emissions and easy to substitute. The first one is coffee, and we will replace it with its low-emission counterpart, tea; the other one is dairy, and we will replace it with its low-emission counterpart, vegan milk. Furthermore, as a supplementary recommendation, we have also identified chocolate as our third target. Although its overall agricultural emissions are not particularly high, the impact differs between dark and white chocolate (Bianchi et al., 2020). Therefore, by substituting white chocolate with dark, we are hoping to further improve AMS' supply chain emissions.

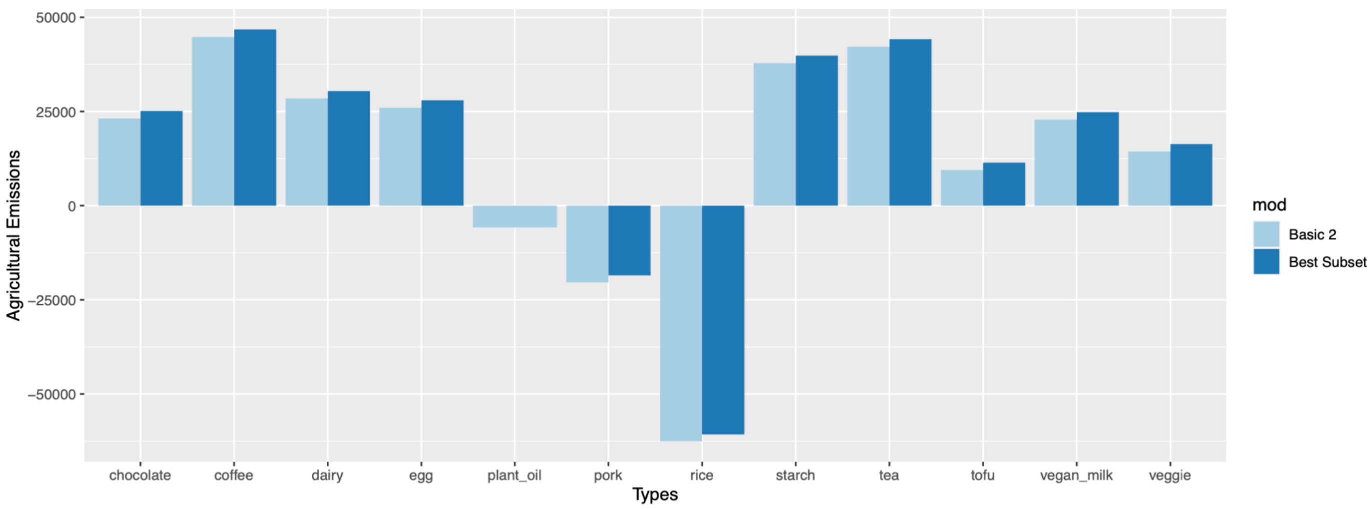

Figure 2. Comparing the agricultural impacts of different food types

6. Discussion

6.1 Robustness Check and Alternative Specifications

Under Model Basic 2 and Best Subset, the null hypothesis is that our models have homoscedastic errors – the variance of the error term keeps constant. To check this assumption, we first plot the residuals against the fitted values for both models. We can see that the majority of the residuals are distributed around 0, especially in the central parts of the graphs. However, there are also some scattered points at the edges of the graphs that are far from 0; it is hard to tell from this visual inspection if they are outliers or if they indicate the underlying heteroscedasticity. Therefore, we further implement the Breusch-pagan test so that we are able to obtain numerical evidence to examine our assumption. Table 5 shows the resulting p-values for Model Basic 2 and Best Subset, which are 0.0836 and 0.0613 respectively. Taking a 5% significance level as the rejection criterion, both results appear to be insignificant since they are larger than 0.05. Thus, there is no sufficient evidence to reject our null hypothesis, meaning our assumption of homoscedasticity remains valid for our two candidate models. However, it is possible that our test result is subjected to the sample size of our dataset; the homoscedasticity might not necessarily hold if more data points were observed.

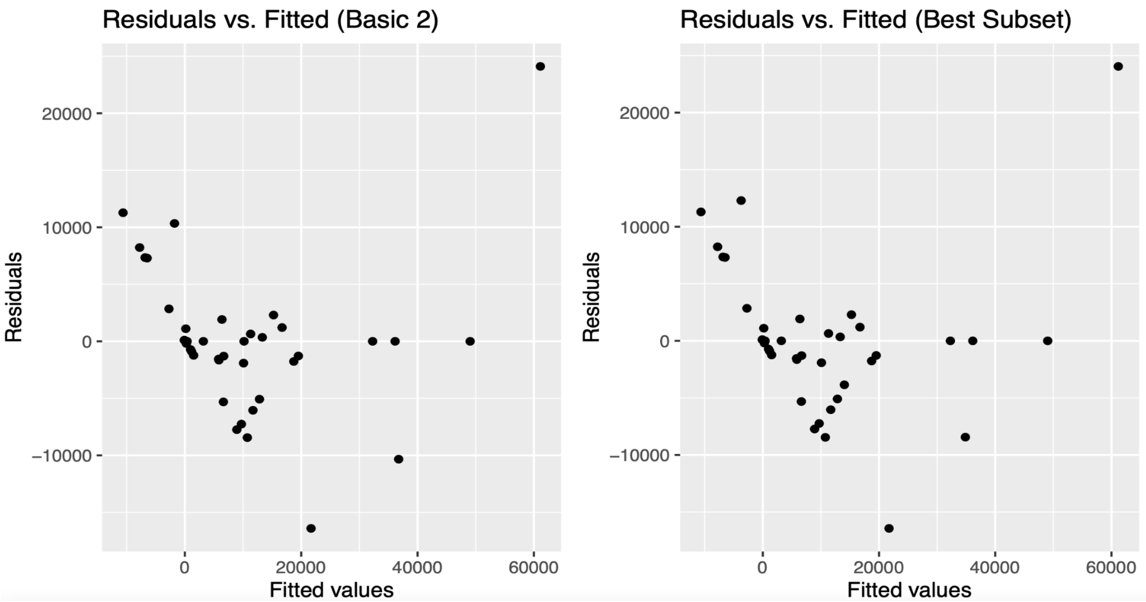

Figure 3. Residuals against fitted values for Model Basic 2 and Best Subset

Table 5. Breusch-pagan p-values for Model Basic 2 and Best Subset

	Basic 2	Best Subset
p-value	0.0836	0.0613

The second assumption implied by the candidate models is that the error terms are normally distributed. A quantile-quantile plot (QQ-plot) is used to check for this assumption. As Figure 4 shows, the points do not quite align on a straight line. Specifically, large deviations are seen at the ends, which indicates that the actual distribution of the errors has heavier tails instead of being normal. With this being said, we take this as one of our limitations. Although our data may not follow an exact normal distribution, it is still appealing to make such an assumption since it allows clear and easy-to-interpret models for analysis.

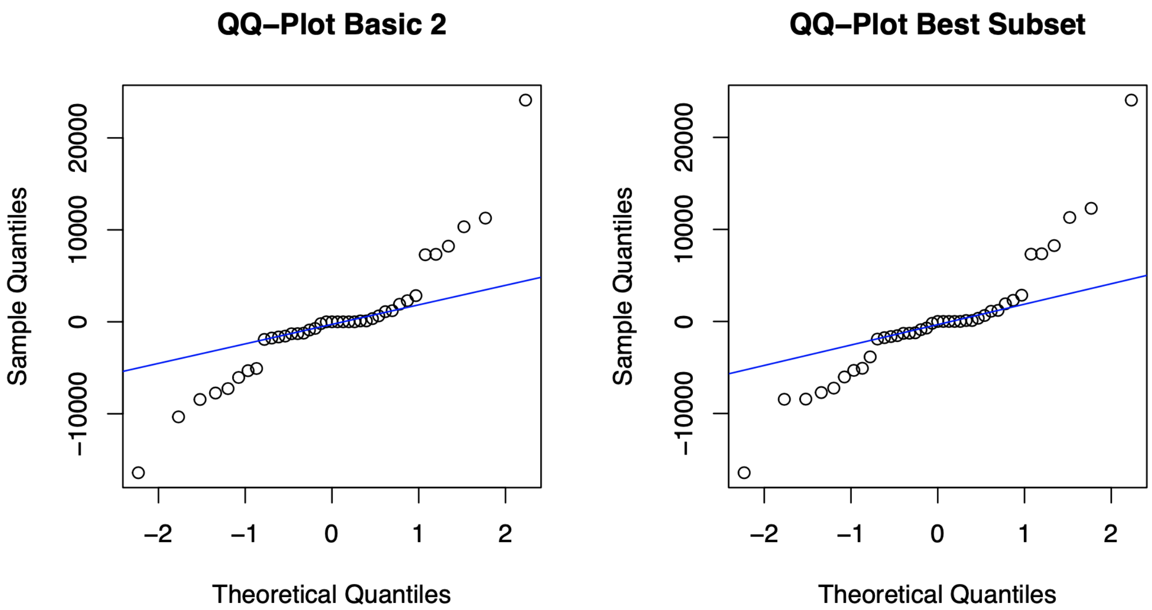

Figure 4. QQ-plots for Model Basic 2 and Best Subset

When building our basic regressions, we implicitly assume that for all food types and packaging materials, the per-kg emissions are the same. However, this assumption can be over-simplified since it is likely that different food types may vary in the emission rates during their agricultural production. Moreover, it is possible that different packaging materials also differ in their kg-emission rates. To account for these, we will now incorporate interactions into the candidate models (Equation (5) & (6)).

$$(5)\quad totalE_i = \alpha_0 + \alpha_1 totalW_i + (\beta_1 + \delta_1 totalW_i)T1_i + \ldots +$$

$$(\beta_{12} + \delta_{12} totalW_i)T12_i + (\gamma_1 + \eta_1 totalW_i)P1_i + (\gamma_2 + \eta_2 totalW_i)P2_i +$$

$$\alpha_2 shipdist_i + \alpha_3 truckdist_i + e_i$$

$$(6)\quad totalE_i = \alpha_0 + \alpha_1 totalW_i + (\beta_1 + \delta_1 totalW_i)T1_i + \ldots +$$

$$(\beta_{11} + \delta_{11} totalW_i)T11_i + (\gamma_1 + \eta_1 totalW_i)P1_i + (\gamma_2 + \eta_2 totalW_i)P2_i + e_i$$

Equation (5) is the model when interactions are added for Model Basic 2. It includes all food types and controls for both packaging materials and transportation distances. Equation (6) is the expanded version for Model Best Subset. Based on the exhaustive search algorithm, it includes all food types except for plant oil, and the transportation also gets excluded. With the interaction terms, not only do we control for the kg-emissions of the packaging material used, but we also enable the per-kg agricultural emissions to change across different food types.

The estimated coefficients of Model (5) and (6) are presented in Table 6. Column (1) corresponds to Model Basic 2 with interactions and Column (2) corresponds to Model Best Subset with interactions. We observe that the results obtained from the two models are generally similar, though discrepancies occurred for the fixed agricultural impacts (β) of chocolate and dairy. However, notice compared to the per-kg emissions of food types (δ), the fixed impacts appear to be much less significant. This indicates that after adding the interactions, most of the variations in the data are explained by the agricultural emission rates. It is worth noting there are some null values in Table 6. Again, this is likely due to the issue of insufficient data. Since for some of the products, we only have one or two records, it would cause problems when trying to regression lines with different slopings (models with interactions).

Furthermore, the Model (5) and (6) also reinforce our previous findings. In particular, coffee, chocolate and dairy are three types that we identified as foods to be replaced, and they still remain high in their estimated agricultural impact in the extended models. For instance, in Column (1), the fixed agricultural impact of coffee is estimated to be 3164 kgCO2 more than the reference type, chicken; and its per-kg emission rate is also quite high, achieving 8.38 kgCO2/kg more, compared to chicken. In terms of chocolate, despite a small (yet highly insignificant) fixed agricultural impact, it is estimated to have the second largest per-kg emission rate, which is 12.6 kgCO2/kg more than chicken. Similar to dairy, among all food types, it is estimated to have the highest per-kg emission rate.

Overall, our results remained robust under different tests and alternative specifications. Moreover, with the interactions added, our models become more flexible and closer to real-life situations, thus, we will use this specification to provide quantitative assessment for our recommendations. Since Model Basic 2 with interactions has a slightly higher adjusted R^2, it is the model that we prefer when simulating the substitution plans.

Table 6. Coefficient table for Model Basic 2 and Best Subset with interactions

	Dependent variable:	
	total_emission	
	Basic 2 + inter	Best Subset + inter
	(1)	(2)
Constant	−24,223.940 p = 0.000***	−26,761.620 p = 0.00000***
total_weight	6.100 p = 0.000***	6.219 p = 0.00000***
chocolate	0.000 p = 1.000	2,537.676 p = 0.414
coffee	3,163.943 p = 0.317	5,701.619 p = 0.265
dairy	0.000 p = 1.000	2,537.676 p = 0.348
egg	12,155.060 p = 0.243	14,692.730 p = 0.382
plant_oil	−6,602.112 p = 0.0001***	
pork	7,491.000 p = 0.006***	9,217.311 p = 0.026**
rice	−18,970.810 p = 0.00004***	−17,509.440 p = 0.005***
starch	512.624 p = 0.812	3,005.621 p = 0.385
tea	3,163.943 p = 0.297	5,701.619 p = 0.245
tofu	−3,294.060 p = 0.050**	−882.986 p = 0.718
vegan_milk	2,407.399	4,945.075

	p = 1.000	p = 0.531
paper	21,060.000 p = 0.00000***	21,060.000 p = 0.0002***
plastic	24,223.940 p = 0.000***	24,223.940 p = 0.000***
weight:choc	12.600 p = 0.00001***	12.481 p = 0.001***
weight:coff	8.380 p = 0.072*	8.261 p = 0.260
weight:dairy	15.100 p = 0.000***	14.981 p = 0.000***
weight:egg	−8.523 p = 0.209	−8.643 p = 0.427
weight:poil		
weight:pork		
weight:rice		
weight:starch		
weight:tea	−6.220 p = 0.898	−6.339 p = 0.937
weight:tofu		
weight:vmilk	−6.786 p = 0.121	−6.905 p = 0.321
weight:vegg	−5.600 p = 0.177	−5.719 p = 0.389
weight:paper	2.020 p = 0.616	2.020 p = 0.758
weight:plastic		
R^2	0.999	0.996
Adjusted R^2	0.996	0.990
Residual Std. Error	1,022.986 (df = 15)	1,671.362 (df = 16)
Note:		*p<0.1; **p<0.05; ***p<0.01

6.23 Recommendations

Based on the results, we generate three main practical recommendations. For each recommendation, we will replace different portions of food types that have high agricultural emissions with alternatives that have lower agricultural emissions.

The first recommendation is replacing white chocolate with dark chocolate. According to existing research, white chocolate emits 4.3 kgCO2eq while dark chocolate emits only 1.9 kgCO2eq (Bianchi et al., 2020). AMS is currently purchasing a large percentage of white chocolate, thus, cutting the purchase of white chocolate is essential for reducing CO2 emission. We present three different percentages (30%, 40%, and 50%) of white chocolate to be replaced by dark chocolate. The emission reductions are 579.93, 773.24, 966.55 kgCO2eq respectively (Table 7). Compared with the original amount of emissions for chocolate (39094.22 kgCO2, see Figure 5), by our three replacement plans, 1.48%, 1.98%, 2.47% of the total chocolate emissions can be reduced. Although the percentage change is not that significant, the actual amount of reduction is considerable.

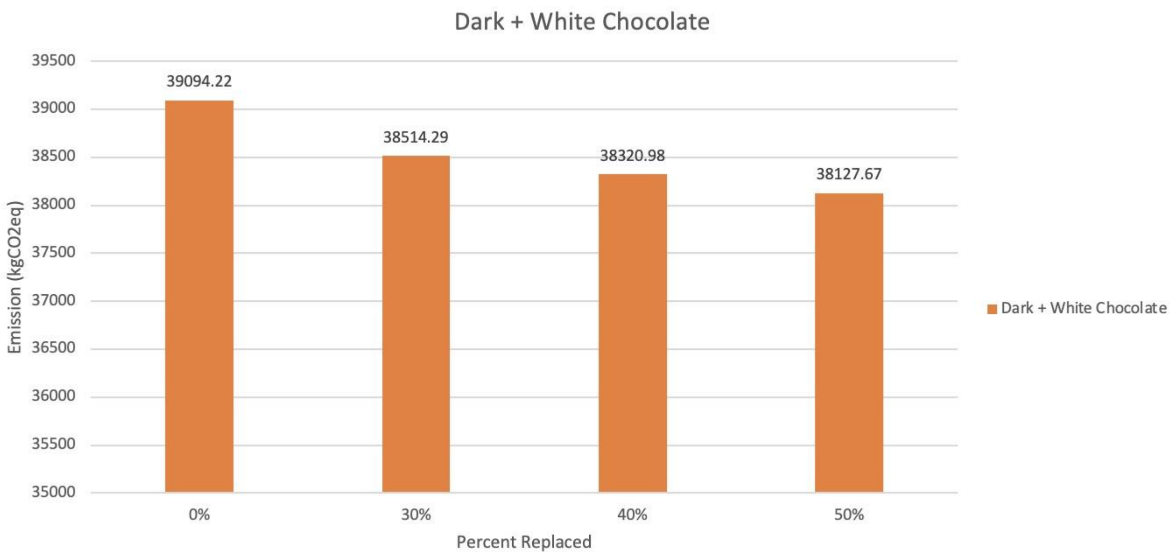

Figure 5. Changes in total emissions of chocolate
(0%, 30%, 40%, 50% white chocolate replaced by dark)

Table 7. Reductions in total emissions of chocolate
(30%, 40%, 50% white chocolate replaced by dark)

	30%	40%	50%
White/Dark Chocolate	579.93 (1.48%)	773.24 (1.98%)	966.55 (2.47%)

Note: Under each substitution plan, the first value is the absolute reductions, the second value (in parenthesis) is the percentage reduced compared to current total emissions of chocolate.

The second recommendation is replacing coffee with tea. In the result section (section 5.3), we figure out that the agricultural production of tea generates less emission than coffee, and hence, we consider it as the substitute of coffee. Figure 6 shows the changes in carbon emissions when decreasing coffee and increasing tea by three different percentages. The amount of CO2 reductions are 5359.97, 7146.62 and 8933.28 kgCO2eq respectively (Table 8). When we reduce 25% of coffee and replace it with 25% of tea, up to 24.85% of original emission is successfully reduced.

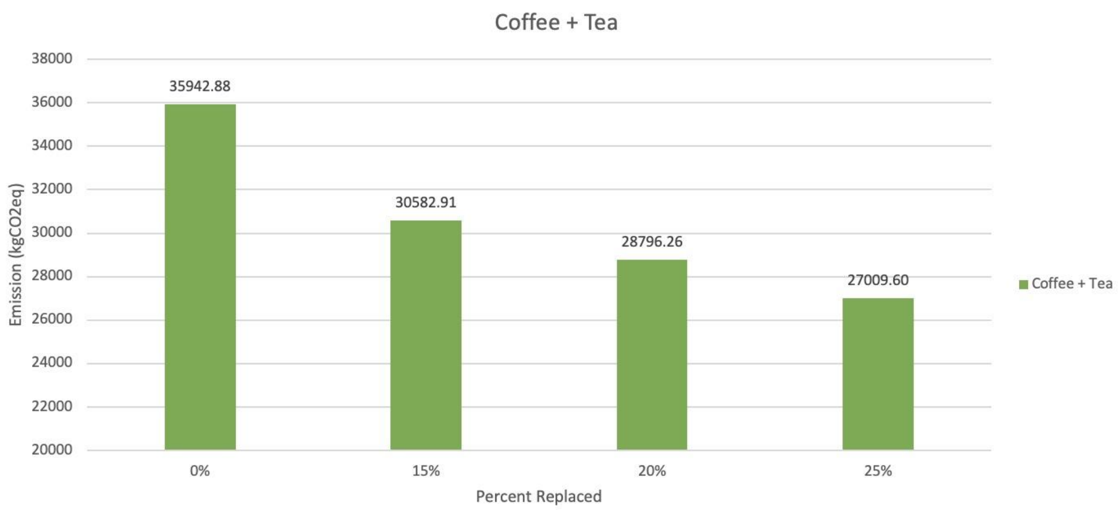

Figure 6. Changes in total emissions of coffee and tea
(0%, 15%, 20%, 25% coffee replaced by tea)

The third recommendation is replacing dairy with vegan milk. In section 5.3, the result shows that vegan milk has less agricultural emissions than dairy. Therefore, we suggest that AMS can use vegan milk to replace dairy to reduce carbon emissions. When we decrease 15%, 20%, and 25% of dairy and correspondingly increase 15%, 20%, and 25% of vegan milk, the emission reductions are 9134.76, 18608.92, and 28083.08 kgCO2eq. We also have an interesting finding that soy and nut milk can be used to make vegan cheese (Alfaro, 2021). With this being said, besides the direct shifting from milk to vegan beverages, the use of animal-based cheese can also be replaced by plant-based ones, which can further reduce the carbon emissions.

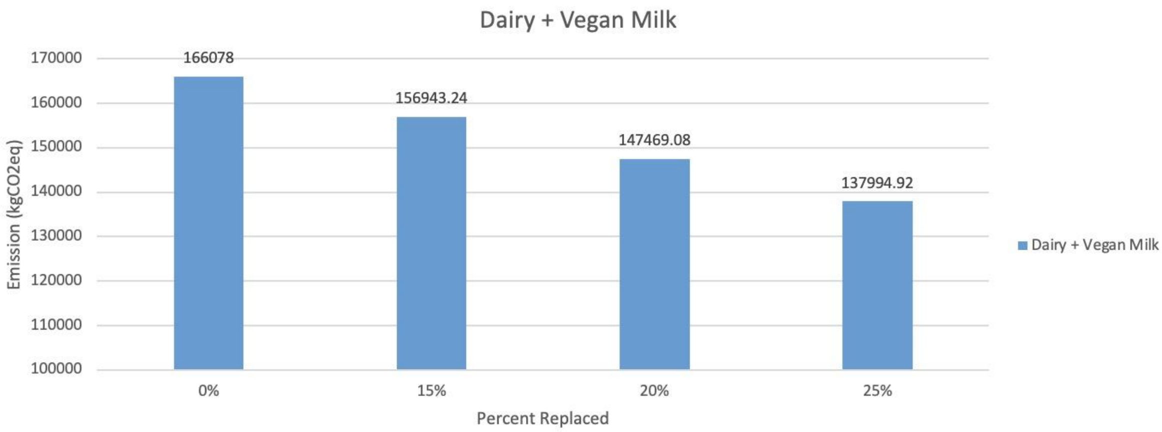

Figure 7. Changes in total emissions of dairy and vegan milk
(0%, 15%, 20%, 25% dairy replaced by vegan milk)

Table 8. Reductions in total emissions of coffee/dairy and tea/vegan milk
(15%, 20%, 25% coffee/dairy replaced by tea/vegan milk)

	15%	20%	25%
Coffee/Tea	5359.97 (14.91%)	7146.62 (19.88%)	8933.28 (24.85%)
Dairy/Vegan Milk	9134.76 (5.50%)	18608.92 (11.20%)	28083.08 (16.91%)

Note: Under each substitution plan, the first value is the absolute reductions, the second value (in parenthesis) is the percentage reduced compared to current total emissions of coffee/dairy and tea/vegan milk.

6.3 Economic meaning

Our primary goal of this paper is to help reduce AMS' carbon emissions. But how does our research align with the economy? Carbon emission has already become a critical problem all around the world, thus, how to balance carbon reduction and economic growth is an important issue (Fei et al., 2019). As UBC Climate Action Plan 2020 stated, the implementation of provincial carbon tax significantly affects UBC's financial feasibility, UBC needs to pay $55 per tonne of CO2 emission. Hence, our research on ways to reduce AMS' carbon emissions not only aims to build a eco-friendlier campus, but can also help release UBC's financial burdens. The highest emission reduction results we generate is in recommendation 3, which is 28083.08 kgCO2eq. Suppose that our dataset is collected over a time span of two terms in the winter session, this recommendation can help AMS save about 1544.6 CAD in 8 months. According to UBC Climate Action Plan 2020, once we reduce the carbon emissions for AMS, we are reducing the carbon costs for both AMS and UBC.

6.5 Limitations

Throughout this research, there are several limitations that may affect our results. The first limitation is that the sample size is small, which means that our data is not adequate. There are only 39 observations in the dataset, leaving some food types with only one or two products for us to analyze. Back to Figure 1, the distribution of some food types is just a line instead of a range in the graph. This means that we only have a few data points for this food type, which can cause a lot of variances when trying to fit a regression line. The more data we have, the more accurate our result will be. Therefore, the results for some food types, such as egg, oil, pork, rice, starch, tea and tofu, would not be as reliable as chicken, chocolate, coffee and dairy, which are associated with more data. If we had a bigger sample size, we could overcome this issue and the results will be much better.

The second limitation to our model is that there are omitted variables that we did not consider. As we mentioned in section 4.2, the impact of retail, processing and food waste are not explicitly controlled in the models. These variables are not included because we do not have access to related data. Moreover, for retail and processing, it is difficult to come up with a concrete measurement based on which their impact on emissions can be quantitatively estimated. However, all of these appear to be potential contributors of the dependent variable *total_emission,* and they are correlated to other explanatory variables in the models (Our World in Data, 2022). Therefore, the omission of these factors may lead to underestimated model outputs, creating bias that deteriorates the accuracy of our results.

The last limitation is that we did not consider quantity supply and demand in our research. When we are generating our recommendations, we do not take into account the students' actual demand of the products. If the increase of the alternatives exceeds the demand, as a drawback, it may cause a lot of food waste. For example, although tea and coffee are substitutes, most of the consumers of AMS are college students, and their demand for coffee may be much greater than their demand for tea. Therefore, if AMS greatly reduces the purchase of coffee and replaces it with tea, it may lead to too much supply of tea and little demand, thus leading to food waste. The same is true for other recommendations where our proposal may not match the market demand of AMS. The emissions caused by food waste cannot be ignored, in fact, food losses and waste are found to be responsible for ¼ greenhouse gas emissions from food (Ritchie, 2022). Therefore, if the replacements are conducted blindly without a thorough understanding of the market demand, the consequent food wastes may result in adverse impact, causing even more CO_2 emissions. This is also the motivation behind our provision of different percentage options in the recommendation section. We hope that AMS can pick the one that best fits their needs, considering both the supply and demand.

7. Conclusion

In this paper, we analyze the environmental impact of different food products with the dataset provided by AMS, using different regression models. We focus on the agricultural emissions of different foods, hoping to reduce carbon emissions by replacing foods that have large agricultural emissions with alternatives that are low in agricultural emission. Based on the original data provided by AMS, we first conducted a secondary research to find the total emissions of various foods in the whole supply chain. We started with a basic model and kept adding controls until we reached the full model. Then, we implemented the *regsubsets* algorithm to get the best subset model which highlights variables that are most important in explaining the variance in the data. By comparing the results of these models, we identify that chocolate, dairy and coffee should be replaced due to their high agricultural emission. After that, interactions were incorporated into the previous models, which not only makes our specification closer to real-life situations, but also helps us check the assumption of uniform per-kg emissions that we adopted in the basic models. Based on the results of the interaction model, three recommendations were offered for AMS to reduce carbon emissions. With various replacement percentages, AMS can successfully reduce at least 579.93 kgCO2eq and at most 28083.08 kgCO2eq. This not only makes AMS more environmentally friendly, but also helps it save on carbon tax overhead.

We acknowledge that there are limitations in the study and may affect the above results. For example, our estimations are subject to a small sample size and omitted variables, which may influence the accuracy of our results. Besides, another limitation is that we do not consider the market conditions in reality – if the increase of the alternatives exceeds the demand, the reduction of total emission may be offset by the subsequent food wastes, which may affect the feasibility and effectiveness of our recommendations. In future study, if AMS could collect more data on student's demand for different food types, this information can be incorporated into the analysis, enabling the recommendations to be more relevant to real life and thus avoiding carbon emissions from wasted food. In addition, in order to establish more rigorous models, further factors can be investigated and controlled, such as the techniques that the foods are produced and the ways that the foods are stored. Though our research may still be preliminary at this stage, we hope it can be an informative attempt that brings inspiration for future study and policy-making.

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