

# C7083 Assignment

<https://github.com/joebmitchell/C7083-Assignment>

Joseph Mitchell

22356500

2023-02-28

## Contents

<b>1</b>	<b>Food Consumption Analysis</b>	<b>1</b>
1.1	Shiny App . . . . .	1
1.2	Introduction . . . . .	1
1.3	What variation is there in consumption of food categories? . . . . .	2
1.4	Do different food categories have different carbon footprints? . . . . .	3
1.5	Does Consumption affect Carbon Footprint? . . . . .	4
1.6	What are different countries doing? . . . . .	5
1.7	Is there a global pattern to emissions from food? . . . . .	5
1.8	How could we improve? . . . . .	5
<b>2</b>	<b>Graph Critique</b>	<b>8</b>
2.1	Bad Graph . . . . .	8
2.2	Good Graph . . . . .	10
<b>3</b>	<b>References</b>	<b>10</b>

## 1 Food Consumption Analysis

### 1.1 Shiny App

The graphs can all be viewed on this **shiny app**.

### 1.2 Introduction

The data for this analysis is sourced from Tidy Tuesday's Github(GitHub) and is an webscrape from nu3. 'nu3' is a German nutrition company that sells fitness, food and health products including a vegan range. They have created a table which consolidates information from the FAO (Food and Agriculture Organization of the United Nations) relating to consumption of selected foodstuffs as well as median global emissions of CO2 equivalent per KG eaten. The data was collated in 2018 and most of the data is from 2013. There

are limitations to this data set as it doesn't take into account different countries emissions of CO2, the nutritional benefits of the foodstuff and it uses a selection of foodstuffs without justifying their inclusion.

The data from this webpage was scraped, tidied and exported into a csv file with 1430 rows of data, comprising of 130 countries and 11 food categories and has the following variables.

Variable	Class	Description
country	character	Country Name
food_category	character	Food Category
consumption	double	Consumption (kg/person/year)
co2_emmission	double	Co2 Emission (Kg CO2/person/year)

### 1.3 What variation is there in consumption of food categories?

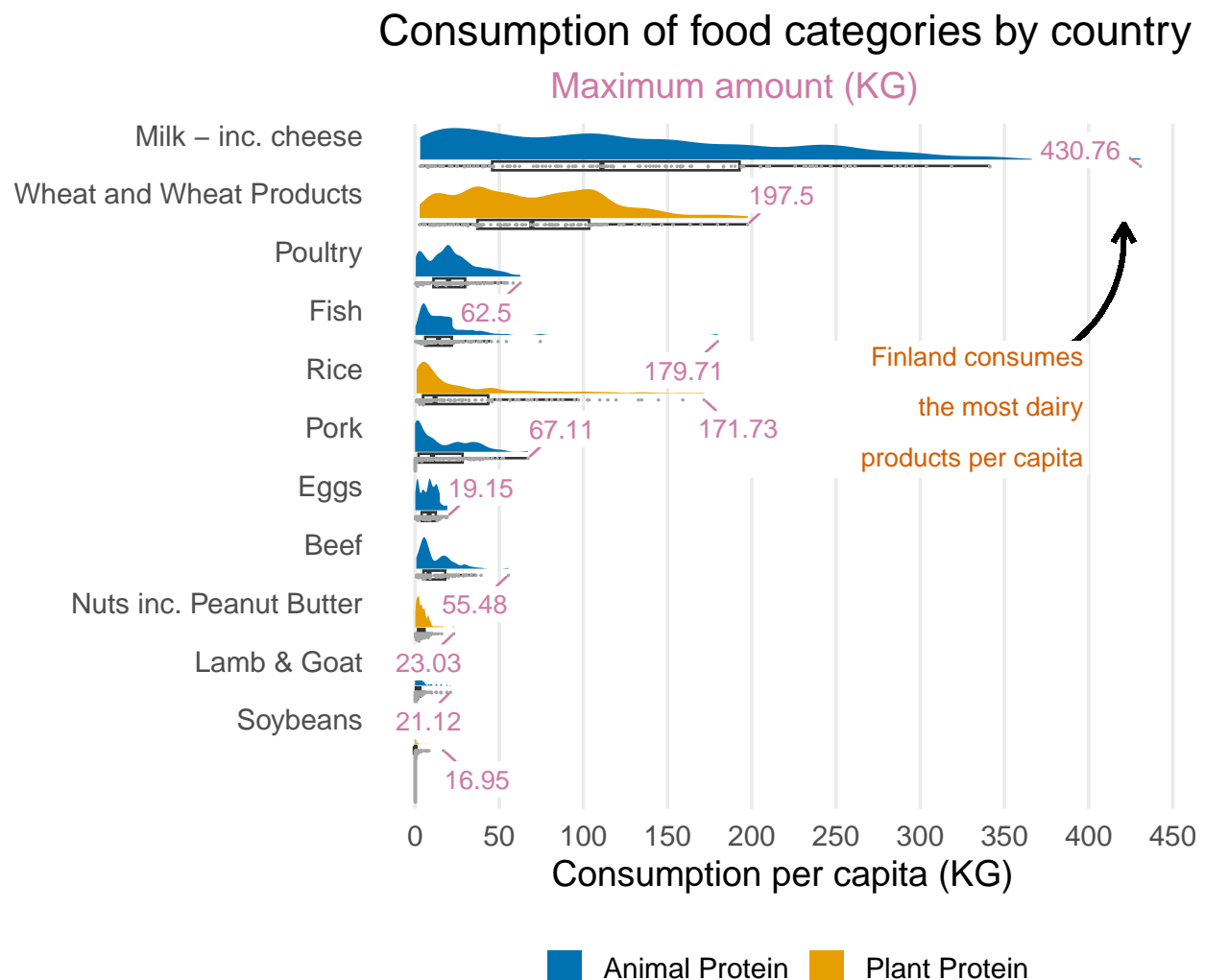


Figure 1: Raincloud plot of Consumption (KG) of food categories

The first question to ask from the data is what is the distribution of consumption of different food categories? Figure 1 allows us to see that there is a significant variation in consumption. For example we can see that Milk - inc cheese has the highest median consumption and the highest individual consumption and that Soybeans are the least consumed of the food categories. As well as the differences in median and maximum values there is a big range in consumption even among categories that have similar median values such as Pork and Eggs.

With the worlds increasing knowledge of the need to reduce our collective carbon footprint does the carbon footprint of a food category impact its consumption or is it not impacted by carbon footprint?

#### 1.4 Do different food categories have different carbon footprints?

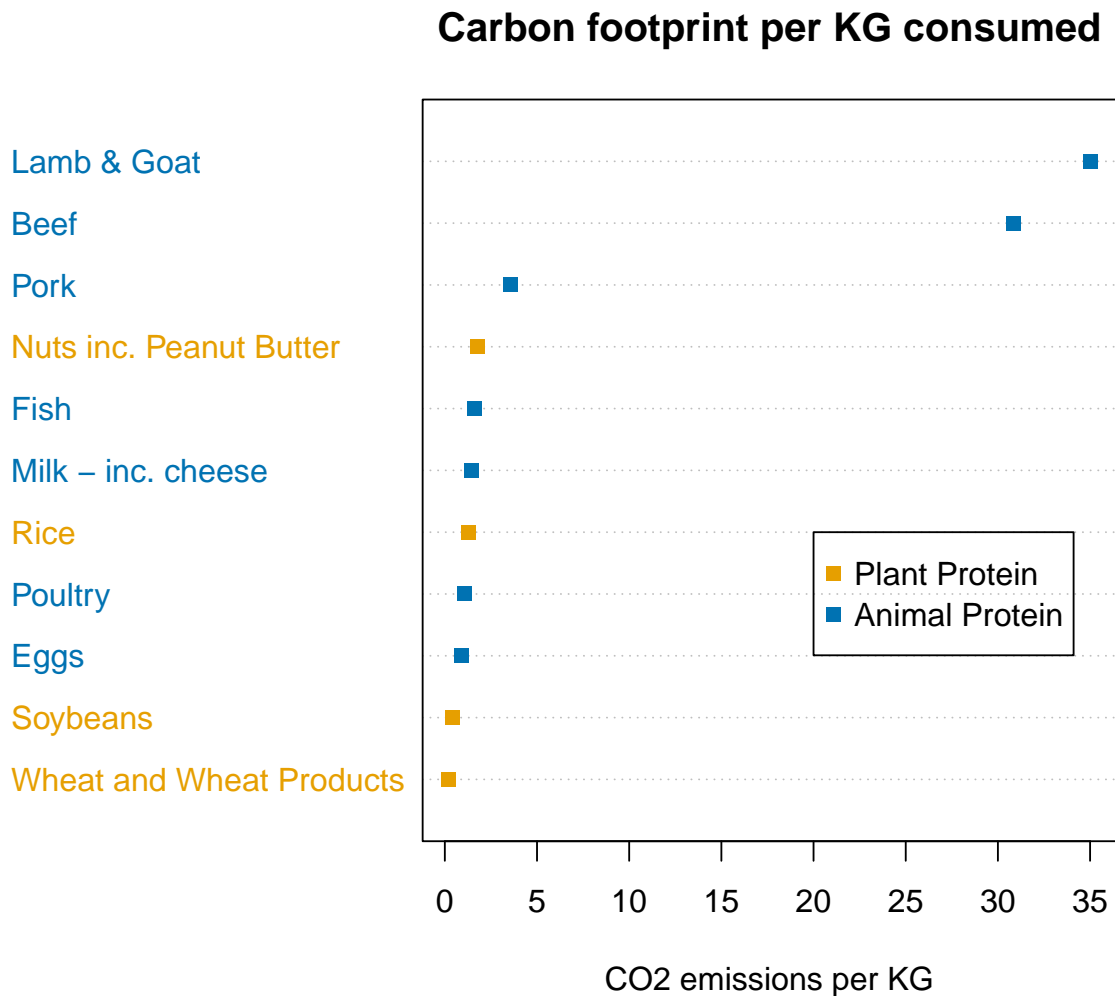


Figure 2: Base R plot of Carbon Footprint of 1KG of each food group

Figure 2 shows that there is significant variation in the carbon footprint of food types with Beef and Lamb having the highest emissions by KG consumed with everything else being significantly less. We can also see an overall pattern that generally plant based proteins have a lower carbon footprint than animal proteins.

## 1.5 Does Consumption affect Carbon Footprint?

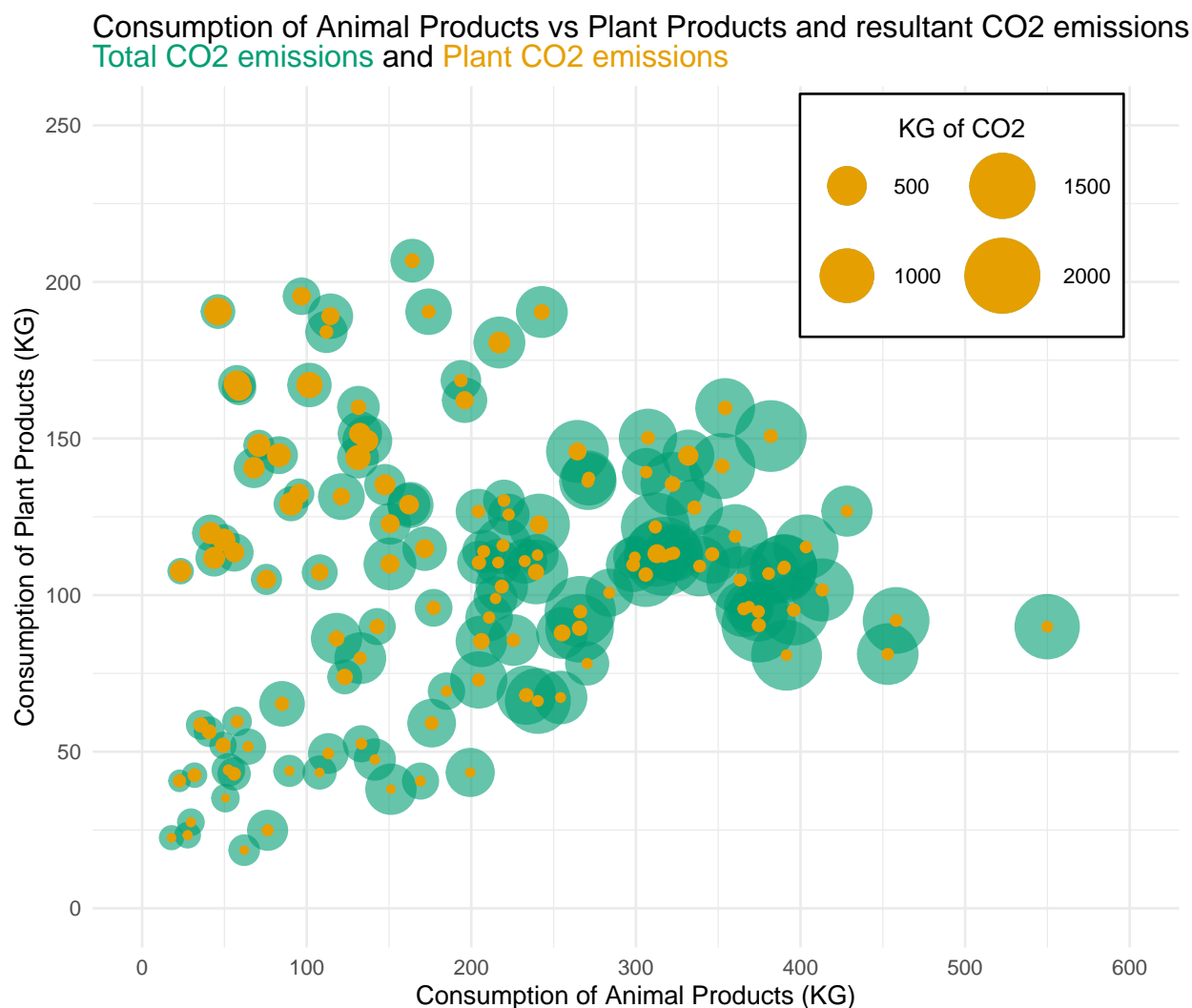


Figure 3: CO2 Emissions by country

Figure 3 explores whether a country's consumption of animal vs plant protein affects its overall carbon footprint. We can see that the largest bubbles appear to the right of the plot with high animal protein consumption. Although it is worth noting the pattern that as animal protein consumption increases, plant protein generally increases too, but the converse isn't true. There are many countries with a high level of plant protein consumption that don't have a high consumption of animal protein.

Another interesting point from this graph is that for the majority of countries the majority of their emissions come from animal products as the area of their point is mainly attributable to non-plant CO2 emissions. We can begin to explain this by using what we've learnt from figure 1 and 2, namely that animal products are consumed in large amounts and have a high carbon footprint. We can explore this relationship further in the interactive version of this graph as clicking on each data point gives the country's name and shows a breakdown of its consumption and CO2 emissions as seen in Figure 4.

## 1.6 What are different countries doing?

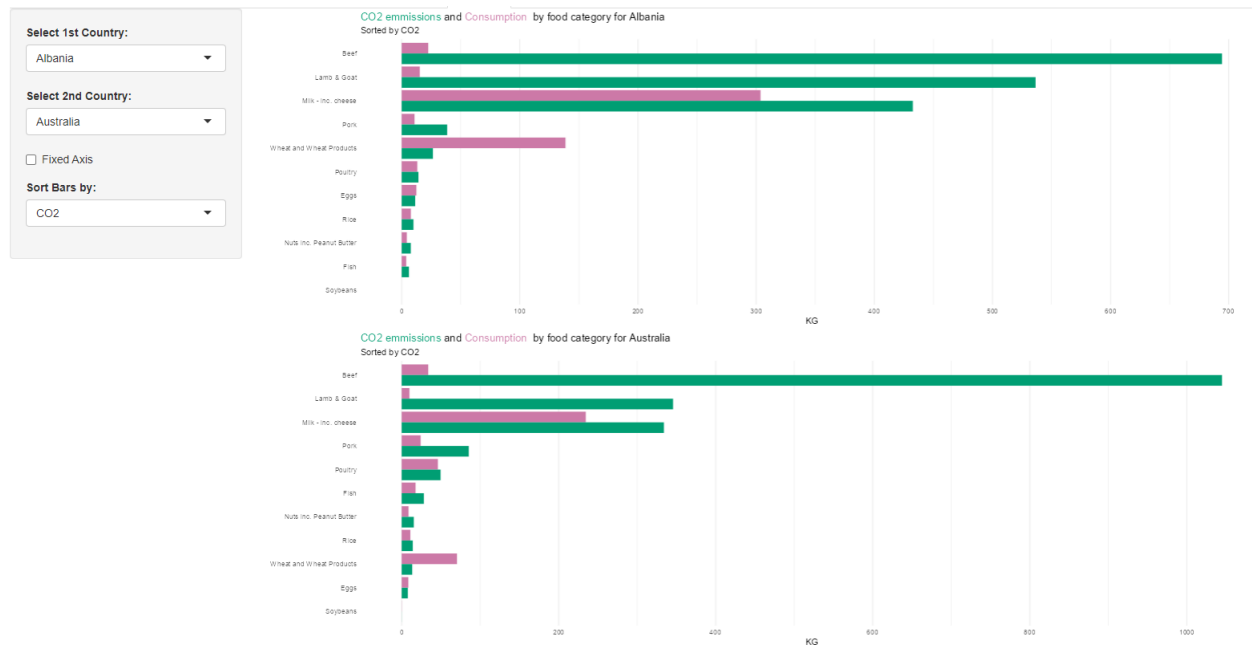


Figure 4: Screenshot of an interactive bar chart allowing user inputs of country, whether to fix the axis and bar sorting criteria

Figure 4 shows a bar chart which can either be accessed by clicking on a point in Figure 3 or by selecting a country from a dropdown menu as shown in the figure. It includes a tick box option to fix the x axis at 0 - 1750KG in order to facilitate comparison between countries but removing this option allows for the finer details of countries with smaller consumption to be better visualised. Additionally we can sort the bars alphabetically (to allow for easy comparison) or by consumption or emissions. These user inputs are included in the plot title and subtitle.

## 1.7 Is there a global pattern to emissions from food?

In order to determine if there is a global pattern to CO2 emissions per person this information was plotted on a map (figure 5). This shows an interesting pattern whereby the lowest carbon footprint appears to be in Africa, Asia and Eastern South America with the highest emissions coming from Europe and North America. Beneath this map is included a measure of wealth of countries and this appears to follow a very similar pattern apart from notably Argentina which has a far higher level of emissions than other countries of a similar level of wealth, which when we look at a breakdown of its consumption as in figure 4 it is because of its very high beef consumption.

## 1.8 How could we improve?

So far we have seen that there is a huge variation in countries carbon footprint from these selected sources of protein. This effect is down to amount of consumption as well as what food types countries are eating. One current global trend is to convert to veganism which involves forgoing any animal protein.

## Mapping of per capita CO2 Emissions and Wealth

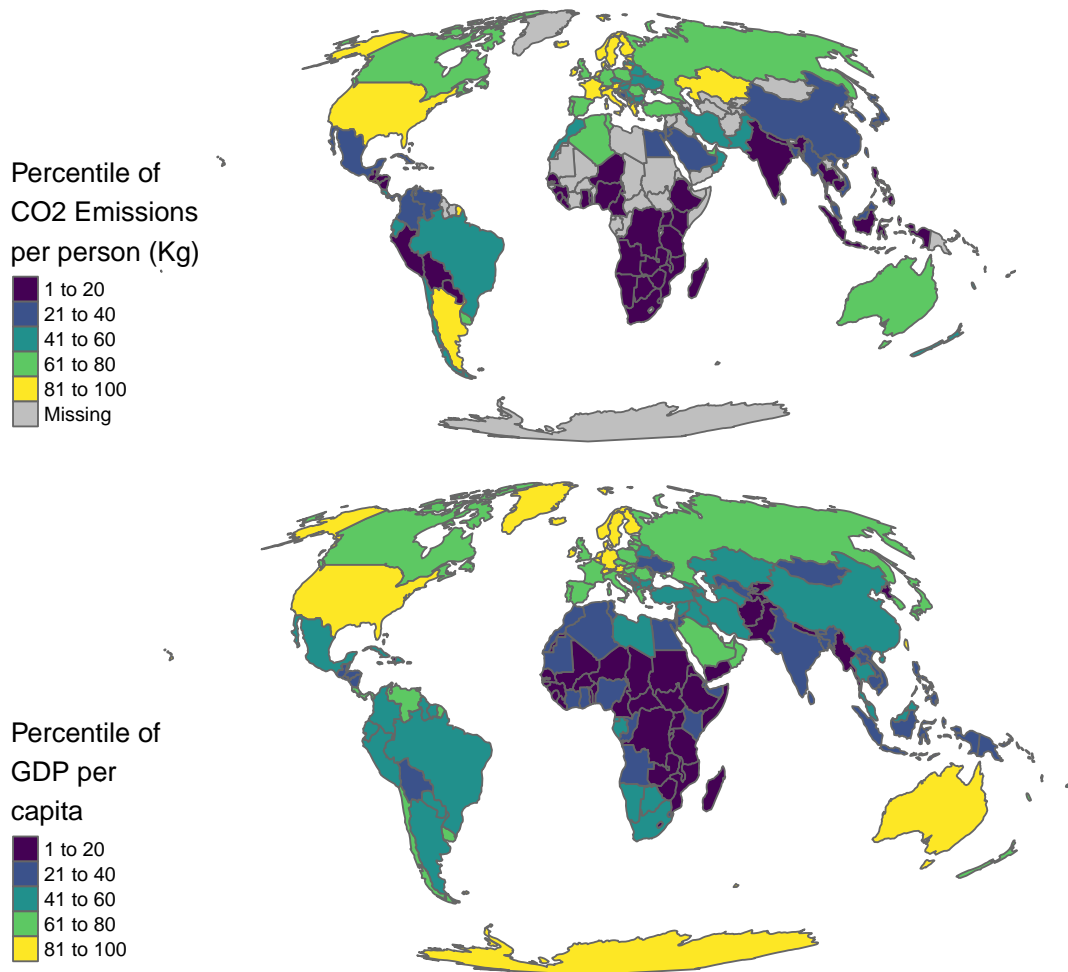


Figure 5: Static map of CO2 emissions and wealth

## CO2 Emissions of the world: Current and Potential Plant and Animal CO2 emissions

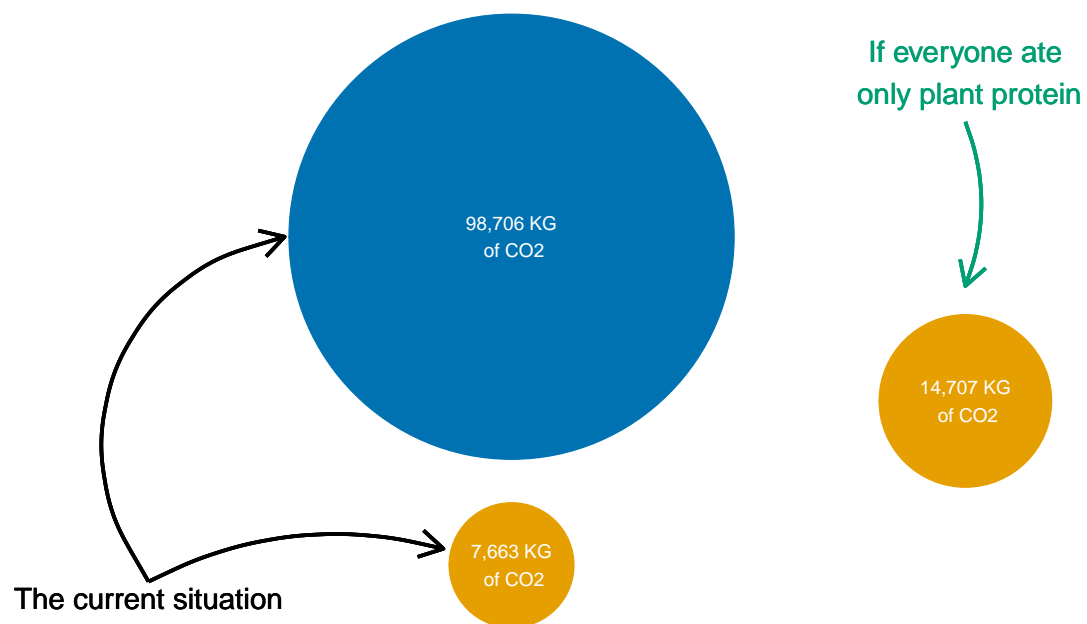


Figure 6: What effect would everyone just eating plant origin protein souces have

In order to explore if this is a potentially beneficial move, the global emissions from transferring every KG of animal protein consumed globally to a plant protein source was calculated and shown in Figure 6. This graphic shows that there is a massive potential to reduce the emissions from global food consumption. A complete removal of animal protein is probably not a sensible move but this graphic does provide a useful starting point in the discussion about reducing our meat consumption especially in the developed world.

## 2 Graph Critique

### 2.1 Bad Graph

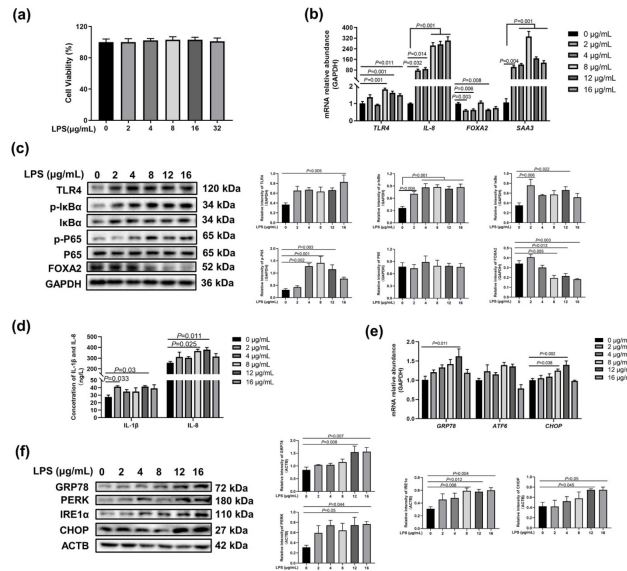


Figure 7: How the bad graph is originally presented by Xie et al (2022)

Figure 7 shows how this graph is originally presented as a part of a figure in the paper by Xie et al (2022). I have appraised graph (b) below but the way in which it is included in the paper surrounded by so much other information and relatively small makes interpretation difficult.

Figure 8 is quite difficult to make any inferences from as it is very cluttered and the message of the graph is very difficult to discern. It lacks a lot of key information, such as a title (D), although an equivalent to this is included in the figure caption. Of more significance is the lack of a legend title (F) as although we can infer that this is probably LPS concentration from the figure information it is possible that it could relate to something else. The legend (F) also suffers from a poor choice of colour scale as although it is consistently used across x-axis categories the colours are so similar it makes comparing the same concentration across categories very difficult. Either direct labeling of the points or a better choice of colour scale would have made this much better. The x-axis is missing a title (C) and so although we can tell there are different categories it isn't clear what these are categories of. The y-axis of this graph (A) although labeled, has two major flaws as it is split and so jumps from 2 to 80 and then has a vastly different scale for the higher numbers. This makes interpretation very difficult and is misleading as to the magnitude of differences between groups. Finally the labeling of P-values (B) adds a lot of clutter to the graph and a more minimal way of labeling such as letters to show significance levels would improve this graph's readability.



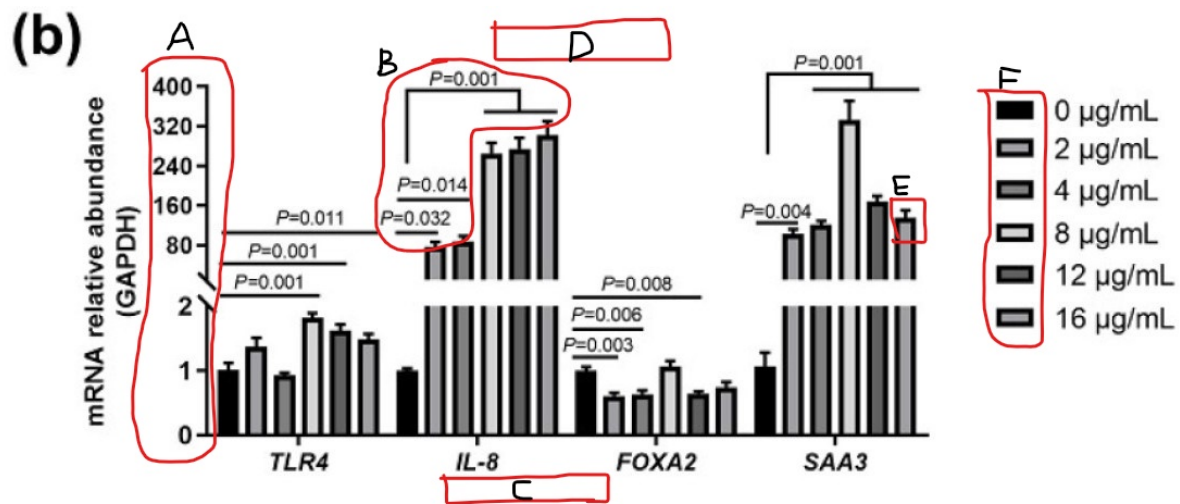


Figure 8: The effect of different concentrations of LPS on bovine hepatocytes by measuring the relative expression of different inflammatory genes to a non-inflammatory gene (GAPDH) from Xie et al (2022)

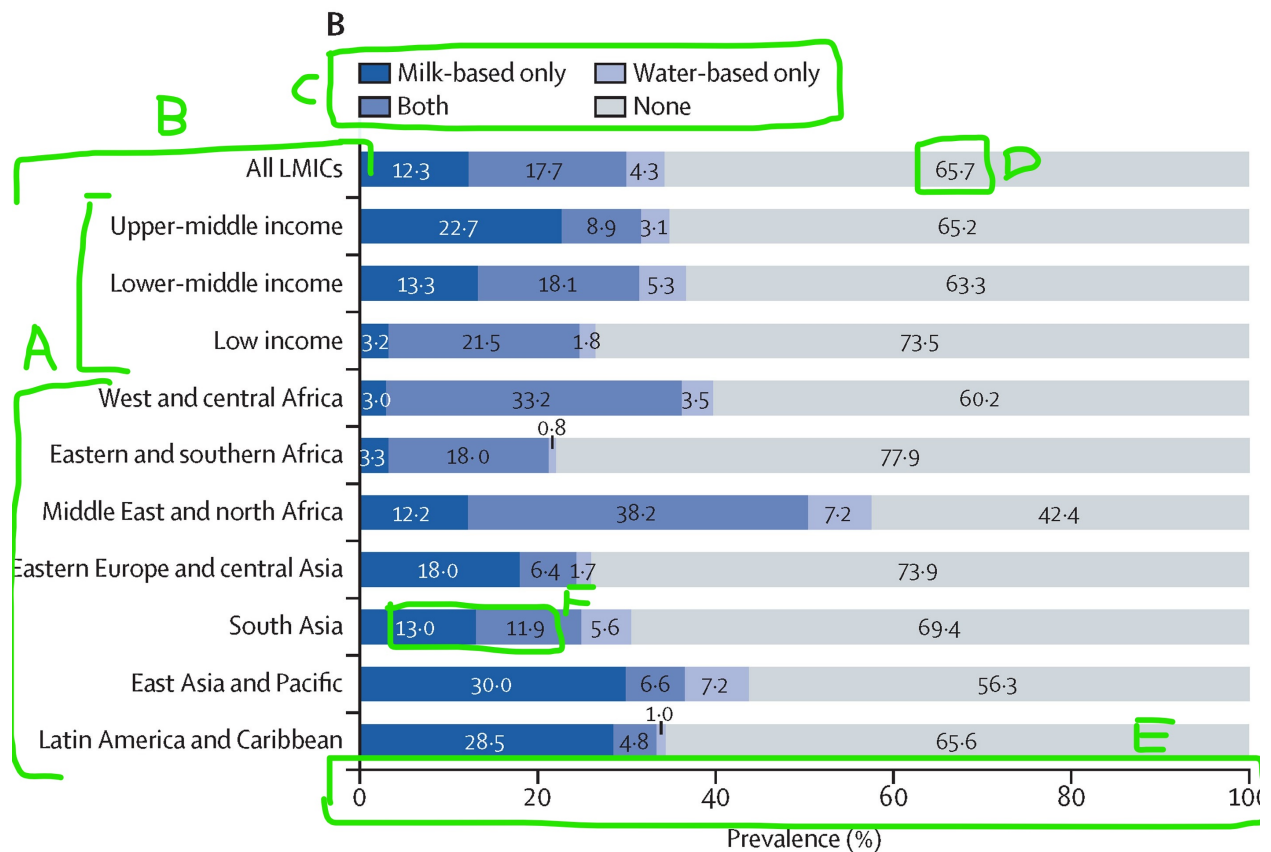


Figure 9: The use of prelacteal feeds in Low and Middle income countries and is from a paper by Baker et al (2023)

## 2.2 Good Graph

Figure 9 manages to convey the information required in an efficient manner although the purpose of the graph isn't clear as it is lacking a title but this information is included in the figure caption. The choice of a stacked bar is appropriate as it is showing the prevalence of categories that will add up to 100%. The axes on this graph are very clear with the x-axis (E) having good sensible breaks and the y-axis has good groupings of variables for comparison (A) and the rotation of the graph allows the y-axis categories (B) to be easily read. The colour choice of the stacked bars (C) allows for clear differentiation between categories. With the direct labeling (D) of the sections of the bar, allow for the exact size of each segment to be read without relying on the reader's inference as this can be difficult to judge with a stacked bar chart. I especially like to draw attention to detail with the changing of colour of the text (F) depending on the background to ensure the text remains clear.

## 3 References

Baker, P., Smith, J.P., Garde, A., Grummer-Strawn, L.M., Wood, B., Sen, G., Hastings, G., Pérez-Escamilla, R., Ling, C.Y., Rollins, N. and McCoy, D. (2023). The political economy of infant and young child feeding: confronting corporate power, overcoming structural barriers, and accelerating progress. *The Lancet*, [online] 401(10375), pp.503–524. doi:[https://doi.org/10.1016/S0140-6736\(22\)01933-X](https://doi.org/10.1016/S0140-6736(22)01933-X).

GitHub. (n.d.). tidyuesday/data/2020/2020-02-18 at master · rfordatascience/tidyuesday. [online] Available at: <https://github.com/rfordatascience/tidyuesday/tree/master/data/2020/2020-02-18> [Accessed 15 Feb. 2023].

Xie, W., Xue, Y., Song, X., Zhang, H., Chang, G. and Shen, X. (2022). Forkhead box protein A2 alleviates toll-like receptor 4-mediated inflammation, endoplasmic reticulum stress, autophagy, and apoptosis induced by lipopolysaccharide in bovine hepatocytes. *Journal of Dairy Science*. [online] doi:<https://doi.org/10.3168/jds.2022-22252>.