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Inequality and Diet: How Are Environmental Impacts from Food Consumption Distributed Across Different Socioeconomic Groups Globally?

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MASTER THESIS

for

Student Kristin Müller Thomassen

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Inequality and Diet: How Are Environmental Impacts from Food Consumption Distributed Across Different Socioeconomic Groups Globally?

Ulikhet og Matvaner: Hvordan Er Miljøpåvirkningen fra Matforbruk Distribuert Mellom Forskjellige Sosioøkonomiske Grupper Globalt?

Background and objective

In the last decades, the part of the world population living in poverty has been decreasing. However, still around 700 million people are still classified as extremely poor while about 800 million are living in chronic hunger. In the Sustainable Development Goals expressed by the UN in 2016, the first ambition is described as "End poverty in all its forms everywhere", aiming at achieving this within 2030. Though positive development in average Human Development Index (HDI) and Gross Domestic Product (GDP) has been observed over the years, a recent report from the Food and Agriculture Organization elucidates that even though inequality *between* countries seems to be improving, the inequality *within* countries has been increasing. Consequently, the eradication of poverty within 2030, even before 2050, have been suggested to be an impossible goal to achieve with current development patterns.

Important drivers for causing larger disparities in income on national levels are increased globalization and changes in international trade patterns. Research reveals that current trends of displacement of manufacturing activities from development countries to lower income areas is causing larger income inequalities. Further, important keys towards reaching the SDGs are found in the agricultural sector through sustainable production approaches and achieving food security.

The work conducted prior to this paper focused on the relationship between average development, food consumption patterns and its effect on three environmental footprints; the carbon footprint, land use footprint and blue water consumption. The results revealed slight correlations between development and some of the footprints, however, they did not reflect the impacts caused by the different in-country socioeconomic groups. The habits and impacts caused by people of contrasting economic status is beneficial for carrying out a more comprehensive analysis on global development, which is why this aspect will be taken into account in this paper.

To achieve greater insight into the development and consumption patterns of the world's poor, the Gini coefficient for both income and the three footprint indicators caused by food consumption will be investigated. By simulating data and comparing results from 2004 and 2011, the effect of increased globalization on environmental and economic displacement of impacts within countries will be assessed. If time allows, different scenarios will be assessed to explore the scale of impacts towards 2030.

The following tasks are to be considered:

1) Conduction of a literature review on:
    a. Globalization and trade patterns.
    b. Drivers for increased poverty.
    c. Link between agriculture/food production and poverty alleviation.
    d. Environmental impacts of different economic groups on both a global and regional level.

2) Modelling of environmental footprints for different socioeconomic groups, as well as calculation of environmental and income Gini coefficients.

3) Analysis of relationships between trade patterns, inequality and environmental displacement.

4) Discussion of possible future scenarios and development patterns.

Within 14 days of receiving the written text on the master thesis, the candidate shall submit a research plan for his project to the department.

When the thesis is evaluated, emphasis is put on processing of the results, and that they are presented in tabular and/or graphic form in a clear manner, and that they are analyzed carefully.

The thesis should be formulated as a research report with summary both in English and Norwegian, conclusion, literature references, table of contents etc. During the preparation of the text, the candidate should make an effort to produce a well-structured and easily readable report. In order to ease the evaluation of the thesis, it is important that the cross-references are correct. In the making of the report, strong emphasis should be placed on both a thorough discussion of the results and an orderly presentation.

The candidate is requested to initiate and keep close contact with his/her academic supervisor(s) throughout the working period. The candidate must follow the rules and regulations of NTNU as well as passive directions given by the Department of Energy and Process Engineering.

Risk assessment of the candidate's work shall be carried out according to the department's procedures. The risk assessment must be documented and included as part of the final report. Events related to the candidate's work adversely affecting the health, safety or security, must be documented and included as part of the final report. If the documentation on risk assessment represents a large number of pages, the full version is to be submitted electronically to the supervisor and an excerpt is included in the report.

Pursuant to “Regulations concerning the supplementary provisions to the technology study program/Master of Science” at NTNU §20, the Department reserves the permission to utilize all the results and data for teaching and research purposes as well as in future publications.

The final report is to be submitted digitally in DAIM. An executive summary of the thesis including title, student’s name, supervisor's name, year, department name, and NTNU's logo and name, shall be submitted to the department as a separate pdf file. Based on an agreement with the supervisor, the final report and other material and documents may be given to the supervisor in digital format.

☐ Work to be done in lab (Water power lab, Fluids engineering lab, Thermal
☐ engineering lab) Field work

Department of Energy and Process Engineering, 15. January 2018

Richard Wood

Academic Supervisor

Abstract

In the age of globalization, rapid population growth, increased flow of products across borders and a rising demand for food, have been rising concern amongst international organizations. On the other hand, globalization has also largely contributed to increasing the level of world development, thus lifted millions out of poverty. However, recent reports reveal that this has failed to include everyone – even though average development is rising, inequality is becoming an escalating problem. With expectations of a population of 9.15 billion by 2050, the agricultural sector will be required to expand its production significantly in the coming decades to ensure food security for everyone. Moreover, through the Sustainable Development Goals (SDGs) of the UN published in 2016, the aspirations to mitigate climate change, reduce inequality and eradicate hunger were expressed, which further rose awareness around these issues. However, an arising challenge with the SDGs is how the policies towards them may negatively affect each other. Eradicating hunger might mean that increased food production is necessary, which again might influence the climate negatively – a factor that has been shown to increase inequality. Further, some studies have pointed towards a correlation between rising development levels and environmental footprints, however, few have addressed this on a socioeconomic level. Also, some researchers have found Environmental Gini Coefficients (EGCs) from consumption of all commodities, however, conspicuously few have considered only food products. Therefore, even though rising environmental impacts from food are observed, addressing *who* – i.e. which regions and income quintiles – is actually responsible for this and how this might further affect inequality is yet to be examined. The question comes down to this – how can we ensure food security while at the same time foster climate change mitigation and reduce inequality? – an issue that will be approached by delving into consumption habits of people in different socioeconomic levels.

In this study, the environmental impacts of food consumption were measured for 44 countries and 5 regions over an eight-year period (2004-2011) for five different income quintiles. The impacts were assessed in terms of three footprint categories; global warming potential (GWP), land use (LU) and blue water consumption (BWC). To address the footprint distribution across the quintiles, the Environmental Gini Coefficients (EGC) were calculated for each year. Further, Income Gini Coefficients (IGC) and the Human Development Index (HDI) were included to see the results in a development perspective. Ultimately, the contribution to the footprints of each food product was calculated. Information on quintile consumption from the environmentally extended Input-Output database EXIOBASE, income shares from The World Bank and World Income Inequality Database and HDI from the UNDP were imported to MATLAB for calculations.

The results argue that all global footprints from food consumption have been increasing in absolute and per capita values since 2004. The largest rise was observed for the two upper quintiles, which additionally had a share of 59-61% combined of total global footprints from food consumption in 2011. Globally, the upper middle class (quintile 4) was found to have the most increasing GWP FP and LU FP. Further, the global GWP FP and LU FP were observed to be decreasing during The Global Financial Crisis around 2008, where the footprints from the poorest quintiles were found to be the most sensitive to the economic changes caused by the crisis. The EGCs were observed to be steadily increasing from 2004 to values of 0.379 (GWP), 0.389 (LU) and 0.374 (BWC) in 2011. Regionally, China, United States, Indonesia and RoW Africa were found to experience rising footprint inequality, whereas Norway and Brazil were growing more equal. Meat from cattle, milk and dairy were observed to have the most impact on GWP and LU, whereas wheat and nuts were most important for BWC. The global results indicate that environmental impacts from food is increasingly caused by those of higher income groups, thus the distribution of footprints is growing more unequal.

Sammendrag

I de siste årene med globalisering har et raskt voksende folketall, økt strøm av produkter over grenser og en økende etterspørsel etter mat vært en kilde til bekymring for internasjonale organisasjoner. På en annen side, har globalisering i stor grad bidratt til å øke verdens utviklingsnivå og dermed løftet millioner ut av fattigdom. Riktignok viser nylige rapporter at ikke alle har blitt inkludert i dette – selv om gjennomsnittlig utviklingsnivå har økt, har også ulikhet mellom mennesker blitt et stigende problem. Med forventninger om å nå en folkemengde på 9.15 milliarder innen 2050, er jordbrukssektoren nødt til å utdvide produksjonen betydelig i de kommende tiårende for å sikre mat til alle. Videre uttrykte FN målene om å motarbeide klimaendringer, redusere ulikhet og utrydde sult gjennom sine Bærekraftsmål i 2016, hvilket videre økte oppmerksomheten rundt disse temaene. En stigende utfordring med Bærekraftsmålene er imidlertidig hvordan forsøk på å nå en av dem kan negativt påvirke tiltak for å nå et annet. Å utrydde sult vil mulig bety at økt matproduksjon er nødvendig, noe som igjen vil påvirke miljøet negativt – en faktor som har blitt vist at bidrar til økende ulikhet. Noen studier har pekt på sammenhengen mellom stigende utviklingsnivå og miljøfotavtrykk, men få har foreløpig undersøkt dette på et sosioøkonomisk nivå. Tillegsvis har noen forskere funnet Miljøbaserte Gini-koeffisienter fra forbuk av alle produkter, men påfallende få har fokusert kun på mat. Derfor, selv om et økende miljøfotavtrykk fra mat har blitt observert, gjenstår det fremdeles å analysere *hvem* – det vil si hvilke regioner og inntektskvintiler – som er ansvarlig for disse og hvordan dette kan påvirke fremtidig ulikhet. Problemet kommer ned til følgende – hvordan kan vi oppnå matsikkerhet og samtidig motarbeide klimaendringer og ulikhet? – et spørsmål som vil bli besvart ved å gå i dybden av menneskers forbruksvaner i ulike sosioøkonomiske nivåer.

I dette studiet ble miljøpåvirkningen av matforbruk målt i 44 land og 5 regioner over en åtteårsperiode (2004-2011) for fem ulike inntektskvintiler. Påvirkningen ble målt i i form av tre fotavtrykk-kategorier; Global oppvarming (GWP), Landforbruk (LU) og Blått vannforbruk (BWC). For å undersøke fordelingen av fotavtrykkene mellom kvintilene, ble Miljøbaserte Gini-koeffisienter (EGC) kalkulert for hvert år. Videre ble Inntektsbaserte Gini-koeffisienter (IGC) og Inndeksen for Menneskelig Utvikling (HDI) inkludert for å se resultatene i et utviklingsperspektiv. Til slutt ble bidraget til fotavtrykkene per matprodukt regnet ut. Informasjon om kvintilforbruk fra den miljøutvidede kryssløpsdatabasen EXIOBASE, inntektfordeling fra The World Bank og World Income Inequality Database og HDI fra UNDP ble importert til MATLAB for utregninger.

Resultatene argumenterer for at alle globale fotavtrykk fra matforbruk har økt i både absoluttverdi og per innbygger siden 2004. Den raskeste veksten ble observert for de to øvre kvintilene, hvilket tillegsvis kombinert var ansvarlige for 59-61% av globale fotavtrykk fra matforbruk i 2011. På et globalt nivå ble øvre middelklasse (kvintil 4) funnet til å ha mest voksende GWP- og LU fotavtrykk. I tillegg ble det funnet at GWP- og LU fotavtrykkene sank under Den Globale Finanskrisen rundt 2008, hvorpå påvirkningen fra de fattigste kvintilene var mest sensitive til de økonomiske endringene under krisen. EGC-ene ble funnet til å stige jevnt fra 2004 til verdier på 0.379 (GWP), 0.389 (LU) og 0.374 (BWC) i 2011. På et regionalt nivå, ble Kina, USA, Indonesia og RoW Afrika funnet til å oppleve økende ulik fordeling av fotavtrykk, hvorpå Norge og Brazil viste motsatte tendenser. Kjøtt fra storfe, melk og melkeprodukter ble funnet til å ha størst påvirkning på GWP og LU, mens hvete og nøtter var viktigst for BWC. De globale resultatene indikerer at miljøpåvirkninger fra mat i økende grad er forårsaket av mennesker i de øverste inkomstkvintilene og at fordelingen av fotavtrykk fra matforbruk dermed tenderer mot å bli gradvis mer ulik.

Preface

This thesis concludes my Master of Science in Energy and Environmental Engineering at the Norwegian University of Science and Technology (NTNU) at the Department of Energy and Process Engineering (EPT).

After coincidently stumbling upon a documentary on the environmental impacts of livestock three years ago, my interest around footprints from food consumption sparked significantly. First believing the statements in the documentary to be false, I eventually realized after further investigation, that they certainly were not. Since then, world food consumption has interested me largely, not solely because of its potential environmental impacts, but also largely because of the ethical aspect of production of animal-based foods. Through choosing a specialization within Energy and Environmental Analysis, I was able to follow the input-output course from the Program of Industrial Ecology, which fortunately enabled me to explore the footprints from food consumption even further.

My project thesis focused on the development of food footprints over a 17-year period for 49 regions. The outcomes from the analyses provided me with a deeper understanding of the topic and inspired me to continue the research of the subject.

Firstly, I would like to express my gratitude to my supervisors, Professor Richard Wood and PhD candidate Gibran Vita, for excellent guidance and support during the work on this thesis. They have provided me with valuable help, feedback and thought-provoking discussions which have been of particulate importance to me this semester. Secondly, I would like to thank my family, Ingrid, Bjørn Harald, Håkon and Harald for their moral support and important advices throughout the process of completing this 5-year master program.

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Abbreviations

BWC	Blue water consumption
CF	Carbon footprint
EE	Emerging economies
EF	Ecological footprint
EGC	Environmental Gini Coefficient
EU	European Union
GC	Gini Coefficient
GHG	Greenhouse gas
GTP	Global temperature change potential
GWP	Global warming potential
ICT	Information and Communication Technology
IGC	Income Gini Coefficient
IPCC	Intergovernmental Panel on Climate Change
LU	Land use
N.e.c	Not elsewhere classified
OECD	Organization for Economic Cooperation and Development
RoW	Rest of World
SDG	Sustainable Development Goal
SEI	Stockholm Environment Institute
SES	Socioeconomic status
SVG	Scalable Vector Graphic
UN	United Nations
USA	United States of America
USDA	United States Department of Agriculture
WF	Water Footprint
WIID	World Income Inequality Database
WTO	World Trade Organization

1 Introduction

1.1 Background: Linking globalization, inequality and food consumption

Introducing the Sustainable Development Goals (SDGs) in 2015, the United Nations (UN) expressed their mission of working towards a world free of hunger, climate destruction and significant inequality (United Nations, 2016). However, despite many actions already being exercised, later evaluations show that significantly more policy changes are needed in order to fulfill the goals (Klapper et al., 2016). In particular, the UN recently declared that the targets of eradicating hunger and alleviating poverty to be unachievable with the current trends of rising inequality (United Nations, 2017b). This rise in inequality has been further strongly linked to globalization and climate change, which is further interconnected with the agricultural sector and food production (IPCC, 2014a; United Nations, 2017b). Thus, it could be argued that the link between globalization, inequality, climate change and food consumption is not only highly relevant, but perhaps also vital to study to a larger extent in order to ensure inclusive development.

Inequality plays a key role in the pursue of securing sustainable development (United Nations, 2017a), which is why it is of high importance when studying social improvements and advancements. Recent economic growth has lifted millions out of extremely scarce living conditions and created opportunities at a faster speed than ever before (United Nations, 2017b). As a main driver of this, globalization has also provided people access to increasingly advanced technologies and raised the flow of commercial products over borders (United Nations, 2017a). However, globalization has failed at one point – *inclusion* – as it has tended to leave a generous number of people behind (Mills, 2009). Studying the implementation of the SDGs, Klapper et al., (2016) stated that *"[...] income inequality between rich and poor in advanced economies remains at its highest level in decades"*, also pointing towards similar tendencies in developing countries. Further, globalization has not only contributed to increasing inequality. Especially, through e.g. escalating the speed of trade and product demand, hence accelerating the emissions from commodity consumption, the climate has been changing faster than ever, particularly affecting those living in already scarce conditions (FAO, 2016; The World Bank, 2010). Therefore, a key to ensure the goal of ending hunger is not only to provide food in itself, but also to mitigate climate change and to support equality.

An essential point is the significant impact food consumption has on the climate itself (Steinfeld et al., 2006). In the age of globalization and decreasing food prices, the prevalence of more emission-intense diets has expanded, significantly increasing the environmental footprints from food demand (Kearney, 2010). From this we can observe how the policies towards the SDGs are counteracting – eradicating hunger and poverty demands changes in food production and increased income – however, as the affluency is rising, so are the footprints from food consumption. This does not only potentially contravene aspirations to ensure equality, but can also have unwanted consequences for the work of preventing hunger and poverty. Consequently, this accentuates the importance of studying the relationship between globalization, inequality, climate change and diets.

Several studies have been done on the relationship between globalization and inequality (Alsamawi et al., 2014; Mah, 2002; Mills, 2009; Sutcliffe, 2004). Furthermore, a large span of literature has been written on the correlation between diet and climate impacts (Bajzelj et al., 2014; Foley et al., 2011; Gephart et al., 2016; Kearney, 2010; Steinfeld et al., 2006; Tilman and Clark, 2014). However, markedly few have attempted to combine these four topics. As these four are interconnected, it is important to understand the link between them to ensure that future policy-making will come to benefit all SDGs, and not only some of them. The goal of earlier work was to investigate the correlation between development in terms of the Human Development Index (HDI) and footprints resulting from food consumption, attempting to investigate the link between poverty alleviation and environmental impacts (Thomassen, 2017). However, the HDI is given in terms of the average development of a country and does not take inequality into account. Therefore, the HDI does not say anything about in *which* socioeconomic level development has taken place, which is what will be assessed in this study. E.g. if the 10% richest of an arbitrary nation experience an increase in income and literate levels while the remaining 90% encounter no change, the HDI will still be increasing. To state that the nation has been developing could therefore be misleading, as the people that needed improving their living conditions experienced no change at all. For this reason, to fully understand the link between development, food consumption and environmental impacts, including inequality levels might be certainly beneficial. Poverty alleviation and hunger eradication are urgent matters that call for action – not only on a political level, but also through research. Certainly, there is an obvious gap in the literature combining climate change, food and inequality – an important gap this study will be attempting to fill.

1.2 Relevant questions and goal of research

This research aims at investigating the environmental impacts from food consumption in terms of Global Warming Potential (GWP), Land use (LU) and Blue water consumption (BWC). Further, to open for deeper understanding of the correlation between development and consumption patterns, a time span of 8 years (2004 - 2011) will be analyzed. The following research questions will be answered:

- How are the footprints from global food consumptions from the different quintiles changing with time?
- How are the footprints distributed between global income classes in terms of Gini Coefficients?
- Which income quintiles are contributing the most to the footprints?
- Are these outcomes different when analyzing consumption on a regional level?

Firstly, previous studies on inequality and globalization will be assessed, followed by elaborations on consumption patterns and footprints from food consumption. Then, research attempting to estimate future scenarios will be evaluated. In the method section, applied materials and analysis approaches will be presented, followed by a presentation of the outcomes of the analysis in the result section. Thereafter, the findings will be discussed and compared with previous literature.

2 Literature review

2.1 Inequality and development

2.1.1 Approaching the term "Inequality"

First and foremost, it is vital to get a comprehensive understanding of the word "inequality", as it can be highly complex. As stated by Sutcliffe (2004), the term "inequality" can be approached in different ways. There is a distinction between inequality between countries and within countries, as well as various types of inequality. Are we addressing differences in incomes, between genders, access to environmental resources or levels of development? The importance of specifying the exact utilized measures is elucidated by Mills (2009), as it may impact the outcomes significantly. Approaching the question of why some researchers asserts that globalization has accentuated inequality while others claim this to be entirely wrong, Mills (2009) explains this to be a cause of different factors, such as unweighted vs. population-weighted approaches, the use of a comparative currency (Unadjusted Foreign Exchange Rates or Purchasing Power Parity) and the way inequality is measured. Importantly, most of the recent literature on the matter seem to agree that inequality, both inter-country as well as intra-country for all currencies, is in fact rising (United Nations, 2017a).

Inequality can be measured in several ways, where applying the Gini Coefficient is one of the more popular ones (Mills, 2009; Sutcliffe, 2004). The term was first defined in the paper *"Variabilità e Mutabilità"* by Corrado Gini in 1912, and represents the inequality between values of a distribution, e.g. numbers of income (Ceriani and Verme, 2012). In an income perspective, a Gini Coefficient of 0 implies perfectly equal incomes, whereas a value of 1 signifies that one individual earns 100% of possible income (Ceriani and Verme, 2012). Between 2009 and 2011, The World bank could report world Income Gini Coefficients (IGCs) starting at 0.25 in Ukraine and Slovenia at the lowest, until 0.61 in Namibia and 0.63 in South Africa at most (The World Bank, 2017). Other numbers of specific interest of this paper are given for China (0.43), Brazil (0.54), United States (0.40) and Norway (0.25). The IGC has been applied in several studies of inequality (Alsamawi et al., 2014; Mah, 2002; Teixidó-Figueras et al., 2016; White, 2007), however, various alternative measures exist (Mills, 2009). Integration of income distributions (WDI), mean logarithmic deviation of income (MLD), the Theil index (Sala-i-Martin, 2006), the Pareto distribution and the lognormal distribution (Cowell, 2009) are all ways of measuring inequality, however, the Gini Coefficient seems to be the most dominant choice (Mills, 2009). Understanding the Gini Coefficient or other measures of inequality of a nation may be highly important to sufficiently comprehend how inequality is affecting the general development of the country (Madsen et al., 2018).

2.1.2 Importance of equality for development

Understandably, large disparities in a society contravene with the sense of fairness, especially when the affected ones have no power to change them (The World Bank, 2006). Growing up in extreme poverty may in many cases lead to social exclusion, as well as increasing despair of not being able to change one's living conditions, consequently enticing violent acts (United Nations, 2005). The number of criminal incidents has been found to increase in correlation with in inequality, both within and between countries (Fajnzylber et al., 2002). Agreeing with the findings of Fajnzylber et al. (2002), Morenoff et al. (2001) also addresses the topic by pointing towards crime rates being affected by proximity to violent areas, i.e. individuals living close to atrocity will be more likely to take part destructive actions themselves. A more violent society is not as capable as more peaceful nations to ensure security and sustainable living conditions for its inhabitants, thus counteracting the fight for equality (United Nations, 2005). Further, an interesting study by Klein (2006) exemplifies the social pressure to fit in to a certain *"perfect picture"* as being a large driver for high school kids turning into bullies in The United States. Those who could not meet the felt expectations from the society, independent of economic status, would be more prone to behave unacceptably (Klein, 2006). This broadens the inequality term, as it not only encompasses incomes, living conditions, access to resources et cetera, but also personal conditions such as intelligence, athletic talents, sexuality and relationships. In general, increasing incidents of social conflicts rooted in rising inequality, environmental degradation, climate change and scarcity of resources are all factors that threatens the aspirations to secure sustainable development, and importantly, these are all interconnected with globalization (SEI, 2015).

Even though globalization has been credited for contributing to overall economic enhancements of nations, it has been criticized for increasing intra-country inequality, both economically (Alsamawi et al., 2014; Mah, 2002; Mills, 2009) and environmentally (Hubacek et al., 2017; Teixidó-Figueras et al., 2016; White, 2007). According to the UN, almost every country globally has seen rising inequality within their borders, the drivers being mainly due to changing labor markets, climate change and quick advancements in technology (United Nations, 2017a). Interestingly, these factors does not only affect developing countries with lower social security – also high-income countries face challenges (OECD, 2011). For instance, the rapid development in the high-tech sector have created several opportunities for highly skilled people in developed countries, leaving those with lower education behind (United Nations, 2017a). With increasing demand for people with university degrees and emerging tendencies to replace low-skilled workers with technical equipment, inequality remains increasing (OECD, 2011). However, this shift might have positive impacts for developing countries (Mills, 2009). As developed nations have tended to displace manufacturing processes to lower-income countries, wages and job opportunities for lower-skilled workers have risen, accompanied by a decrease in income for people in higher-skilled occupations (Mills, 2009). Conclusively, technological advancement might improve equality levels in developing countries, while supporting inequality in others. Importantly, the solution does not lie in the overall economy, but rather in the hands of policymakers (The World Bank, 2006). Through policies aiming at providing access to assets and opportunities for all socioeconomic groups, improving the possibility for secure employment and enhancing social integration, inequality can be ameliorated (United Nations, 2005), however, this has not yet been conducted to a sufficiently large extent.

Furthermore, the climate is changing conspicuously more rapidly than ever. Emerging trends of urbanization and lifestyle changes are important factors for increasing the need of resources and energy, something that cause an increasing stress on the environment (United Nations, 2017a), consequently impacting economic conditions of individuals. Through threatening e.g. the agricultural sector, the livelihoods of most of the world's poor, climate change is a phenomenon that largely impacts inequality (FAO, 2016). Attempting to find a relationship between climate change and inequality, Islam and Winkel (2017) designates a "viscous cycle", where those whose social standards are low are more prone to environmental changes, consequently decreasing their standards even more. Roberts (2001) addresses the same issue, while also pointing out that the ones who suffer in general are not those who caused the problem in the first way, something that can be perceived to be unfair. In 2015, top 10% emitters were responsible for around 45% of all global emissions (Chancel and Piketty, 2015). The world's poor are not only affected through decreased yields, also global warming could lead to higher mortality rates in warmer areas, increased appearances of damaging tropical storms, as well as leading to decreased productivity in low-income labor sectors with outdoor working conditions, e.g. construction and mining (Hsiang et al., 2017). Clearly, environmental change and damage have significant impacts on inequality, which is why elaborating on one of the main drivers of climate change – globalization – is highly relevant for achieving a deeper understanding of inequality.

2.1.3 The effect of globalization on inequality

2.1.3.1 Definition of globalization

As with inequality, *globalization* undoubtedly gravitates towards being a term of high complexity. Over the last decades, many experts have attempted to formulate a definition for the term (Al-Rodhan and Stoudmann, 2006; Reich, 1998). In his comprehensive literature review, Reich (1998), defines the concept in four different manners that all take the interplay between culture, economics and politics into account. However, the four interpretations are all based on distinctive approaches; historical, economic, sociological and technological, thus making the process of creating one single definition difficult (Reich, 1998). Further, in a similar literature research, Cuterela (2012) points towards the tendency that many of earlier definitions has been based on seeing globalization from a Western imperialistic point of view, arguing this to be intrinsically wrong. The concept involves the world as a whole; its cultures, politic views, goods and people, and should therefore be defined from a global standpoint (Cuterela, 2012), even though this might be a troublesome chore. While agreeing with the invention of a single description of globalization being severely challenging, Al-Rodhan and Stoudmann (2006), still proposes the following definition: *"Globalization is a process that encompasses the causes, course and consequences of transnational and transcultural integration of human and non-human activities"*, a result after reviewing 113 suggested descriptions formulated from 1974 until 2006. In their recent report from 2017, the United Nations utilizes a slightly different approach, stating that *"Globalization refers to the growing integration of trade and financial markets, the spread of technological advancements, the receding geographical constraints on social, cultural and migratory movements and the increased dissemination of ideas and technologies"* (United Nations, 2017a). Even though the cited definitions are distinct, they portray the same concept of a world in economic, cultural and political development that increases the interconnectedness among its people. The complexity of this phenomenon is intricated, and in order to parse its correlation with inequality, diving into its underlying drivers and trends might be highly advantageous.

2.1.3.2 Trends and drivers

Globalization is an elaborate phenomenon that is caused by numerous drivers (Bang and Markeset, 2012; Lane and Milesi-Ferretti, 2008; Tvaronavičienė et al., 2011; Yip, 1989). Yip (1989) points towards four tendencies that affect the increasing of international trade – market, cost, governmental and competitive drivers. With the rapid expansion of technological advancements, the possibility of trade over country borders continues to grow, giving customers the option to choose products from a foreign producer (Yip, 1989). This tendency is also underpinned by the report from United Nations (2017), also stating that the rapid speed of technical development in the last century is not only highly affecting consumer choices, but also the labor market. Further, due to contrasting wage levels of different regions, producing costs may be significantly reduced if the manufacturing process is moved from a developed to a lower-income country (Yip, 1989). This is further elaborated on by (Tvaronavičienė et al., 2011), where the authors specifically focus on the lower tax-burdens of less developed countries as one of the main drivers. In contrast, the main cause of globalization in developed countries is their capacity of consumption (Tvaronavičienė et al., 2011). Moreover, for some companies a market of a single-country may not be large enough to fill their potential scope of economies, giving them incentives to spread to wider levels (Yip, 1989). With increased flow of goods over country borders, also market competition may increase significantly, pressuring companies to globalize (Bang and Markeset, 2012). An example of this is the trade liberalization connected to the implementation of the Euro in the EU (Lane and Milesi-Ferretti, 2008). After reviewing several papers on the drivers of globalization, Bang and Markeset (2012) chooses to summarize them to the following: decreases in trade barriers, transportation costs, as well as communication costs, in addition to development of Information and Communication Technology (ICT) and spreading of technology. This is also in alignment with the findings of Tvaronavičienė et al. (2011).

According to the World Trade Organization, the distribution of market shares have been changing since the mid 50's (WTO, 2008). From 1955 to 2006 the share of developed countries in global produced exports has declined steadily, especially within textile, clothing and office equipment manufacturing (WTO, 2008), thus somehow decreasing inter-country inequality. Some developing countries, on the other hand, have faced massive growth in exported goods; China being a descriptive example of this (Feenstra and Wei, 2010). In their study of trade patterns of this country, Feenstra and Wei (2010), found that the exports from China rose by 500 percent between 1995 and 2010, especially that of hard manufactures, like computers, electronics and appliances. Just as thought-provoking as important, the researchers also point towards the trend of Chinese goods being steadily decreasing in price, possibly contributing to the rise of global competition among goods (Feenstra and Wei, 2010). In 2008 developing economies were responsible for around two thirds of all clothing exports and more than a half of all internationally traded textiles and telecom equipment (WTO, 2008).

A recent report from the UN underpins that the rate of trade increased twice as fast as GDP until 2007, but interestingly, it has appeared to be stagnating by 2012, only barely beating economic growth (United Nations, 2017a). However, by implementing a new agreement that focuses on streamlining custom procedures and increase speed of trade over borders – The Trade Facilitation Agreement – The World Trade Organization (WTO) is expecting to turn this trend around and secure a trade growth of 2.7 percent every year until 2030 (WTO, 2017). Notably, some products are already showing an export growth of high magnitude, such as agricultural goods, where exports have increased by 70% since 2006 (WTO, 2017). According to their newest report, the WTO asserts that international trade is continuing to support development and economic growth, as well as contributing to further alleviation of poverty (WTO, 2017), though not all socioeconomic groups have experienced the same benefits (United Nations, 2017a). Further, while other studies agree with this (Dollar and Kraay, 2004; Higgins and Prowse, 2010), some also points towards rather more negative effects of increased trade, such as higher embodied carbon emissions (Peters et al., 2011; Peters and Hertwich, 2008). The impacts of globalization on climate change and inequality are many and perplex, however, not all them are necessarily defined as negative. Clearly, in many cases, the impacts may also be favorable for development and the environment, something that will be delved into in the following chapter.

2.1.3.3 Impact on inequality, development and climate

Globalization has presented both challenges as well as advantages for the global population. Through increased mobility of products, technology, labor and services, globalization has gradually influenced sustainable development and economic growth (United Nations, 2017a). Especially the ICT sector have experienced an accelerating technical and financial development over the recent years, increasing the accessibility of such products for small businesses and fresh entrepreneurs (WTO, 2017). Through technical development and increased flows of products and knowledge, agricultural yields from developing countries doubled from 1960 to 2000, and child mortality decreased by 60% (Johnson, 2002). Further, globalization has offered exceptional enhancements for the education sector and helped expose violations of human rights in outlying places in the world (OECD, 2007). Clearly, trade growth has had an overall positive impact on poverty reduction and hunger eradication (United Nations, 2017a). The mentioned improvements have had a significant positive impact on the developing world, and their participation in the world trade of merchandise has increased to 41% (WTO, 2017). However, for the least developed countries, the share still remains at below 1%, something that has been looked upon with worry by international organizations (WTO, 2017).

While presenting various opportunities for world improvement, globalization has also been criticized for not fulfilling its promise of sustainable development and equality (United Nations, 2017a). Firstly, the increased flow and production speed of goods highly impacts the extraction of natural resources, something that weaken the chance of ensuring future economic prosperity (Najam et al., 2016). Also, trade and transportation are highly interconnected, thus more products in circulation leads to greater demand for conveyances (Rodrigue, 2006), escalating the pressure on the environment through e.g. higher GHG emissions and material use (IPCC, 2014b). As mentioned, climate change is in many ways worsened by globalization and raises global disaster risks, resulting from varying patterns of precipitation, sea levels and temperatures (IPCC, 2014b). Further, with more access to mechanized equipment and robotics, low-skilled labor is expected to be increasingly replaced by machines, resulting in the number of lost jobs by 2030 being as high as 2 billion (United Nations, 2017a), which may work as a driver for people emigrating to different countries. Labor-based migration has been argued to be positive for financial development in many nations (Smith, 2016), while on the other hand, in some countries it has been shown to be causing local disruption and cultural tension on a local level, due to the arising of groups of right-radicals in Europe (Guibernau, 2010). Conclusively, the impacts of globalization are many, two of its biggest concerns being its tendency to decrease socioeconomic equality and increasingly impact the environment (The World Bank, 2006). Furthermore, in order to fully understand the link between these two, it may be beneficial to scrutinize the contribution to climate change from contrasting socioeconomic classes.

2.1.4 Environmental footprints of different socioeconomic groups

Many studies show that the distribution of environmental footprints within and between nations is far from even (Hubacek et al., 2017; Teixidó-Figueras et al., 2016; White, 2007), some of them blaming this on the rising expansion on international trade (Teixidó-Figueras et al., 2016). In the meticulous study of the trade-off between carbon dioxide emissions and income equality, Grunewald et al. (2017) found that higher income inequality was associated with lower emissions per capita in low and middle income nations, and higher emissions in developed countries. Further, Hubacek et al. (2017) estimated that one-third of all worldwide greenhouse gas emissions are caused by the richest 10%, whereas the lowest 50% are culpable for solely 15% of released GHGs. These differences in emissions are studied by Teixidó-Figueras et al. (2016) by applying the Environmental Gini Coefficient (EGC). The researchers found the worldwide consumption-based carbon emissions to have a value of 0.579 (Teixidó-Figueras et al., 2016). Interestingly, the analysis showed that other footprints were more evenly distributed (0.362 - 0.479), implying that carbon emissions are more dependent on economic income (Teixidó-Figueras et al., 2016). Other indicators, such as Land Use (LU) and Blue Water Consumption (BWC) might be more tied to geographical endowments than carbon, thus making them less dependent on money and rely more on local natural conditions (Teixidó-Figueras et al., 2016). White (2007) did a similar analysis focusing on the Ecological Footprint (EF), an indicator representing the area of bioproductive land required to meet a certain consumption demand (Wackernagel and Rees, 1998). The findings revealed contrasting worldwide results for the different components of the footprint – land used for energy purposes were more unevenly distributed (EGC = 0.553) than that is applied for growing e.g. food (EGC = 0.272) (White, 2007). An important notice is that these findings are accounting consumption of all products, and not only food products, which will be investigated in further detail in the next section.

The correlation between rising incomes and incrementing environmental footprints are one of the key issues when addressing sustainable development (The World Bank, 2010). The urgent need of mitigation of global emissions has been commiserated in several reports (Alexandratos and Bruinsma, 2012; FAO, 2016; The World Bank, 2010; United Nations, 2005), however, research has shown that many developing nations will require to elevate their release of GHGs in order to secure equal living conditions as in industrial countries (Steinberger and Roberts, 2010). Importantly, in the pursue of global sustainable development, this also urges developed nations to assuage their emissions, and thereby aim for a more equal global distribution of environmental pressure than the world is experiencing at this point (IPCC, 2014c). Further, as significant impact of food consumption on the climate has been elucidated in several studies (Gerbens-Leenes et al., 2010; Steinfeld et al., 2006; Westhoek et al., 2014), and aliment is central in some of the Sustainable Development Goals of the UN (United Nations, 2017b), looking further into the correlation between food consumption and socioeconomic status might be beneficial.

2.1.5 Food consumption habits of different socioeconomic groups

The literature on environmental impacts caused by food consumption by different socioeconomic classes is conspicuously limited, however, numerous studies have been done on the relationship between food consumption habits and income (De Irala-Estévez et al., 2000; Hatløy et al., 2000; Hulshof et al., 2003; Inglis et al., 2005; Monsivais and Drewnowski, 2009; Roos et al., 1996, 1998; Zagorsky and Smith, 2017; Zhu et al., 2015). The findings from these may further be applied to estimate the environmental footprints for various income groups, as literature on footprints from food consumption is highly available. Interestingly, the relationship between socioeconomic status (SES) and food choices seem to be contrasting between developing and higher income countries (Bhurosy and Jeewon, 2014; Kumanyika et al., 2002; Zagorsky and Smith, 2017; Zhu et al., 2015). Studying worldwide obesity levels, Kumanyika et al. (2002) found that consumption of corpulence-promoting foods were more prevalent in groups with low SES in developed countries, whereas people with higher income were more likely to ingest these products in developing countries. This is in alignment with the findings of Kearney (2010), that further underlines that this tendency is strongly connected to steadily decreasing food prices and availability, giving wealthier individuals in developing countries access to more “westernized” options, such as animal products and processed foods. Clonan et al. (2016) also addresses the topic, concluding that intake of red and processed meats seems to be decreasing in high income countries and elevating in the developing world. Moreover, Zhu et al. (2015) found that because of ingesting products high in fats and glycemic load and low fiber, people of higher SES in China were more likely to suffer from lifestyle-related diseases than those with lower income. Notably, these results might not only be caused by dietary conditions, but also physical activities, as lower-income groups in China are more likely to have higher levels of movement during the day (Xu et al., 2008).

On the other hand, regional studies in Australia (Inglis et al., 2005) and The United States (Monsivais and Drewnowski, 2009) points at the opposite tendency; people with higher SES tend to consume a diet in closer alignment with dietary recommendations. However, Zhang and Wang (2004) found a decreasing trend of the correlation between lower incomes and poorer diets in the US, suggesting a decoupling between economy and diet and a rather stronger connection between social-environmental factors and food choices in developed countries. In comparison, Inglis et al. (2005) explains the difference by elucidating a perception of healthier foods being costlier and constrained time schedules due to work among lower SES women. People in better economic situations also tend to be more health conscious (Inglis et al., 2005), in addition to be eating more fruits and vegetables (De Irala-Estévez et al., 2000). However, as De Irala-Estévez et al. (2000) commiserate, over-reporting is a common phenomenon in surveys regarding health consciousness, thus one can hardly trust the results with absolute confidence. Nevertheless, many papers seem to agree that there is indeed a connection between income and healthier food choices (Hulshof et al., 2003; Roos et al., 1998; Zagorsky and Smith, 2017). Importantly, one should keep in mind that the definition of “healthy food” varies across regions. Even though national dietary guidelines mostly agree on less fatty meals higher in fiber and vegetables being more optimal, local recommendations may vary (Margetts et al., 1997). Further, even though national guidelines have been set and promoted, individuals perception of what “healthy” means may be dissimilar (Margetts et al., 1997). Obviously, food consumption habits varies widely between the continents and is not only linked to social status, but also deeply interwoven with culture (Feeley-Harnik, 1995). Therefore, strictly linking habits with specific income groups is an ambitious task when looking at the world as a whole. As mentioned earlier, global food consumption today has a significant impact on the environment (IPCC, 2014a), and to grasp the impacts caused by aliment consumption of different socioeconomic groups, one should take a deeper look into the actual footprints from food products.

2.2 Environmental footprints of food consumption

2.2.1 Footprints assessed in this paper

One of the biggest challenges the global society is facing today is the increasing emissions of greenhouse gases (GHGs), and the agricultural sector is responsible for around a quarter (~ 10-12 GtCO_2-eq/year) of this (IPCC, 2014a). Additionally, increasing population and rapid growth of demand and international trade have been putting a larger pressure on the environment, where water consumption and the use of biologically productive land area stands out as particularly important (IPCC, 2014a). With higher food and biomaterial demand, agricultural production have grown to become one of the largest sectors of land occupation and water consumption (IPCC, 2014a). Moreover, when performing environmental analyses, taking all these three impacts into account might be highly beneficial, since their performance are commonly interconnected and might influence each other (Steen-Olsen et al., 2012). In the paper from 2012, Steen-Olsen et al. (2012) explains how attempting to alleviate one of the footprints may affect the others negatively, thus suggesting that considering all three footprints in environmental analyses might be favorable.

Galli et al. (2012) defines a set of indicators to measure human pressure on the planet called "The Footprint Family". This consists of the Ecological Footprint (EF), Carbon Footprint (CF) and the Water Footprint (WF). The EF represents the amount of biological resources given by the amount of biologically productive land area needed to produce this in global hectares (gha). Further, the CF expresses the total amount of GHGs emitted during the life cycle of a product and is given in terms of CO_2-equivalents. An important notice is that the EF also accounts for emissions of GHGs associated with land use, thus overlapping the CF in some cases. Lastly, the WF gives the total consumption of water in cubic meters m^3 and is divided into three categories; green, blue and grey water (Galli et al., 2012). The different types of water are classified by the Water Footprint Network in their 2009-manual, and states that green water represents stored rainwater in the soil, whereas blue water answer to that which is stored in ground and surfaces (Hoekstra et al., 2009). Finally, grey water is measured in the amount of required water to dilute pollution, and is a representation of water pollution (Hoekstra et al., 2009).

In this study, the CF as described by Galli et al. (2012) is analyzed, however, it is denoted in terms of Global Warming Potential (GWP). The GWP was first introduced in the first assessment report of the IPCC in 1990, and represents the warming effect over time resulting from the release of 1 kg of a greenhouse gas in respect to that of 1 kg of carbon dioxide (IPCC, 1990). In this thesis, the GWP100, which symbolize the warming potential in a time-horizon of 100 years is analyzed. However, an important notice is that the use of GWP as a measure for climate change is somewhat controversial, due to its nature to assume the memory of a short-lived GHG to still remain in the atmosphere after its decay to zero (Shine, 2009; Shine et al., 2007). Therefore, suggestions to apply a measure that gives the change in surface temperature, the Global Temperature Change Potential (GTP), has been made, due to its tendency to present a clearer picture of the actual warming impacts of the emissions (Chang-Ke et al., 2013; Shine et al., 2005). Nevertheless, GWP still holds many advantages (Fuglestvedt et al., 2003) and is commonly used by the IPCC (IPCC, 2014c), which is why it is the measure that is applied in this paper. Further, to avoid overlapping with the carbon footprint, a modification of the EF as described by Galli et al. (2012) is used in this paper . This is the land use footprint (LU), which is the same as the EF, but neglecting the carbon emissions from land use. This unit was also used by Steen-Olsen et al. (2012) under the abbreviation LF. Lastly, only the blue water footprint from Galli et al. (2012) is applied in this analysis, under the name blue water consumption (BWC). Blue water usually has a higher opportunity cost and is generally the most scarce of the three water types, hence making it a relevant target in water consumption analysis (Hoekstra et al., 2011). Further, several elements in the ecosystems are highly dependent on blue water, thus anthropogenic overconsumption may lead to severe damage of the surroundings (Hoekstra et al., 2011). On the other hand, one should keep in mind that green water is vital for many plant species and production practices and should therefore not be neglected in more comprehensive water consumption analyses (Falkenmark, 2003)

The use of these three footprints in environmental analysis is greatly common, as it allows for regarding the impacts from global consumption and production in an in-depth perspective. Climate change because of emissions of GHGs is something that has drawn large attention the last decades, something that makes measuring the GWP highly relevant. Especially, poverty, development and inequality is greatly affected by environmental changes from GHG emissions, making the carbon footprint significantly relevant for this study (FAO, 2016; OECD, 2011). Also, in relation to food consumption, several researchers have decided to include this footprint (Gephart et al., 2016; Pradhan et al., 2013; Tilman and Clark, 2014;

Westhoek et al., 2014). The importance of including the WF in environmental analyses regarding sustainable development is clear, as access to water is necessary for several anthropogenic activities and human survival (Hoekstra et al. 2011). Further, number 6 of the Sustainable Development Goals of the UN (SDGs) is to *"Ensure availability and sustainable management of water and sanitation for all"* (United Nations, 2017a), increasing the relevance of this footprint. As with GWP, the WF is also prevalent in many analyses regarding food consumption (Gephart et al., 2016; Steinfeld et al., 2006), although it is not entirely as common as for the carbon footprint. Moreover, also the ecological footprint has been pointed out as particularly important, since making sure that the ecological diversity of the biosphere stays protected is key to ensuring food security and future sustainable development (Ewing et al., 2010). Further, the Global Footprint Network also expresses the concerns regarding land degradation, as once land is deteriorated, subsequently restoring it may be profoundly difficult and expensive (Ewing et al., 2010).

Conclusively, the footprints in focus in this study are GWP, LU and BWC, all selected based on their importance in relation to sustainable development and prevalence in literature based on environmental analysis. These will all be investigated in detail in relation to food consumption in the coming chapters.

2.2.2 Carbon footprint

Several recent studies elucidate a significant connection between food consumption and impacts on the environment (Bajzelj et al., 2014; Gerbens-Leenes et al., 2010; Steinfeld et al., 2006). In their 5th assessment report, the Intergovernmental Panel on Climate Change (IPCC) gave the agricultural sector the responsibility for about 10-12% of worldwide GHG emissions in 2005, partly due to manure management (7-8%), biomass burning (6-12%) and paddy rice cultivation (9-11%), but mainly because of agricultural soils and enteric fermentation (IPCC, 2014c). However, later adjustments suggests a contribution of 21% to global GHGs (FAO, 2016), with 14.5% stemming from the livestock sector (FAO, 2013). Further, due to manure management, enteric fermentation and land-use changes because of the requirement of land space for feed crops and pasture area, Steinfeld et al. (2006) blames the livestock sector for being responsible for around 18.5% of world emissions of greenhouse gases. This is a notable higher estimation than what was stated by the FAO in 2013, something that might be caused by several factor, such as unequal allocation of impacts (e.g. if transportation of livestock products is allocated to either the livestock sector or transportation sector) and that the estimation of Steinfeld et al. (2006) was done seven years before that of the FAO (2013). Additionally, according to several studies, plant-based foods has been found to cause less emissions than animal-derived products (Gephart et al., 2016; Tilman and Clark, 2014; Westhoek et al., 2014).

The largest atmospheric effects are caused by carbon dioxide, methane and dinitrogen oxide (IPCC, 2014a), CO_2 being mainly emitted through deforestation practices (Steinfeld et al., 2006). Enteric fermentation i.e. low-oxygen decomposition of organic matter in ruminants is largely the main source of CH_4 emissions, whereas manure management is responsible for releasing N_2O (IPCC, 2014a). Notably, 53% of all anthropogenic emissions of dinitrogen oxide are discharged from livestock production (FAO, 2013).

The resulting climate change from GHG emissions are related to concerns regarding more frequent occurrences of damaging, tropical storms (Steinfeld et al., 2006), flooding and salinization caused by sea level rise, as well as decreasing crop yields because of temperature rise (The World Bank, 2008). Further, Zhou et al. (2017) points towards a strong correlation between climate change, agriculture, human well-being and poverty alleviation, implying that increased GHG emissions severely reduce the speed of poverty amelioration, even though it is a product of increased wealth in developing countries. Especially the destruction of coastal areas and coral reefs caused by climate change has received international attention the last years (Barbier, 2015).

The carbon footprint from different food products may vary significantly depending on type, climate, production practices and regional policies (de Vries and de Boer, 2010), which is why defining one exact value to represent the emissions from a product is highly challenging. Table 1 displays the carbon footprints for different products found in the literature. Note that some products have largely variating footprint values.

Table 1: List of food products and their corresponding carbon footprints according to the cited literature.

Food product	Carbon footprint (kg CO_2eqv/kg)	Reference
Beef from cattle	8.6 – 35.2	de Vries et al. (2015)
Pork	3.6	Dalgaard et al. (2007); Reckmann et al. (2012)
	3.1	Ngyuen et al. (2011)
Poultry	3.7 – 6.9	de Vries and de Boer (2010)
	2.8 – 3.4	Kalhor et al., 2016; Wiedemann et al. (2017)

Milk	1.06 – 1.22	Rice et al. (2017)
	2.4	FAO (2010)
Butter	7.3	Vergé et al. (2013)
Cheese	5.3	Vergé et al. (2013)
Cereals	0.29 – 1.3	González et al. (2011)
Vegetables	0.08 – 0.37 (open field)	González et al. (2011)
	2.6 – 10 (heated greenhouse)	González et al. (2011)
Fruits	0.06 – 0.55	González et al. (2011)

2.2.3 Land use footprint

Notably, not solely the carbon footprint is affected by the agricultural sector; also the use of global land space is influenced (Steinfeld et al., 2006; Westhoek et al., 2014). In 2008, is was estimated that 13 million land hectares perished or were degraded each year resulting from agricultural practices (The World Bank, 2008). The quantity of cropland used for producing food differ depending on local conditions – for comparison, Europe and North America use around 40% of cropland for food production, while Asia and Africa dedicate around 80% (Foley et al., 2011). Further, around 75% of land used for food production is used to meet the world's demand for animal-based foods, both for growing feed, as well as assuring grazing area (Foley et al., 2011). This constitutes a total of 30% of the Earth's surface (Steinfeld et al., 2006). Excessive land use has been looked upon with worry because of its potential to affect habitats, increase the emissions of GHG, as well as leading to nutrient loading (MEA, 2005). There is no doubt that food production affect global footprints, however, aliment production is tremendously important for meeting the human demand for feed (The World Bank, 2008). In the pursue of ensuring future food security, a rise in agricultural production is presumably essential (Gerbens-Leenes et al., 2010). Particularly in lower-income countries, a key solution to improve development and alleviate poverty is found in increasing yields (The World Bank, 2008). Importantly, it has been suggested that the solution to upsurge food production lies in boosting land productivity and waste avoidance, rather than through cropland extension (Foley et al., 2011). However, farming intensification has also been connected to elevated emissions of GHGs (The World Bank, 2008). Even though one should not overlook the nutritional benefits of animal-products for development for the poorest in developing countries (Delgado, 2003), switching towards more plant-based diets has been suggested to be a good option for reducing dietary GHG emissions and excessive land use (Gerbens-Leenes et al., 2010; Meier and Christen, 2013; Steinfeld et al., 2006). For instance, in a study by Gephart et al. (2016) it was found that global land use could be decreased by 48.4% if the world's diet consisted of one-tenth grains, nine-tenths vegetables and an insignificant amount of seafood. In comparison, in another study it was found that a reduction of 23% of cropland per capita could be achieved if 25-50% of per capita animal-based foods were replaced by plant-derived food (Westhoek et al., 2014).

The land use footprint of different products varies significantly depending on the type of system (extensive vs. intensive), climate and regional factors (Ibarrola-Rivas and Nonhebel, 2016). An overview of the land use footprints found in the literature is shown in Table 2.

Table 2: List of food products and their respective land use footprints found in the cited literature.

Food product	**Land use footprint (m^2/kg)**	**Reference**
Beef from cattle	12.1 – 47.2	de Vries et al. (2015)
Pork	8.9 – 12.1	de Vries and de Boer (2010)
	5.8	Ngyuen et al. (2011)
Poultry	8.1 – 9.9	de Vries and de Boer (2010)
	9.0 (Northern Africa)	Ibidhi et al. (2017)
	14.0 – 22.5 (Australia)	Wiedemann et al. (2017)
Milk	1.1 – 2.0	de Vries and de Boer (2010)
	1.59	Aguirre-Villegas et al. (2017)
Cereals	0.526	EUROSTAT (2016)
Vegetables	0.44 – 1.54	Ibarrola-Rivas and Nonhebel (2016)
Fruits	0.92 – 3.22	Ibarrola-Rivas and Nonhebel (2016)
Vegetable oils	0.011 – 0.074	Ibarrola-Rivas and Nonhebel (2016)

2.2.4 Water use footprint

Further, global water use is another footprint highly affected by food consumption (FAO, 2016; Gephart et al., 2016; The World Bank, 2008). On a world basis, developing countries are the ones suffering most severely from water shortage (The World Bank, 2010), and interestingly, these nations use around 85% of their freshwater on agricultural activities (The World Bank, 2008). According to Steinfeld et al. (2006), the livestock sector alone is responsible for 8% of anthropogenic water consumption, essentially due to feedcrop irrigation. This is in slight alignment with the findings of Mubareka et al. (2013), where livestock was found to be consuming 5% of total water use in most European countries. Additionally, research commiserate that pollution of antibiotics, hormones, fertilizers, pesticides and animal wastes all contribute to the sector probably being the largest source of water pollution (Steinfeld et al., 2006). Most of the water use in the livestock sector stems from feed cultivation, where blue water consumption has been found to have the most concerning impacts on the environment (Herrero et al., 2015).

Water scarcity is a growing problem around the world, acting as a severe threat to hygiene habits and food cultivation, thus affecting both human well-being and food security (FAO, 2016). Especially developing nations in Asia and Africa are prone to being affected, something that counteracts the ambitions to alleviate poverty (FAO, 2011). Further, scarcity may also negatively impact world inequality, as it is often the world's poor that suffer in times with limited access to water (Nazrul Islam, 2015).

Several studies have analyzed the water impacts of food consumption and production (Gephart et al., 2016; Mekonnen and Hoekstra, 2011; Rost Stefanie et al., 2008). The water used in crop production consisted of 78% green, 12% blue and 10% grey between 1996 and 2005 (Mekonnen and Hoekstra, 2011). The allocation is somewhat different in the livestock sector, where the water use consisted of 87.2% green, 6.8% blue and 6.6% grey, approximately 98% of this stemming from feed production (Mekonnen and Hoekstra, 2010). The total water footprints for different food products are displayed in Table 3. Note that all footprints are based on research from Mekonnen and Hoekstra, as several environmental studies on food tends to gather data from their work (Gephart et al., 2016; Gerbens-Leenes et al., 2010; Rost Stefanie et al., 2008).

Table 3: Average total world water footprints for different food products. Green, blue and grey water are all included. The numbers on animal products and nuts are gathered from Mekonnen and Hoekstra (2010) and the remainders are retrieved from (Mekonnen and Hoekstra, 2011).

Food product	**Average total world water footprint** (m^3/ton)
Meat from beef cattle	15 400
Meat from sheep	10 400
Meat from pig	6 000
Meat from goat	5 500

Meat from chicken	4 300
Chicken egg	3 300
Cow milk	1 000
Pulses	4 000
Oil crops	2 400
Cereals	1 600
Fruits	1 000
Roots and tubers	400
Vegetables	300
Sugar crops	200
Nuts	9000

In Table 3 it is observed that excluding nuts, animal products have in general a much higher water footprint than plant-based products. These numbers are in terms of per unit mass, however, Mekonnen and Hoekstra (2010) states that animal products still have a significantly larger footprint when measuring in terms of per calorie and per gram of protein (the latter is when products of particularly low protein contents are neglected, such as sugar and fruits). An important notice is, however, that large percentages of the total footprints in Table 3 is green water. The numbers would have been significantly reduced for animal products if solely blue water was taken into account.

2.3 Future trends

2.3.1 Food consumption

One main reason why current trends of food consumption is of high concern is the question whether human kind will be able to ensure food security for all beings in the future (Alexandratos and Bruinsma, 2012; Chen and Kates, 1994; Godfray et al., 2010; Pauly et al., 2005). From 1950 to 2010 food consumption per capita grew faster than population numbers, and this trend is expected to continue towards 2050 (Alexandratos and Bruinsma, 2012). Current food demand creates an increasing competition for energy, land area, water, as well as threatens marine ecosystems through overexploitation, something that might challenge future global food supply (Godfray et al., 2010). On top of this, climate change is an additional threat, especially hitting those whose activities largely depends on natural surroundings, such as farmers, fishermen, pastoralists and foresters in lower-income countries (FAO, 2016). In a report from 2016, the Food and Agriculture Organization of the United Nations stated that *"Unless action is taken now to make agriculture more sustainable […], climate change impacts will seriously compromise food production in countries and regions that are already highly food-insecure"* (FAO, 2016). Another important point here is the distribution of food availability. Even though the earth has the capacity to produce enough food to sufficiently feed everyone (approx. 2700 kcal/person/day), many people are still living in close to starvation, whereas others consume well over 3000 kcal/person/day (Alexandratos and Bruinsma, 2012). This unequal share of nutrition threatens development and is profoundly serious, given that world inequality remains steadily rising (United Nations, 2017b)

Importantly, it is not only growing food demand per capita that is a source of concern among world organizations, also observed shifts in diets may have significant impacts on future food production (Kearney, 2010). Rapidly increasing interest for meat and dairy products, especially in emerging economies such as China and India, has led to rising the numbers of sheep, goats and cattle by 300%, pigs by 500% and chicken by 900% from 1960 to 2010 (Godfray et al., 2010). Especially the consumption of meat from cattle, poultry and eggs are expected to continue increasing towards 2050 (Kearney, 2010). The consumption of fish has been projected to become approximately stagnant in the coming years, likely as a result of overfishing and procreation of carnivorous fishes that consume smaller fishes suitable for being human feed (Pauly et al., 2005). The same tendency has been expected for butter and cheese (Kearney, 2010), though the literature seems to slightly disagree on milk. This product has been predicted to slightly decrease in consumption, at least in industrial countries by Kearney (2010), whereas Alexandratos and Bruinsma (2012) claims that it will continue to steadily increase on a global level. In general, the trends we observe today are rising requests for livestock products in developing countries, and stagnating demand in higher-income regions (Thornton, 2010). Meanwhile, declining consumption levels are observed for roots, tubers, pulses and cereals (Kearney, 2010), and these are expected to continue decreasing towards 2050 (Alexandratos and Bruinsma, 2012).

The reasons why the observed diet shifts are of concern are several. Livestock products are not only associated with higher environmental footprints (see chapter 2.2), which in turn affects the climate and thereby supporting food insecurity – it also requires resources that could have been used for other purposes (Herrero et al., 2013). Today, 42% of grain production in developing countries is fed to livestock, a number that is expected to rise to 59% by 2050 (Alexandratos and Bruinsma, 2012). With a conversion efficiency for turnings plants into animal matter of approximately 10%, it is clear that significant amounts of calories are lost during the feeding process (Godfray et al., 2010). Further, 33% of total arable land is allocated for feed production, and 70% of all agricultural land is occupied by the livestock sector (Steinfeld et al., 2006), areas that could be used for growing more efficient food items. Further, the trend of transitioning towards diets consisting of more animal products have also been followed by increases in obesity rates and other chronic diseases, such as cancer, diabetes and cardiovascular diseases (Fung T.T. et al., 2004; Kearney, 2010; Micha et al., 2010). However, even though large proportions of the literature support decreasing intake of animal products, one should not forget that such foods are highly beneficial for many populations around the world (Alexandratos and Bruinsma, 2012). For example, Randolph et al. (2007) explains the importance of livestock for many poor people in the developing world, as it may provide vital nutrients that are difficult to get elsewhere. Further, the researchers highlight how keeping livestock serve as a way to produce food on non-arable land areas (e.g. keeping goats on the drylands of Namibia) and serving as “living bank accounts”, as they may sell their animals as needed (Randolph et al., 2007). All these factors may provide the poorer population ways to better health and economic status, thus supporting further development.

Detailed and comprehensive literature on future food choices by socioeconomic status is rather limited, however, some research has been published (Dammann and Smith, 2009; Delgado, 2003; McLaren, 2007). Interestingly, we observe that a transition from a lower-income group to a higher is expected to have different effects depending on the general development of the country. If the transition happens in an emerging economy, the diets tend to shift more towards becoming more meat-heavy and unhealthy (Delgado, 2003), whereas it shifts towards becoming healthier in industrialized countries (Dammann and Smith, 2009; Drewnowski, 2009; McLaren, 2007). However, a reason for this may be poor people not having sufficient access to livestock products in developing countries, and the availability increases in parallel with their income. On the other hand, in industrialized countries where the availability of livestock is much higher, poorer people often choose cheaper, processed animal products, in favor of fresh fruit or vegetables (Dammann and Smith, 2009). From this, one may draw the conclusion that the future food choices among unequal social classes depend on the general income and food availability of the country, which again is highly unequal between world nations. To acquire a more profound understanding of this, a deeper look into future predictions of changes in inequality and globalization might be favorable.

2.3.2 Globalization and inequality

As mentioned in chapter 2.1.3, the observed increasing intra- and intercountry inequality is largely driven by globalization. As not much indicate that current trends of globalization will cease in the near future, the future of global inequality is of large concern (United Nations, 2017b). Klapper et al. (2016) explains how rising inequality likely may trigger more frequent armed conflicts and breed political instability in the future. Further, these trends may also slow economic growth (Dabla-Norris et al., 2015). In a global study 2015, Dabla-Norris et al. (2015) found that GDP growth would be reduced by 0.08% if the income share of the richest 20% increased with 1%, whereas it would increase the growth by 0.38% if the income share of the poorest 20% was pushed up by 1%. Interestingly, Li and Zou (1998) found results in stark contrast to this, claiming that inequality in fact had a significant positive effect on economic growth. However, in light of their results not matching previous research on the topic, the researchers also concludes by stating that inequality studies are notably complex and results may vary (Li and Zou, 1998). Further, one should also take into account that this study was performed 17 years before Dabla-Norris et al. (2015), and that several societal factors may have changed during this time period. On the other hand, an interesting study by Tselios (2011) elucidate a correlation between rising inequality and innovation, claiming that inequality works as a driver for new inventions and entrepreneurships. However, there seems to be a clear agreement in reports from the United Nations (United Nations, 2017b, 2017a, 2005), the Organization for Economic Cooperation and Development (OECD, 2011) and the World Bank (The World Bank, 2006), that increasing inequality is threatening future development and new policies are needed to prevent current trends from persisting.

It is predicted that emerging economies (EE), such as China, India, Argentina and Brazil will take a larger part of the future global economy (OECD, 2011). Therefore, the OECD highlights the importance that *"[...] any comprehensive assessment of inequality trends worldwide considers the emerging economies"* (OECD, 2011). From 1980 to 2005, household consumption of emerging economies rose by 6.1%, more than double the growth in industrialized countries at 2.3% – a trend that is expected to continue in the future (United Nations, 2005). However, although the local economy has been solidly strengthened, intercountry inequality has seemed to be strongly elevating, especially in China, India, South Africa and the Russian Federation (OECD, 2011). Further, the EEs are significantly more unequal income-wise than OECD nations (OECD, 2011), something that elucidate the need of extra focus on these economies when creating international and domestic policies for alleviating inequality.

It is clear that economic growth alone is not enough to prevent inequality from emerging, which is why new policies and structural changes must be implemented in the coming years to ensure the Sustainable Development Goals to be reached (United Nations, 2017b). According to the OECD (2011), the four factors that will be the most determining in this process are to improve the incentives for formal employment, ensure social assistance for those in need, spread knowledge gained through education and prepare to spend more finances on social matters. The United Nations also suggests bettering today's international tax cooperation, implementing policies based on the potential positive contribution of migration and strongly attempt to counteract climate change to be beneficial initiatives for supporting future equality (United Nations, 2017b).

2.4 Summary of literature review

Considering the high amounts of literature and reports created on the topics of globalization, climate change, inequality and food consumption, there is no doubt that these are issues not only highly relevant today, but also will be in the years to come. Globalization has clearly pushed the world towards becoming highly technologically advanced, more affluent and connected. On the other hand, it has accelerated rapid growth in population, unsustainable consumption patterns, environmental footprints and world inequality. Being one of the most important targets for achieving sustainable development, food consumption is also a large contributor to climate change, consequently counteracting aspirations to ensure sustainability and world equity. Even though plenty of studies has been done on correlations between globalization vs. inequality and climate change vs. food consumption, strikingly few has attempted to connect all these four together. Considering how they all correlate and affect each other, expanding the literature on their interrelationship is greatly important and is what this thesis will be endeavoring to do.

3 Methods

3.1 Materials

3.1.1 EXIOBASE

For calculating the environmental impacts, an input-output analysis approach was applied using EXIOBASE, an environmentally extended, global multi-regional input-output and supply and use database (MR EE SUT/IOT). This database has been suggested to be suitable for estimation of environmental stress caused by global consumption by Wood et al. (2015), that expresses that *"EXIOBASE has its major strength in providing more sector detail compared to any other MRIO database which in most cases only distinguish a small number of environmentally sensitive sectors".*

This study was based on the 3rd edition of the database, EXIOBASEv3, which contains information from 1995 to 2016 (Stadler, et al., 2015), in addition to:

- 163 industries
- 200 products
- Water, land and material accounts
- Combustion and non-combustion emission data on stressors
- Emissions on HFC, SF_6 and PFC
- Data on GDP in PPP
- 44 countries (28 EU state members and 16 grand economies)
- 5 regions from Rest of the World (RoW), including nations from Asia, Europe, Middle East, America and Africa

GDP data is gathered from The World Bank database (The World Bank, 2017), while the remaining is retrieved from the paper from Stadler, et al. (2015). Additionally, EXIOBASE contains data on household demand for 5 different economic quintiles in 2010. Every quintile represents 20% of the population, where number 1 is the poorest 20% and number 5 represents the richest 20%. The information for 2010 was applied to estimate quintile demand for a selected time period (2004 – 2011) and is described in further detail in chapter 3.5.2. Due to the information in EXIOBASE being most reliable and detailed until 2011, the following years after this were not taken into account. Further, as information on income shares was rather sparse and not sufficiently detailed for all years until 2003, years before 2004 were not accounted for.

3.1.2 HDI

For achieving a deeper understanding of the relationship between environmental footprints, development and inequality, values for the Human Development Index (HDI) were retrieved from the Human Development Data of UNDP (UNDP, 2016). The data was rather limited, solely providing information on the years 2000, 2005, 2010 and 2011. To obtain a time-span from 2004 to 2011, the data points for 2004 were estimated by using linear interpolation between year 2000 and 2005.

Importantly, EXIOBASE and UNDP both contain information on regions consisting of several countries, however, these are not perfectly matching. In order to combine information from the two databases, an alignment between the regions was created, which is shown in Table 4. This is the same assumption that was applied in the project work prior to this thesis (Thomassen, 2017). Additionally, there were no regions in the UNDP data that could match either the EXIOBASE region "Row Europe" nor the country/region Taiwan, as the latter is computed as a part of The Republic of China. Consequently, these two are not taken into account when global HDI values have been calculated.

Table 4: Alignment between EXIOBASE regions and UNDP regions

EXIOBASE regions	UNDP regions
RoW Asia and Pacific	East Asia and the Pacific
RoW America	Latin America and the Caribbean
RoW Africa	Sub-Saharan Africa
RoW Middle East	Arab States

3.1.3 Income Gini Coefficients

To allow for further analysis of the relationship between footprints and inequality, data on the Income Gini Coefficients (IGCs) for every country was retrieved from the World Income Inequality Database (WIID) of the United Nations University (UNU-WIDER, 2017). This was the most detail-rich data available, however, it was rather limited country-wise compared to the data on HDI. Consequently, analysis with Income Gini coefficients could only be performed on a country-level, as global values were unavailable and conspicuously difficult to estimate. Further, no data was accessible for the EXIOBASE region RoW Africa. Therefore, one African country was chosen to represent the region. Omitting South Africa, the country that was found to have the median HDI of the region was Madagascar (UNU-WIDER, 2017), which is why the IGC of this country was chosen to represent RoW Africa. In contrast, information for the other selected regions (China, Brazil, Norway, United States and Indonesia, see chapter 3.5.3) was satisfyingly detailed and opened for a decent analysis of the development of local inequality.

Importantly, this only applies to the Gini coefficients on *income*, the *environmental* Gini coefficients in this paper were calculated from the outcomes of the simulation and are therefore given for both global and regional levels. A deeper elaboration on the theory behind the Gini Coefficient is found in chapter 3.5.1.

3.1.4 Income shares

In order to estimate the footprints for the different quintiles, data on global income shares was gathered from The World Bank Database (The World Bank, 2018a). Resulting from inconsistent and sparse data until 2003, only the years from 2004 to 2011 were considered. Additionally, for some regions, information on certain years were not available. In these cases, data for that specific year was estimated by linear interpolation between the year before and the following year (e.g. if data on 2007 was estimated by linear interpolation between values from 2006 and 2008). The data that was created using this method can be found in Table 5.

Table 5: The regions and the year(s) that had their data estimated based on linear interpolation

Region	**Year(s)**
Bulgaria	2005
Germany	2005
France	2009
Croatia	2005
Malta	2004
United States	2005 and 2008
Japan	2005
China	2004
Canada	2005 and 2008

South Korea	2007, 2009 and 2011
Brazil	2010
India	2005 and 2007
Australia	2004 and 2006
Switzerland	2005
South Africa	2008 and 2010

Further, the database from the World Bank did not cover all EXIOBASE regions. Therefore, supplementary data on these countries was gathered from WIID (UNU-WIDER, 2017). The regions and year(s) that were covered by this database is found in Table 6. Please notice that data that was found by interpolation are included in the table where the whole time-series from 2004 to 2011 are mentioned.

Table 6: The regions and year(s) where the data is gathered from WIID.

Regions	**Year(s)**
Germany	2004
Croatia	2004 - 2011
Malta	2004 - 2011
Romania	2004 - 2011
Japan	2004 - 2011
China	2004 - 2011
India	2004 - 2011
Mexico	2004 - 2011
Switzerland	2004
Taiwan	2004 - 2011
Indonesia	2004 - 2011

No data from neither the World Bank nor WIID was able to cover the RoW regions in EXIOBASE. Therefore, specific countries were selected as representatives for the regions. These were selected due to three criteria; the countries must be within the regions, sufficient income share data must be available and the level of development (HDI) should be around the mean of the region as a whole. As this study focus on development, basing the choice of country on the HDI is advantageous, as nations with a significantly low or high index relative to the mean might result in misleading results. Data on HDI was gathered from UNDP's Human Development Data (UNDP, 2016) and information on income shares was retrieved from WIID. The selected countries and which regions they represent are shown in Table 7.

Table 7: Alignment between RoW regions in EXIOBASE and income shares regions from WIID.

Region	Representative country
RoW Europe	Serbia
RoW Asia and Pacific	Vietnam
RoW America	Ecuador
RoW Africa	Malawi
RoW Middle East	Georgia

3.2 Foundations of Input-Output Analysis

Input-Output Analysis forms the baseline for this research. The tables in this framework are tools formed to express the correlation between various consumption patterns and economic actors, where the production techniques applied for producing one unit of outcome are represented by each column in the table (United Nations, 1999). Table 8 displays a simplification of an Input-Output table. The **Z-matrix** (industry x industry) consists of the entire input to every industry (columns) and the total output from each industry (rows), thus expresses intermediate consumption and total inter-industry flows. Including net exports, gross capital formation and final consumption expenditures by government and households, the **y-vector** (industry x final demand) represents total final demand. Moreover, the **x-matrix** (industries x input/output) expresses the total input or output given a total final demand. Further, the total value added is given by the **V-matrix** (value added x industry), accounting for measures like capital costs, profits and salaries.

Table 8: Simplification of an Input-Output table

	Industries	Final demand	Total output
Industries	Z	y	x
Value added	V		
Total input	x		

Indicating the balance between total input and output, the Z-matrix may be applied in the description of the *production balance* by using a vector of ones to sum the matrix through the rows, **i** = $\begin{bmatrix} \mathbf{1} \\ \vdots \\ \mathbf{1} \end{bmatrix}$. This is displayed in equation (1).

$$\mathbf{Zi} + \mathbf{y} = \mathbf{x} \tag{1}$$

We may now introduce the A-matrix (industries x industries) by applying the equality $\boldsymbol{a_{ij}} = \frac{\boldsymbol{z_{ij}}}{\boldsymbol{x_j}}$, where $\boldsymbol{x_j}$ represents the total output of industry *j* and $\boldsymbol{z_{ij}}$ shows the flow from industry *j* to *i* for a specified final demand. Thus, the total requirement of industry *i* to generate one unit of total output of industry *j* is represented by $\boldsymbol{a_{ij}}$. The A-matrix and the Z-matrix are related by the equality expressed by equation (2).

$$\boldsymbol{Z} = \boldsymbol{A\hat{x}} \tag{2}$$

Here, $\boldsymbol{\hat{x}}$ means the diagonalization of the x-matrix expressed by $\boldsymbol{\hat{x}} = \begin{bmatrix} x_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & x_n \end{bmatrix}$.

Further, the A-matrix may be given as $\boldsymbol{A} = \begin{bmatrix} \boldsymbol{a_{11}} & \cdots & \boldsymbol{a_{1j}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{a_{ij}} & \cdots & \boldsymbol{a_{ij}} \end{bmatrix}$ on an extended form.

Now we may obtain the production balance by rearranging and applying equation (1) and (2), which is given by equation (3).

$$\boldsymbol{Ax} + \boldsymbol{y} = \boldsymbol{x} \tag{3}$$

Here, the final demand is given by the y-vector, whereas $\boldsymbol{x}$ means the total output. The term $\boldsymbol{Ax}$ represent the intermediate output, and to allow for further calculations, we introduce the Identity matrix, **I** (industries x industries). This matrix consists of ones on the entire diagonal, while the rest is kept as zeroes, $I = \begin{bmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1 \end{bmatrix}$.

By rearranging equation (3) and solving for total output, equation (4) can be obtained.

$$(\boldsymbol{I} - \boldsymbol{A})^{-\boldsymbol{1}}\boldsymbol{y} = \boldsymbol{x} \tag{4}$$

Now we may introduce the Leontief inverse matrix (industries x industries), expressed by $\boldsymbol{L} = \begin{bmatrix} \boldsymbol{l_{11}} & \cdots & \boldsymbol{l_{1j}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{l_{ij}} & \cdots & \boldsymbol{l_{ij}} \end{bmatrix}$.

Here, the coefficients each gives the requirement of industry *i* to produce one unit of final demand of industry *j*. The Leontief inverse matrix is also given by the expression $\boldsymbol{L} = (\boldsymbol{I} - \boldsymbol{A})^{-\boldsymbol{1}}$.

Now a reformulation of equation (4) may be performed by applying the definition of the Leontief inverse, given by equation (5).

$$\boldsymbol{Ly} = \boldsymbol{x} \tag{5}$$

Here, $\boldsymbol{x}$ is the total output, while $\boldsymbol{y}$ represents the total final demand. Now the total impact given a final demand can be found by introducing the **F-vector** (stressors x final demand), displayed in equation (6).

$$\boldsymbol{F} = \boldsymbol{SLy} \tag{6}$$

The emissions per industry are given by **S-matrix** (stressors x industries), where the total quantity of stressor *i* per output of industry *j* is represented by the coefficients $\boldsymbol{s_{ij}}$. Another representation of the S-matrix is:

$\boldsymbol{S} = \begin{bmatrix} \boldsymbol{s_{11}} & \cdots & \boldsymbol{s_{1j}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{s_{ij}} & \cdots & \boldsymbol{s_{ij}} \end{bmatrix}$.

3.3 Environmental indicators and calculations

By applying the product-by-product version of EXIOBASE in combination with equation (6), the environmental impacts were estimated. Then, the results were aggregated into the selected footprints of interest; land use, blue water consumption and global warming potential. The selected units and coverage of the footprints have been applied in former studies (Simas et al., 2017; Tukker et al., 2016) and are presented in Table 9. Furthermore, the unit for expenditure is given in million Euros (MEUR). These indicators are the same as the ones applied in the project work prior to this study (Thomassen, 2017).

Table 9: Selected indicators and their units and coverage

Impact indicator	Coverage	Unit
Global Warming Potential (GWP)	Greenhouse gas emissions Covers CO_2, CH_4, N_2O and SF_6	$\boldsymbol{kgCO_2e}$
Blue water consumption (BWC)	Total blue water consumption	$\boldsymbol{Mm^3}$
Land use (LU)	Total land use Covers forests, pastures and arable land	$\boldsymbol{1000\ m^2}$

Importantly, not every GHGs were included in the GWP. Solely four were considered, and substances like chloroflourcarbons (CFCs) and Ozone (O_3) were not taken into account. Further, only blue water consumption was in focus – grey and green water consumption were not considered. Finally, either productivity nor quality of the land was reflected by the LU indicator, only the size of the area was analyzed. Moreover, only embodied, not direct emissions were considered, and a timespan from 2004 to 2011 (8 years) was analyzed. To investigate the effect of food consumption, the FPs were computed in relation to the quantity of food demanded in expenditure. As EXIOBASE provides a classification of 25 food product categories, the analysis was based on these. Some of the official names for the food products in the database were long and therefore challenging to include in the resulting graphs from the analysis. Therefore, abridgements for the product categories were created and further used in the calculations. These are shown in Table 10, and their corresponding official EXIOBASE names can be found in Appendix G.

Table 10: The food products in EXIOBASE

Paddy rice	Sugar plants	Meat nec	Meat, cattle	Dairy
Wheat	Crops	Animal products	Meat, pigs	Processed rice
Cereal grains	Cattle	Fish products	Meat, poultry	Sugar
Oil seeds	Poultry	Fishing products	Veg. oils and fats	Beverages
Veg., fruit, nuts	Pigs	Raw milk	Meat products	Other processed foods

Further, in order to analyze the total expenditure on different product groups (section 4.3), the products in Table 10 were grouped into six categories. The categories and their containing EXIOBASE products are displayed in Table 11.

Table 11: Categorization of the EXIOBASE products.

Category	**EXIOBASE products**
Meat and Dairy	Cattle, Poultry, Pigs, Meat nec, Animal products, Meat cattle, Meat pigs, Meat poultry, Meat products, Raw milk, Dairy
Fish	Fish products, Fishing products
Cereals	Paddy rice, Wheat, Cereal grains, Crops, Processed rice
Fruits and nuts	Veg., fruit, nuts
Oils and sugars	Oil seeds, Veg. oils and fats, Sugar plants, Sugar
Others	Beverages, Other processed foods

3.4 Estimation of quintile demand

As information on demand on a quintile level only was available for 2010, data for the remaining years was approximated using information on income shares from WIID and the World Bank and total demand for every year. The following steps were used to estimate the quintile demand:

1. First, the total consumption per quintile j in year i $(Cons_{i,j})$, was first estimated by multiplying the total consumption $(Cons_i)$ and share of income per quintile in year i $(Inc_{i,j})$.

$$Cons_{i,j} = Cons_i * Inc_{i,j} \tag{7}$$

2. Then, the change from year i to year 2010 ($Change_i$) was estimated by dividing the estimated consumption of year i on the estimated consumption for 2010.

$$Change_i = \frac{Cons_{i,j}}{Cons_{2010,j}} \tag{8}$$

3. Thereafter, the total expenditure per quintile j in year i ($Exp_{i,j}$) was estimated by multiplying the results from step 2 with the per-quintile expenditure data of 2010.

$$Exp_{i,j} = Change_i * Exp_{2010,j} \tag{9}$$

4. The fourth step was to ensure that the estimated expenditure per quintile would match the total known consumption of year i. This was done by creating a scaling factor (SF) by dividing the known total consumption on the sum of the estimated expenditures for every quintile.

$$SF = \frac{Cons_i}{Exp_{i,j}} \tag{10}$$

5. The scaling factor was then applied to rescale the total expenditures per quintile j in order to match the known, total consumption.

$$Exp_{i,j} = SF * Exp_{i,j} \tag{11}$$

6. Lastly, the demand data from 2010 was used to estimate information for every year, quintile and product k ($Exp_{i,j,k}$). This was done by using a RAS technique – a form of biproportional matrix balancing and entropy optimization process (McDougall, 1999). The aim of this process is to rebalance a coefficient matrix, A, in relation to two adjustment parameters, R and S (Lahr and Mesnard, 2004). Here, the quintile demand per product from 2010 was selected as the A matrix, while the known total demand per product ($Cons_{i,k}$) and the estimated total consumption per quintile for year i ($Exp_{i,j}$) were used as the adjustment parameters R and S.

The RAS technique is described by McDougall (1999), and the following method is the adoption of the original technique, though customized to fit this study: Given that matrix A consists of coefficients a_{ij}, $i = 1\!:\!200$ and $j = 1\!:\!5$, the goal is to find new coefficients v_{ij}, that are as like as the original a_{ij}, but consistent with the row and column total targets of v_{i*} and v_{*j}, hence R and S. By introducing scaling factors, r_i and s_j, correlating to the targets for the rows and columns, the new coefficients v_{ij} may be estimated by:

$$v_{ij} = r_i a_{ij} s_j \tag{12}$$

The data for every quintile for the years 2004 to 2011 was then estimated by consistently creating new scaling factors and looping this process 1000 times.

3.5 Computation tools

Performing the calculations, the computer program MATLAB v. R2016a was applied. This tool developed by MathWorks is able to handle large databases for advanced matrix multiplication (The MathWorks, Inc., 2016), making it a suitable choice for processing the relevant data for this study. All information on consumption (EXIOBASE), income shares (WIID and The World Bank) and HDI (UNDP) was imported, organized and handled in this computer program before being exported to excel for visualization and further calculations. Please see Appendices A-F for full MATLAB scripts.

Furthermore, the open source drawing tool InkScape was used. This software allows the user to edit and create Scalable Vector Graphics (SVG) in a vector format, making it a relevant choice for creating graphs for illustration purposes (Free Software Foundation, Inc, 2008).

3.6 Analysis

3.6.1 Gini coefficient, Lorenz Curves and relative change

First introduced by Corrado Gini in 1912, the Gini Coefficient (GC) has grown to become one of the most common ways of expressing inequality (Ceriani and Verme, 2012). Defining the term as *"the mean difference from all observed quantities",* Gini created 13 different expressions for the coefficient (Ceriani and Verme, 2012). Mathematically, the term can be described based on the Lorenz Curve, and may have any value between 0 and 1, where 0 expresses perfect equality, whereas if one person where to be in possession of 100% of the income, the GC would have a value of 1.

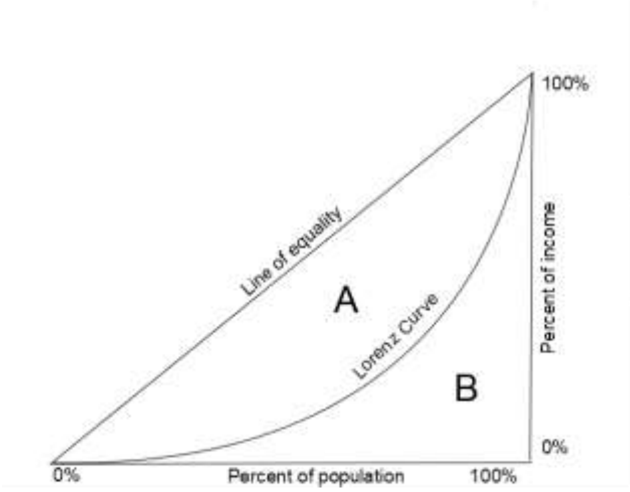

Figure 1: Draft of the Lorenz Curve created in InkScape.

In Figure 1, the line with an angle of 45 degrees displays perfect equality (GC = 0), whereas the Gini Coefficient is represented by the ratio of the area between the Lorenz Curve and the line of equality. This can be expressed with equation (13).

$$G = \frac{A}{A + B} \tag{13}$$

Here G is the Gini Coefficient, and A and B represents the areas marked in Figure 1. A more complex approach applied by Alsamawi et al. (2014) is to create the Lorenz Curve by plotting the normalized cumulative income I(x) for income class x,

$$I(x) = \frac{1}{I_{tot}} \int_{0}^{x} i(x)\, dx \tag{14}$$

against the normalized cumulative population, $P(x)$, in income class x,

$$P(x) = \frac{1}{P_{tot}} \int_{0}^{x} p(x)\, dx \tag{15}$$

If we let μ = 1 represent perfect equality, and increasing inequality as a result of μ → ∞, the Gini Coefficient can be approximated by a power function f,

$$f = P(x)^{\mu} \tag{16}$$

The absolute value of the coefficient, G, can then be retrieved by applying the method already mentioned – calculating the ratio of the area between the Lorenz Curve and the line of equality – this time using the variable μ.

$$G = 1 - 2 \int_{0}^{x} P(x)^{\mu}\, dx \tag{17}$$

Furthermore, to assess the change in footprints from 2004 to a chosen year i, the relative change was found for global, regional and quintile levels and given by equation (18).

$$Change = \frac{x_i - x_{2004}}{x_{2004}} \tag{18}$$

3.6.2 Choice of regions and demand categories

EXIOBASE contains a variety of demand categories, such as governmental expenditures, gross fixed capital formation and household demand. Considering this paper focusing on development and consumption behaviors of the inhabitants of a country, and not their governments, solely household demand is taken into account in the calculations. Further, several nations suffer from governmental corruption, leading to state consumption being significantly different than behaviors on the local level (Gupta et al., 2002), pointing towards household consumption to be a suitable demand category to target in this study. Notably, many inequality studies include all consumption categories (Alsamawi et al., 2014; Hubacek et al., 2017), however, due to limited data on quintile demand, this approach would be challenging to take for this analysis. Conclusively, the footprints of food consumption will be calculated based on household consumption of the 25 food products in EXIOBASE based on the expenditure in MEUR.

Importantly, one should keep in mind that product categories such as “Hotel and restaurant services”, “Health and social work services” and “Education services” are not included when calculating impacts of food in this study. Clearly, food is served at hotels, hospitals and sometimes schools, however, extracting exactly how much of their FPs are allocated to this is a challenging task, as they also provide other services that will have a certain impact. Further, the service sectors are responsible for large amounts of food waste (Silvennoinen et al., 2015; Tonini et al., 2018), making modelling consumption habits of households more complicated if these sectors were to be included. Camanzi et al. (2017) commiserate that food footprints of the service sectors are favorable to include in environmental analyses, as they might affect the results slightly. However, in order to achieve such an analysis, a significantly complete and detailed database is required (Camanzi et al., 2017). Therefore, this study only accounts for direct consumption, and not any purchases through e.g. restaurants and school cafeterias into account.

Moreover, to investigate trends on a regional basis, six regions were selected for further research; China, Brazil, Norway, United States, Indonesia and RoW Africa, the latter covering all African nations excepts South Africa. These six were chosen for allowing for comparison with the results obtained in the project work prior to this thesis (Thomassen, 2017). Further, being grand world economies placed in largely different continents over the globe, China, United States and Brazil were chosen due to their economic strength, massive production quantities of goods and relatively considerable GHG footprints (Boden and Andres, 2014). This study is conducted in Norway, making the country itself a relevant choice for further analysis. More importantly, Norway provides an interesting perspective, as it has a relatively high GDP per capita as well as being a lower populated nation (The World Bank, 2017). As the world’s fourth most populous country (The World Bank, 2018b) and a large exporter of palm oil, Indonesia has been drawing international attention for its agricultural practices the last years (Wicke et al., 2011), making it an interesting target for further analysis. Lastly, RoW Africa contains several less developed and lower-income countries, providing for a contrasting view on development compared to industrial countries. Together, the combination of the six selected regions allows for obtaining an interesting perspective on human development in contrasting economies with unequal population numbers, production practices and cultures.

4 Results

4.1 Total footprints on a global and regional level

The first section will include all total footprints, i.e. not in per quintile terms, to provide an overlook of the development of the impacts over the 8-year period. The development in global footprints per capita from food consumption given by the ratio compared to 2004-values is shown in Figure 2. All results regarding food products were calculated due to the products given in Table 10.

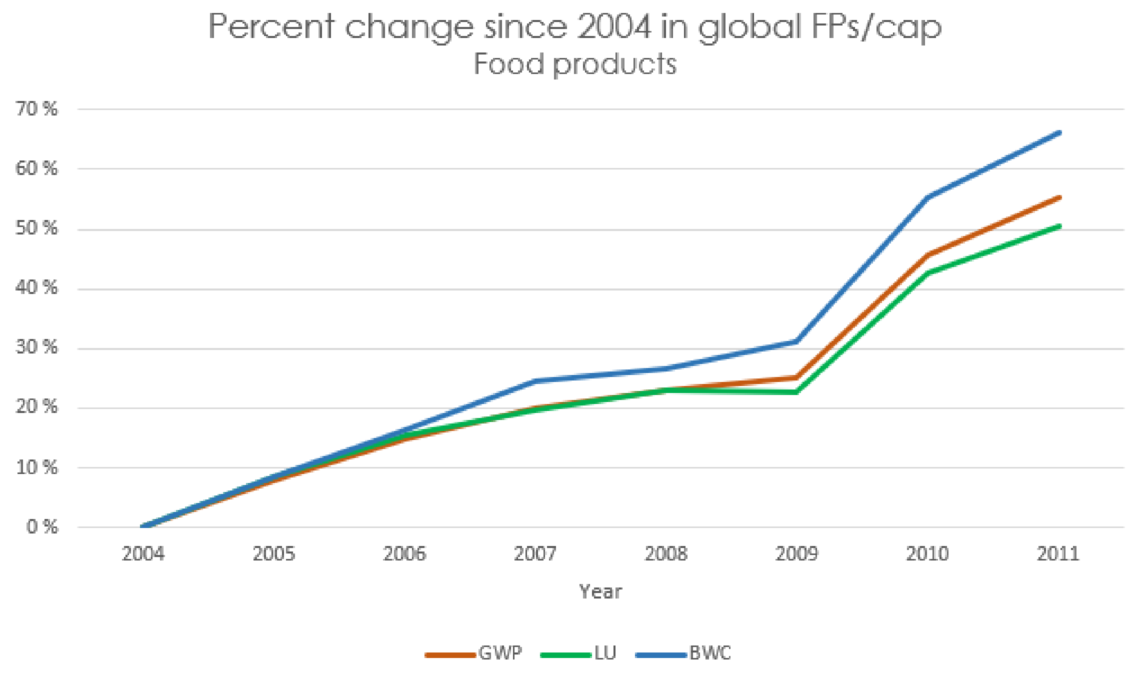

Figure 2: Development in global footprints from food consumption per capita from 2004 to 2011, given by the percent change compared to 2004 values. The footprints encompass Global warming potential (GWP), Land use (LU) and Blue water consumption (BWC).

In Figure 2, we observe increasing trends in all footprints per capita. Especially the BWC has been increasing, whereas GWP and LU tends to be rising at a lower rate. As these results solely encompass food products, comparing them to the same calculations done for all products might be favorable. These results are displayed in Figure 3.

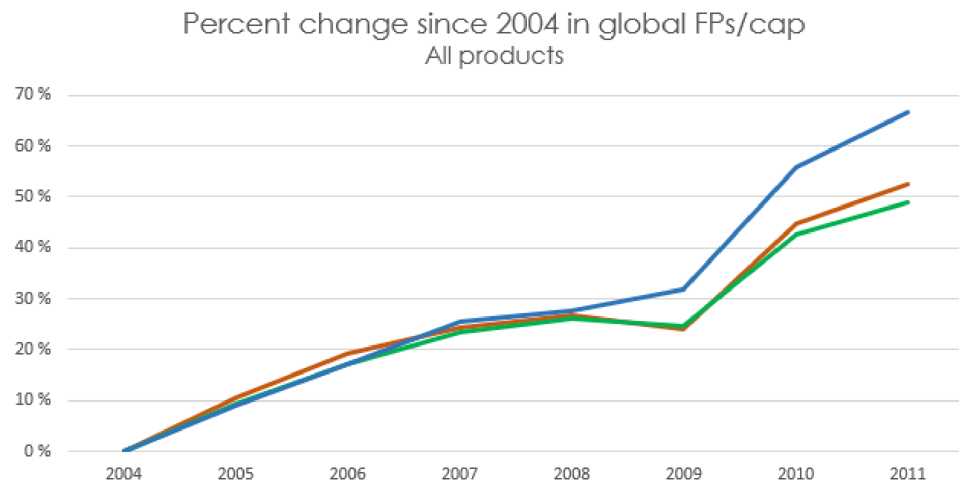

Figure 3: Development in global footprints per capita from 2004 to 2011, given by the percent change compared to 2004 values. The footprints encompass Global warming potential (GWP), Land use (LU) and Blue water consumption (BWC).

Here (Figure 3) we observe the same trends as in Figure 2. The BWC footprint is increasing more than the others and at approximately the same level as in Figure 2 (~ 66% from 2004 to 2011), however, GWP and LU interestingly seem to have increased less (~ 52% and ~49% in Figure 3 and ~55% and ~50% in Figure 2, respectively, from 2004 to 2011). To get a wider perspective on the development of the footprints, looking at the changes for the absolute values might be beneficial. The development of the FPs from exclusively food products is shown in Figure 4.

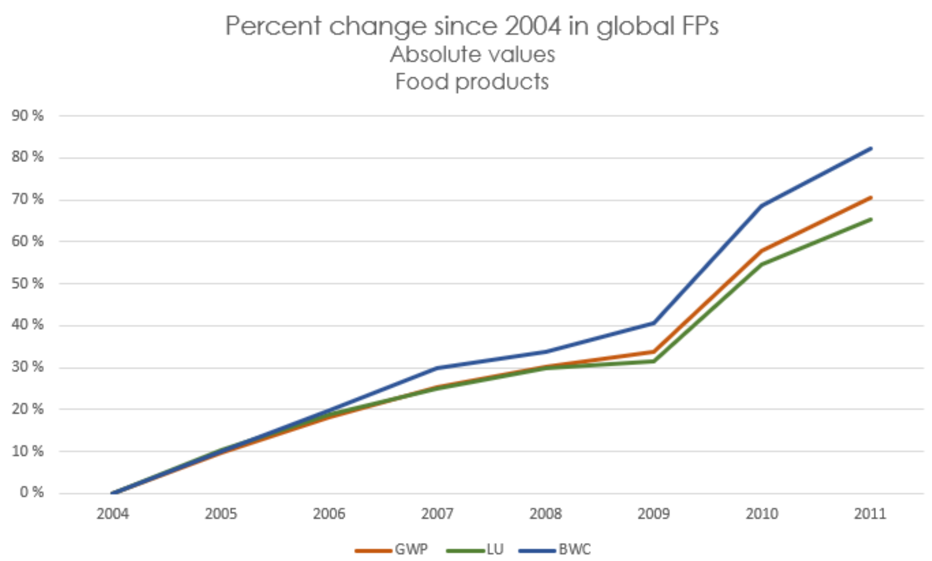

Figure 4: Development in global footprints from food consumption in absolute values from 2004 to 2011, given by the percent change compared to 2004 values. The footprints encompass Global warming potential (GWP), Land use (LU) and Blue water consumption (BWC).

Analyzing the results on absolute values shown in Figure 4, it is observed that the footprints from food consumption has been increasing more than for per capita values (~82% for BWC, ~71% for GWP and ~65% for LU from 2004 to 2011). Absolute values rising more significantly than per capita results is obviously expected, as population numbers have been growing as well (The World Bank, 2018b). To allow for further comparison, looking at the same results for consumption of all products might be beneficial (Figure 5).

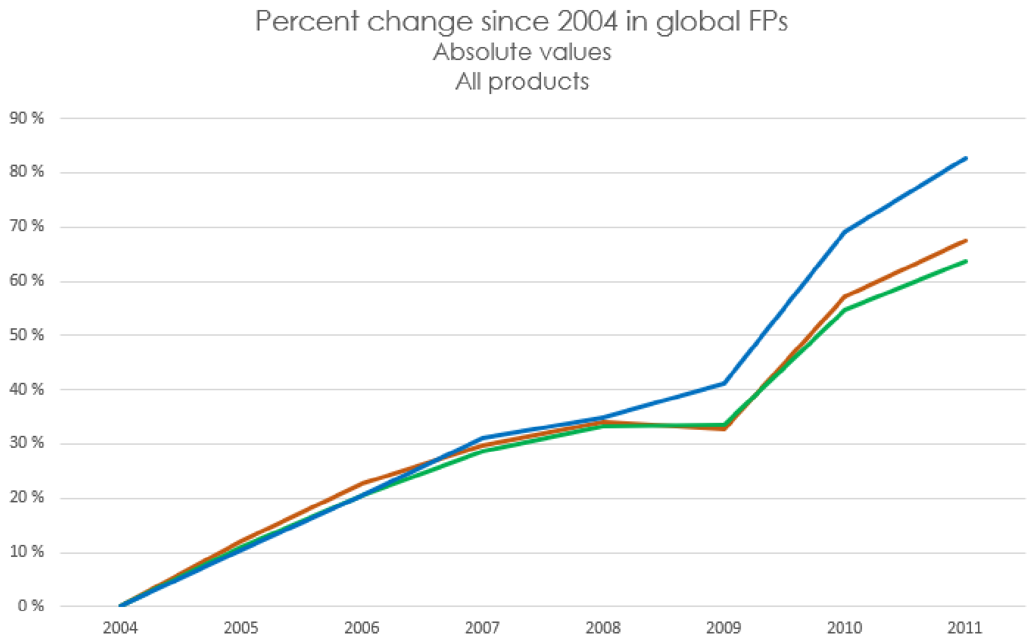

Figure 5: Development in global footprints from consumption of all products in absolute values from 2004 to 2011, by the percent change compared to 2004 values. The footprints encompass Global warming potential (GWP), Land use (LU) and Blue water consumption (BWC).

In Figure 5 it is observed that the BWC footprint from all products has been increasing approximately similarly as for only food products (~82%), indicating that global BWC is largely linked to food consumption. Further, the GWP and LU are rising less for all products than food products (~66% and ~62% respectively), which is expected, due to the same tendency being found for per capita values.

As consumption behaviors and development levels vary significantly across the world, taking a deeper look into regional trends might provide an eye-opening perspective. The percent change from 2004 to 2011 in average footprints from food consumption across the quintiles are displayed in Figure 6.

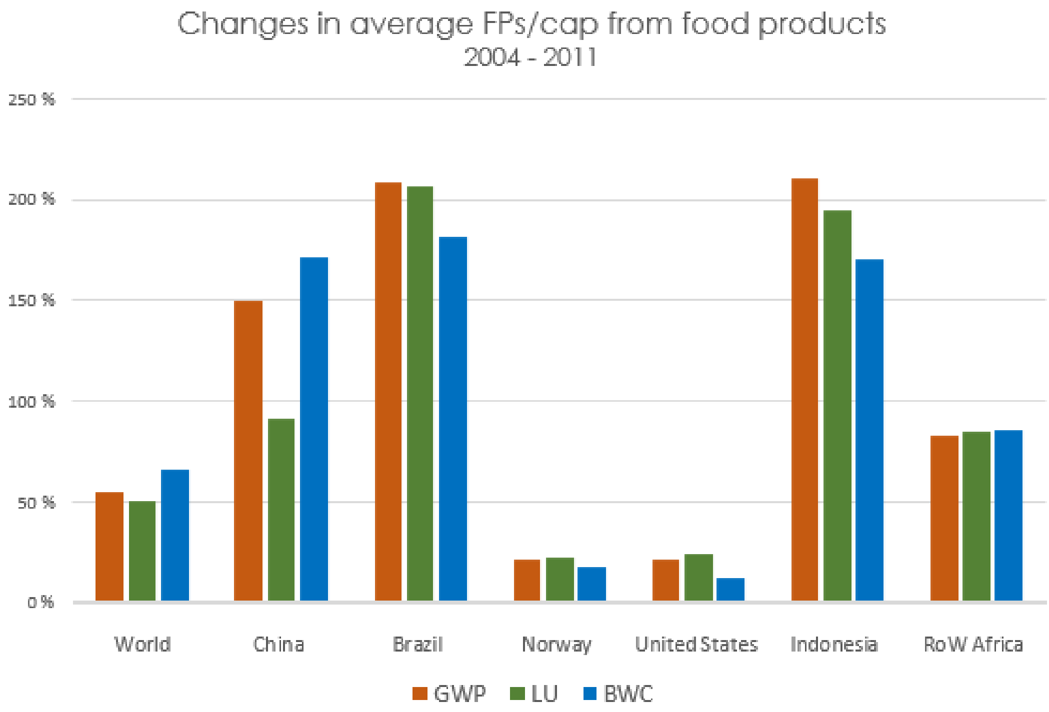

Figure 6: Development in average footprints per capita from food consumption across the income quintiles in China, Brazil, Norway, United States, Indonesia, RoW Africa and the World from 2004 to 2011 given in percent change. The footprints include Global warming potential (GWP), Land use (LU) and Blue water consumption (BWC).

As Figure 6 demonstrates, the variations of footprint development from food consumption are strong across the globe. Brazil and Indonesia stand out as having experienced a significant change in their GWP footprint over the 8 years (~205%). China follows as number three (~150%) and RoW as number four (~70%). In comparison, Norway and United states show smaller changes in GWP (~25%) and are the only ones that increase less than global average (~52%). Further, Brazil and Indonesia had the most rising LU footprints at ~210% and ~195%, respectively. China and RoW Africa beat global values by around 20-30%, whereas Norway and United States show the smallest increases. The BWC footprints show the same tendency by having risen significantly in Brazil (~180%), Indonesia (~170%) and China (~170%), moderately in RoW Africa (~80%) and the world (~60%), and the least in Norway (~15%) and United States (~10%).

An interesting observation is that most regions show somewhat similar levels of increase per footprint – all except China, that appears to have a LU footprint increasing much slower than the other two. Furthermore, it is observed that the largest increases all happen in emerging economies – China, Brazil and Indonesia – whereas developed nations such as Norway and United States have significantly slower increasing footprints. However, an important notice is that Figure 6 only represents the *change* in environmental impact. To gain a wider perspective on where people contribute the most to the footprints, one may find it interesting to examine the footprints per capita in these regions. Firstly, the GWP footprint per capita from food consumption in 2004 and 2011 is represented by Figure 7.

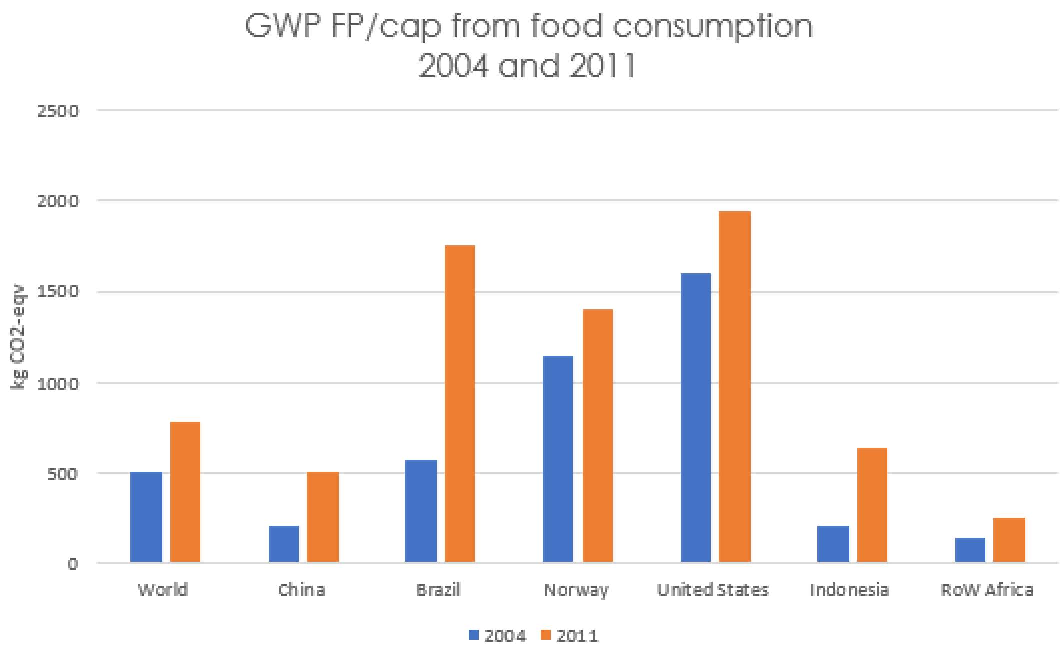

Figure 7: Global warming potential footprint per capita from food consumption in 2004 and 2011, given in kg CO_2*-equivalents.*

Here (Figure 7) it is observed that the developed countries Norway and United States have a significant larger GWP FP/cap than Indonesia, China, RoW Africa and the World. Brazil have been increasing its emissions significantly since 2004 and is the second largest emitter per capita after United States. In Figure 6, Indonesia was observed to be a region with the most increasing GWP footprint, however, as Figure 7 shows, it was not significantly large in the first place. This underlines the importance of looking at results from different angles, and not solely the percentage of change. Secondly, the land use footprint per capita is also important to include. This is displayed in Figure 8.

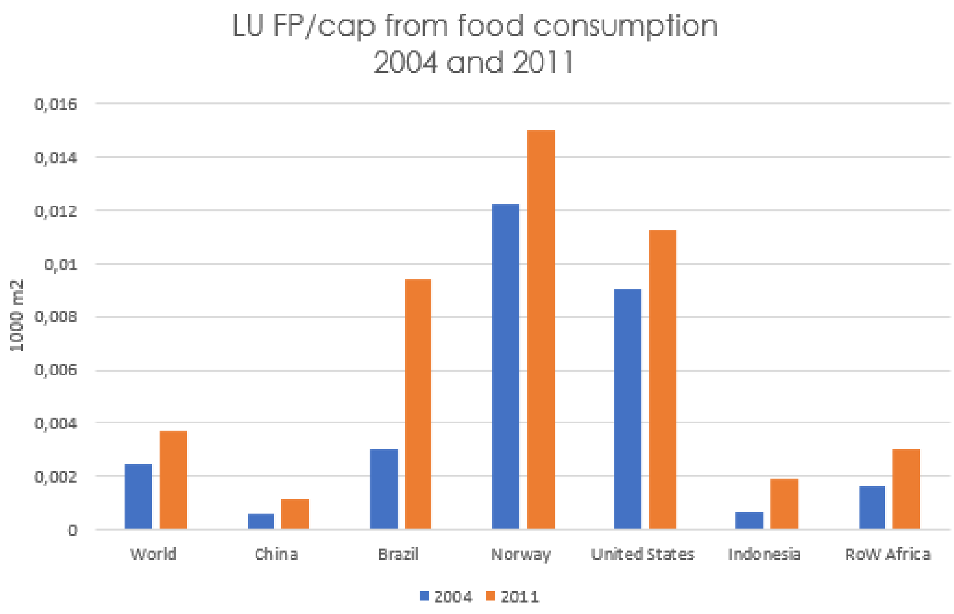

Figure 8: Land use footprints per capita from food consumption in 2004 and 2011, given in 1000 m^2

It is clear that Norway stands out as having the largest LU footprint per capita of all the displayed nations in Figure 8. This can interestingly be compared to Figure 6, where this country was found to be increasing the least compared to the same selection of regions. United States and Brazil both follow with relatively large footprints, whereas China, Indonesia and RoW all have notably lower values than the world average.

Lastly, the BWC footprint per capita from food consumption in 2004 and 2011 is presented by Figure 9.

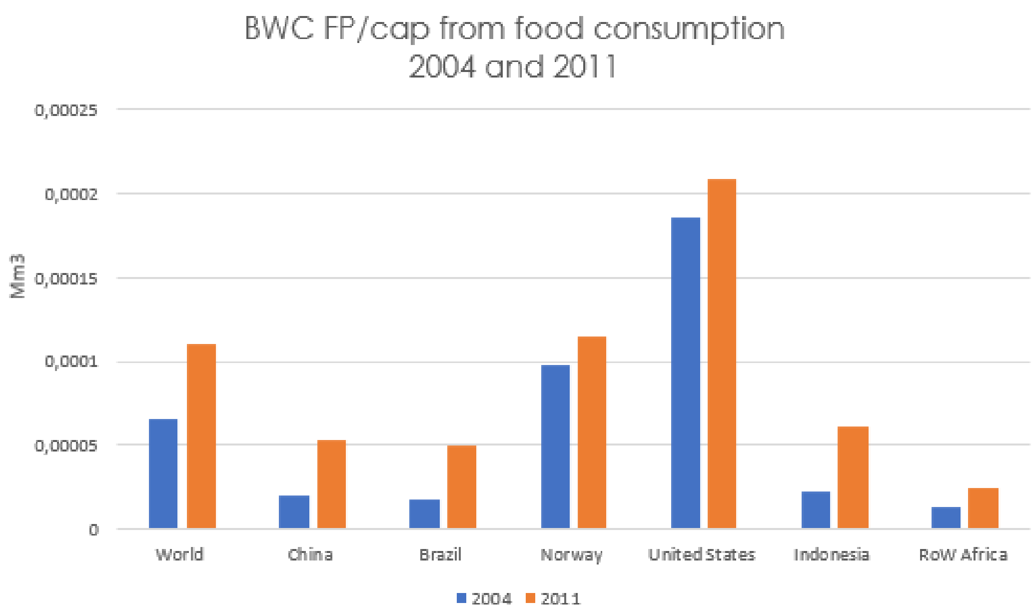

Figure 9: Blue water consumption footprints per capita from food consumption in 2004 and 2011, given in Mm^3.

Compared to the results for GWP and LU shown in Figure 7 and Figure 8, the outcomes for BWC displayed in Figure 9 tend to be following slightly different tendencies. United States clearly stands out as having the largest impact, whereas Norway barely beats world average impacts. The three emerging economies, China, Brazil and Indonesia, all have significantly lower impacts than the global mean, whereas RoW has the lowest consumption of blue water. However, as can be observed here (Figure 9) and Figure 6, the emerging economies have more than doubled their BWC footprint over the 8-year period.

Importantly, it is vital to keep in mind that per capita values do not reflect the absolute emissions of a country. China being the most populous country in the world with over 1.3 billion inhabitants in 2011 (The World Bank, 2018b) would clearly have a larger total environmental footprint than a country that notably less populated, e.g. Norway with 4.95 million people in 2011. Therefore, it is important to consider the impacts in absolute terms as well, in order to gain a fuller perspective on the previous results. These footprints are shown Table 12.

Table 12: GWP, LU and BWC footprints from food consumption in absolute terms in 2004 and 2011 in the world and selected regions. R.A. is an abbreviation for RoW Africa.

FP	Year	World	China	Brazil	Norway	US	Indonesia	R. A
GWP	*2004*	2,9E+12	2,6E+11	1,0E+11	5,3E+09	4,7E+11	4,5E+10	1,1E+11
kg CO_2e	*2011*	4,9E+12	6,8E+11	3,4E+11	6,9E+09	6,1E+11	1,5E+11	2,4E+11
LU	*2004*	1,4E+07	7,9E+05	5,6E+05	5,6E+04	2,6E+06	1,4E+05	1,3E+06
Km^2	*2011*	2,3E+07	1,6E+06	1,8E+06	7,4E+04	3,5E+06	4,7E+05	2,9E+06
BWC	*2004*	3,8E+05	2,6E+04	3,2E+03	4,5E+02	5,5E+04	5,1E+03	1,1E+04
Mm^3	*2011*	6,9E+05	7,2E+04	9,7E+03	5,7E+02	6,5E+04	1,5E+04	2,4E+04

Scrutinizing Table 12, it becomes clear that China has the largest GWP and BWC footprints from food consumption in absolute terms, whereas United States has the largest LU footprint. Further, being the country with the smallest population, Norway has the smallest impacts in all categories. This highlights the importance of considering absolute values in addition to per capita results, as China has notably small impacts on GWP and LU in per inhabitant, but very large in absolute terms. Norway, on the other hand, has significantly lower FPs on the global scale in total, whereas in per capita, it is one of the largest contributors.

In this result section, the total footprints on a world average level, as well as for some regions, have been presented. This builds the basis for understanding how the development of footprints have unfolded over the 8-year period. However, in order to understand the link between food consumption, human development and environmental stewardship, it is essential to look further into *where* these are stemming from within a society. The following section presents the unequal impacts from different socioeconomic groups across nations.

4.2 Footprint distribution and inequality

As will be shown in this section, the footprints are not evenly distributed between the different socioeconomic groups. First, the development of the footprints divided into quintiles will be presented, followed by graphs illustrating the distribution of the impacts for selected years. Thereafter, calculations of Environmental Gini Coefficients will be introduced, subsequently accompanied by analyses of the income Gini Coefficient and Human Development Index (HDI).

4.2.1 Footprint development on a quintile level

4.2.1.1 Global level

The percent change since 2004 in global GWP FP/cap from food consumption for the different quintiles is displayed in Figure 10.

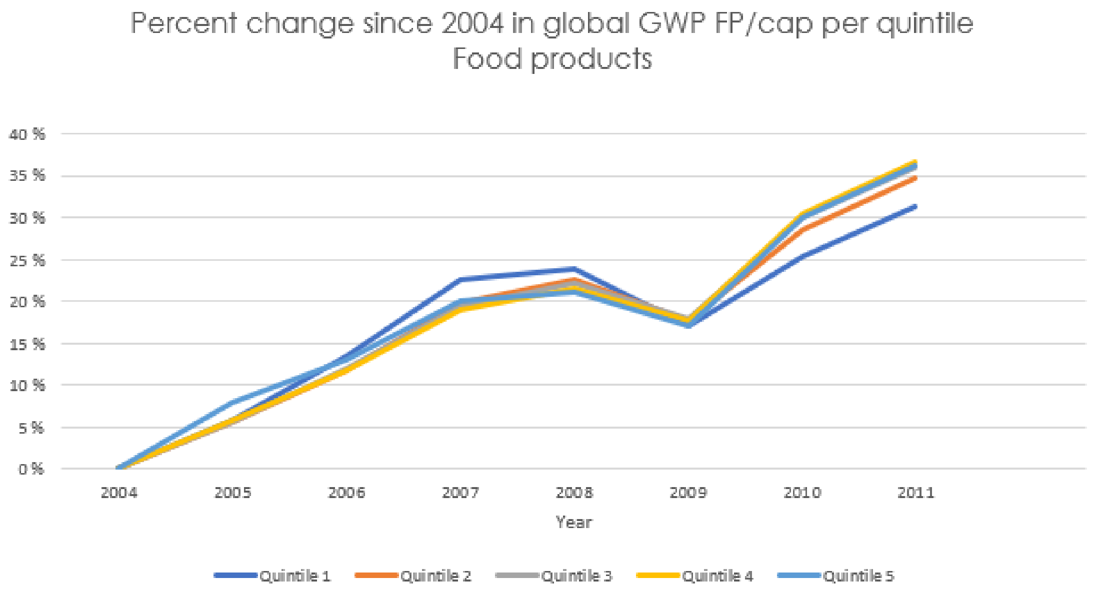

Figure 10: Development in global GWP footprint from food consumption per capita from 2004 to 2011, given for each income group. Quintile 1 represents bottom 20%, whereas quintile 5 is the top 20% of income. The results are population weighted average.

Here (Figure 10) it is observed that quintile 4 has experienced the largest increase in GWP FP/cap (~36%). Quintile 5 follows right after, lagging with ~1% behind the fourth quintile. The two bottom socioeconomic groups (1 and 2) have had the smallest increases at around 31% and 34%, respectively. Interestingly, quintile 1 is observed to be rising the most of all until 2009, before it turns over to be the quintile with the least growing impacts. Furthermore, the year 2009 also stands out, as the increase for every group seems to be more equal at this point. This is explored further in section 5.2. Also, Figure 34 in section 4.3 provides a perspective on which food products contribute the most to the GWP FP.

To get an understanding whether these patterns of contribution from the quintiles are equal for all footprints or not, looking at the results from the same analysis done on LU and BWC is essential. The outcomes for the LU FP/cap from food consumption per quintile are displayed in Figure 11.

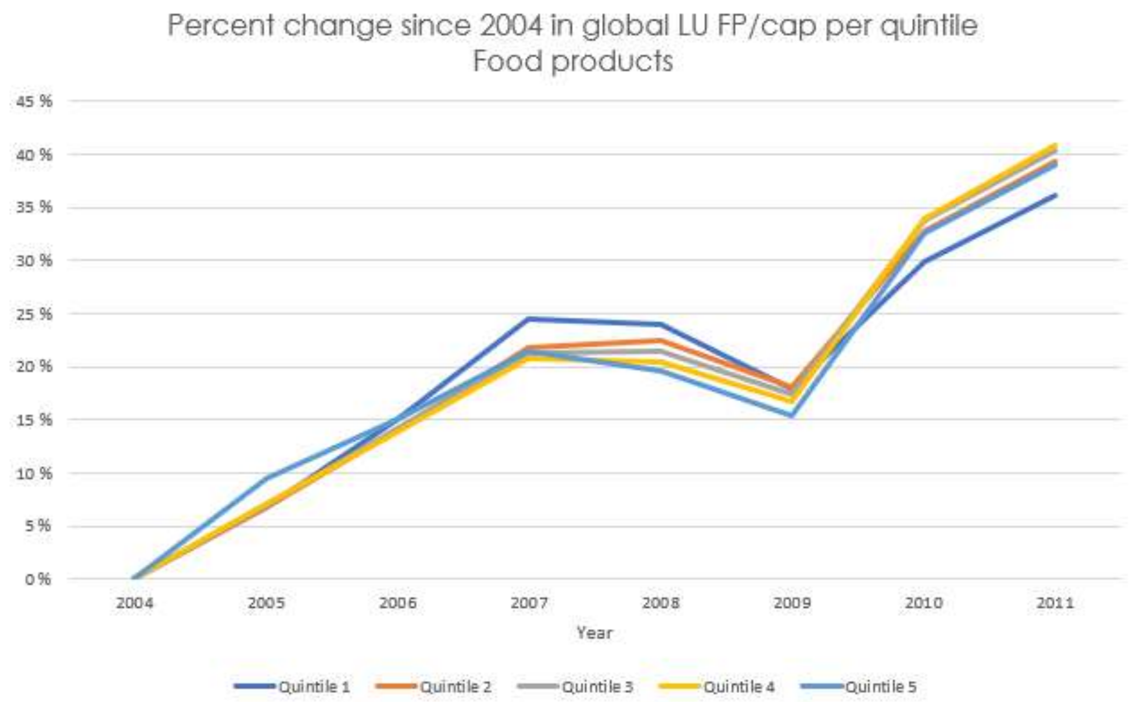

Figure 11: Development in global LU footprint from food consumption per capita from 2004 to 2011, given for each income group. Quintile 1 represents bottom 20%, whereas quintile 5 is the top 20% of income. The results are population weighted average.

Clearly, the development patterns for LU showed in Figure 11 are not equal to the ones for GWP, however, they share some similarities. Quintile 4 stands out again as the group with the largest change from 2004 to 2011, whereas the bottom quintile again has had the smallest. Further, it is also observed that the increase becomes more equal across the quintiles around 2009. Thought-provokingly, quintile 3 and 2 are observed to have experienced larger changes than the top group, something that is unequal to what was found for the GWP FP. Also, quintile 5 seems to be the group that experiences the most change from 2004 to 2006, before the bottom quintile takes over this role until 2009. Figure 35 in section 4.3 provides an overview of which food products contribute the most to the LU FP.

The last footprint to analyze is the BWC FP per capita from food consumption per quintile, and these results are presented in Figure 12.

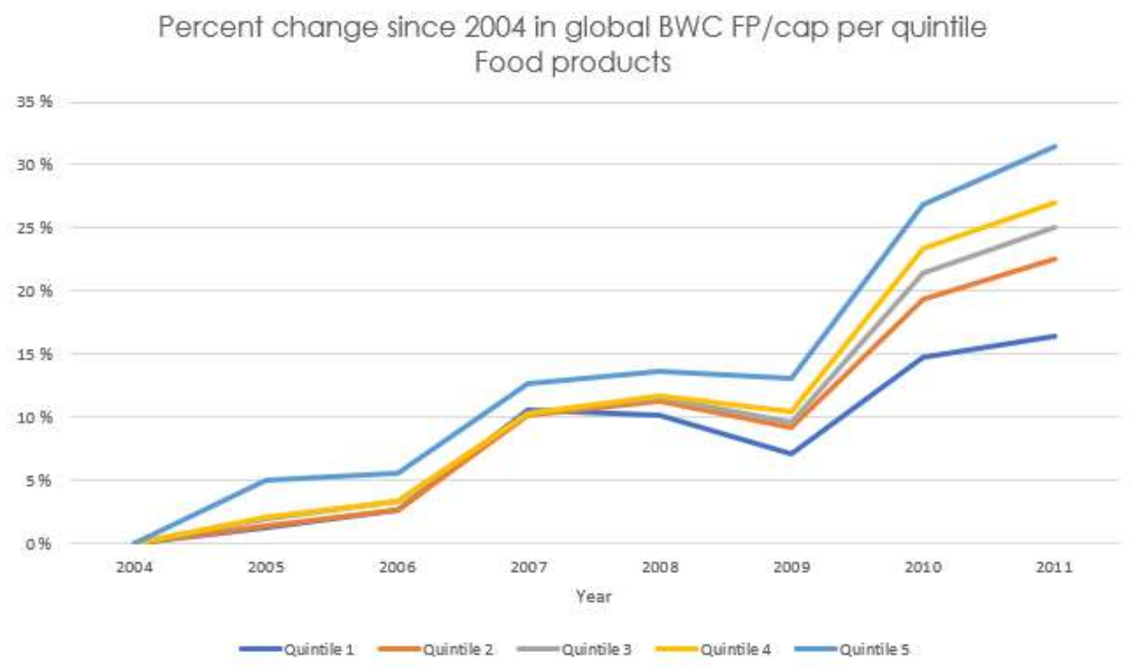

Figure 12: Development in global BWC footprint from food consumption per capita from 2004 to 2011, given for each income group. Quintile 1 represents bottom 20%, whereas quintile 5 is the top 20% of income. The results are population weighted average.

Interestingly, the results in Figure 12 tend to follow a different pattern than what was displayed for GWP and LU. Quintile 5 clearly stands out as the group that experienced the most change from 2004 to 2011 (~32%), whereas the bottom quintile again comes out with the smallest change in the same timespan (~16%). Further, a rather eye-catching result are the disparities between the changes for the quintiles towards 2011. The difference between quintile 1 and quintile 5 for BWC is conspicuously larger the last 3 years than what was found for GWP and LU. Something that further awakens curiosity is how the lines in Figure 12 tends to diverge from 2007 to 2009, whereas the exact opposite tendency was shown for the other two impact categories. This is an interesting finding that is further discussed in section

5.2.2.1. Also, Figure 36 in section 4.3 explains which food products have the largest impact on the BWC FP.

In section 4.1, it was demonstrated that the development of the footprints varied hugely across the regions. Therefore, looking into the quintile development of some of these might provide an interesting perspective.

4.2.1.2 Regional level

In Figure 6, the changes of the impacts for the selected regions were presented. In this section, the development on the quintile level for a selection of FPs and regions will be displayed to open for a further understanding of the driving quintiles behind these changes. As Indonesia stood out as the region having the most increasing GWP FP/cap, this nation is presented first in Figure 13.

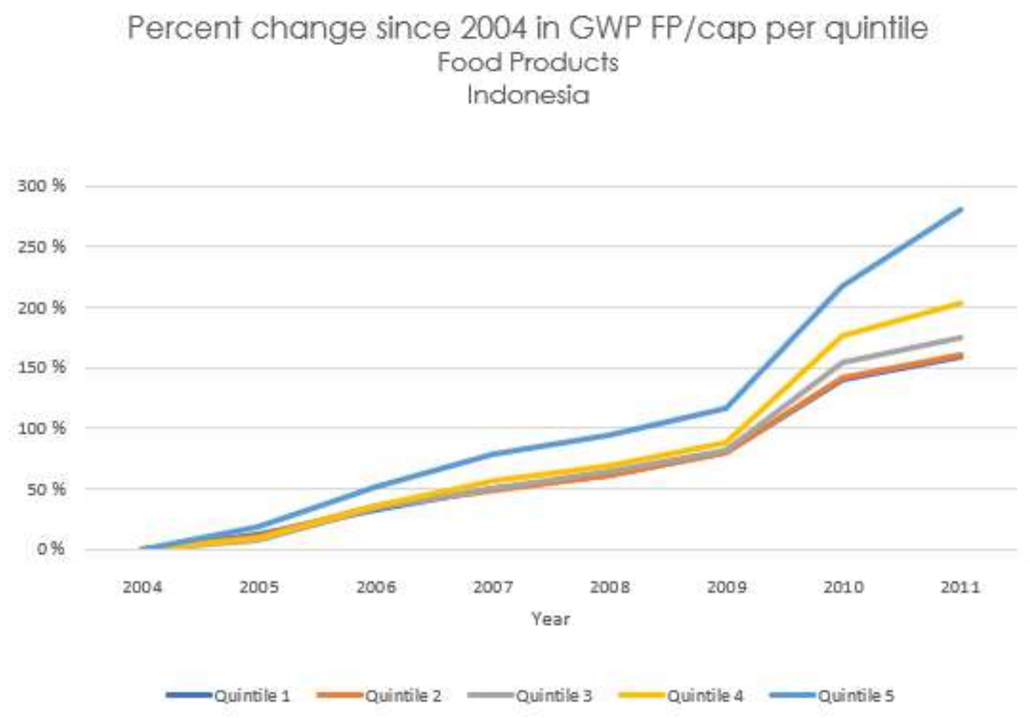

Figure 13: Development in GWP footprint from food consumption per capita from 2004 to 2011 in Indonesia, given for each income group. Quintile 1 represents bottom 20%, whereas quintile 5 is the top 20% of income.

For Indonesia, it is observed that the top quintile has experienced the largest change from 2004 to 2011 (~280%), followed by quintile 4 (~200%). The impacts from the two bottom groups have risen, however, not as much as for the top ones (~155% for quintile 1 and

2). Indonesia is regarded as an emerging economy, comparing these results to the trends in the developing region RoW Africa might provide an interesting perspective.

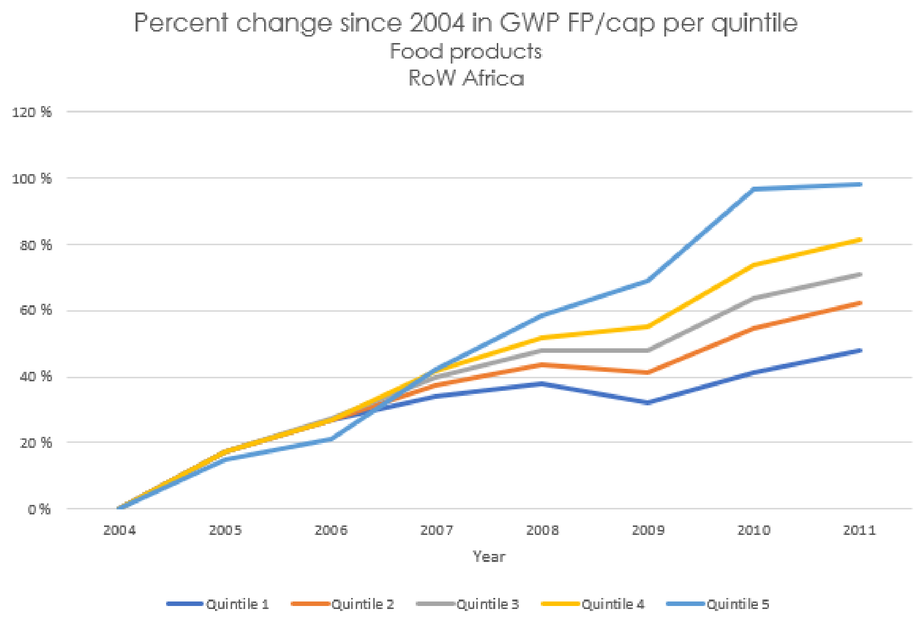

Figure 14: Development in GWP footprint from food consumption per capita from 2004 to 2011 in RoW Africa, given for each income group. Quintile 1 represents bottom 20%, whereas quintile 5 is the top 20% of income.

In Figure 14, it is observed that the change in the 8-year timespan is more diverse among the quintiles in RoW Africa than what was found for Indonesia. Quintile 5 has clearly experienced a significant change compared to the bottom income group (~95% vs. ~45%). These results points towards a more unequal development in Africa compared to Indonesia. As both RoW Africa and Indonesia are not yet considered to be developed economies, comparing these results to an industrial country might provide a thought-provoking perspective. Therefore, the outcomes of the same analysis done on The United States is displayed in Figure 15.

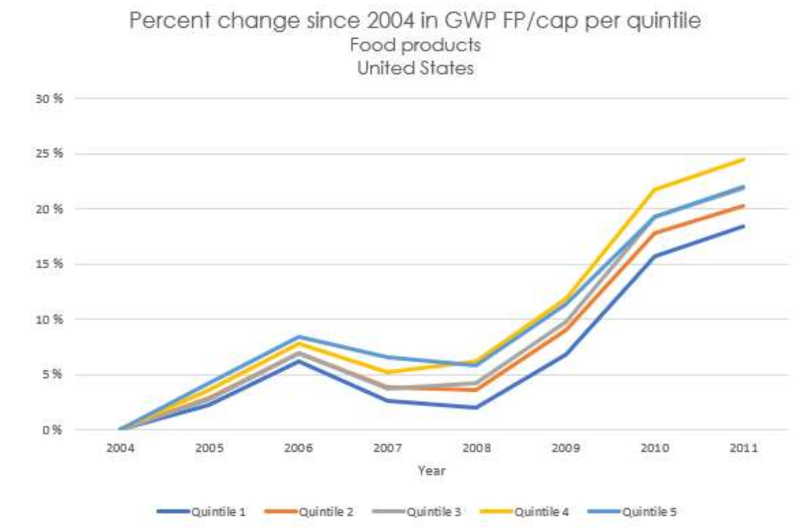

Figure 15: Development in GWP footprint from food consumption per capita from 2004 to 2011 in the United States, given for each income group. Quintile 1 represents bottom 20%, whereas quintile 5 is the top 20% of income.

Interestingly, the trends in United States (Figure 15) seem to follow a different pattern than what was found for RoW Africa and Indonesia. Firstly, the largest increase is taking place from 2008 and not in 2009, as was found for the other two. Secondly, it is the fourth quintile that have experienced the largest increase, followed by the top income group, indicating the shares of the GWP footprint growing towards becoming more equal between the two top income groups.

Further, according to Figure 6, Brazil experienced the largest increases in LU FP/cap from 2004 to 2011, something that may inspire one to take a deeper look into these results.

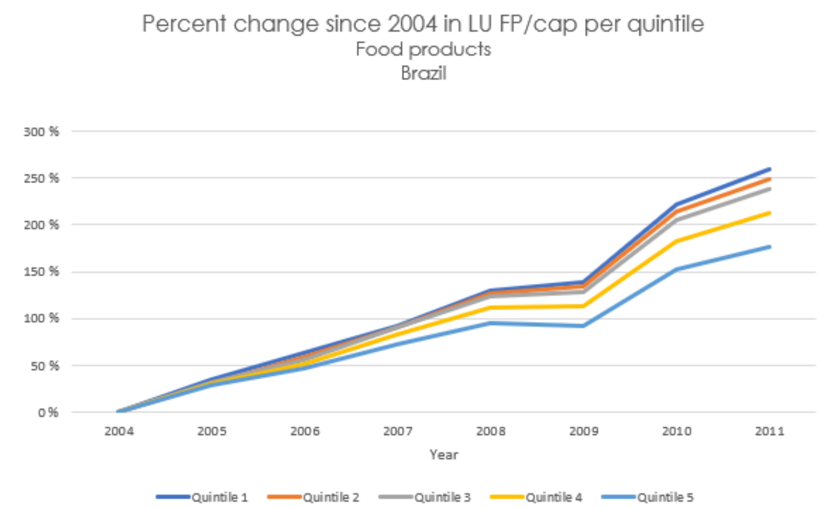

Figure 16: Development in LU footprint from food consumption per capita from 2004 to 2011 in Brazil, given for each income group. Quintile 1 represents bottom 20%, whereas quintile 5 is the top 20% of income.

The results displayed in Figure 16 present some interesting findings compared to what has been shown earlier in this section, as it is quintile 1 and 2 that seem to have been experiencing the largest changes, while the richest and fourth quintile have been growing the slowest. Further, the changes seem to be happening most rapidly after 2009.

As mentioned, Brazil is one of the worlds emerging economies, and therefore, comparing these findings to the ones found for a developed country might provide an interesting perspective.

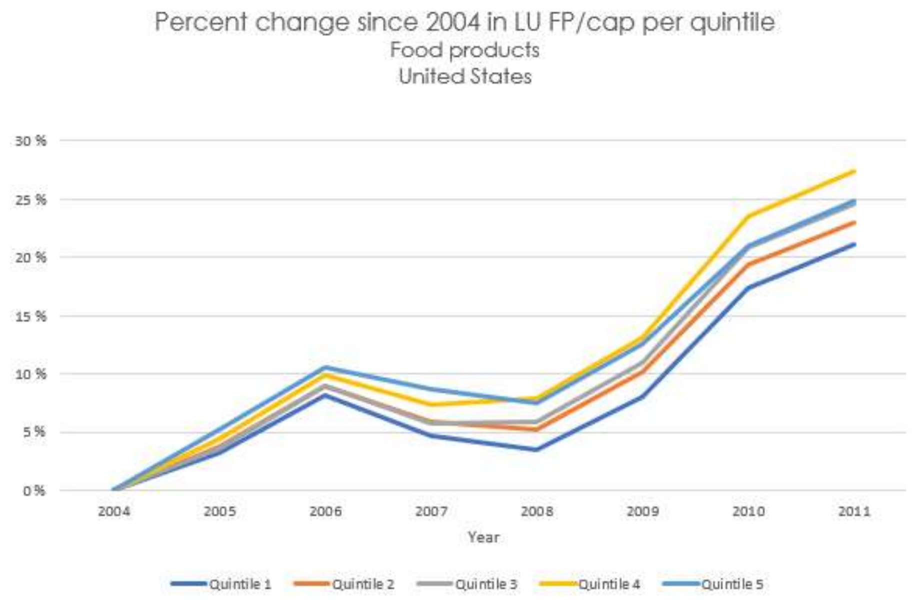

Figure 17: Development in LU footprint from food consumption per capita from 2004 to 2011 in United States, given for each income group. Quintile 1 represents bottom 20%, whereas quintile 5 is the top 20% of income.

According to Figure 17, the LU FP/cap in the United States has not been following the same pattern as in Brazil. Here, the fourth income group seems to be the one that experienced the largest changes, followed by quintile 5 and 3. These trends share large similarities with the development of the GWP FP/cap in the nation (Figure 15).

Further, as China appeared to have experienced one of the most significant changes in BWC, this will be the next region and FP to be analyzed in further detail.

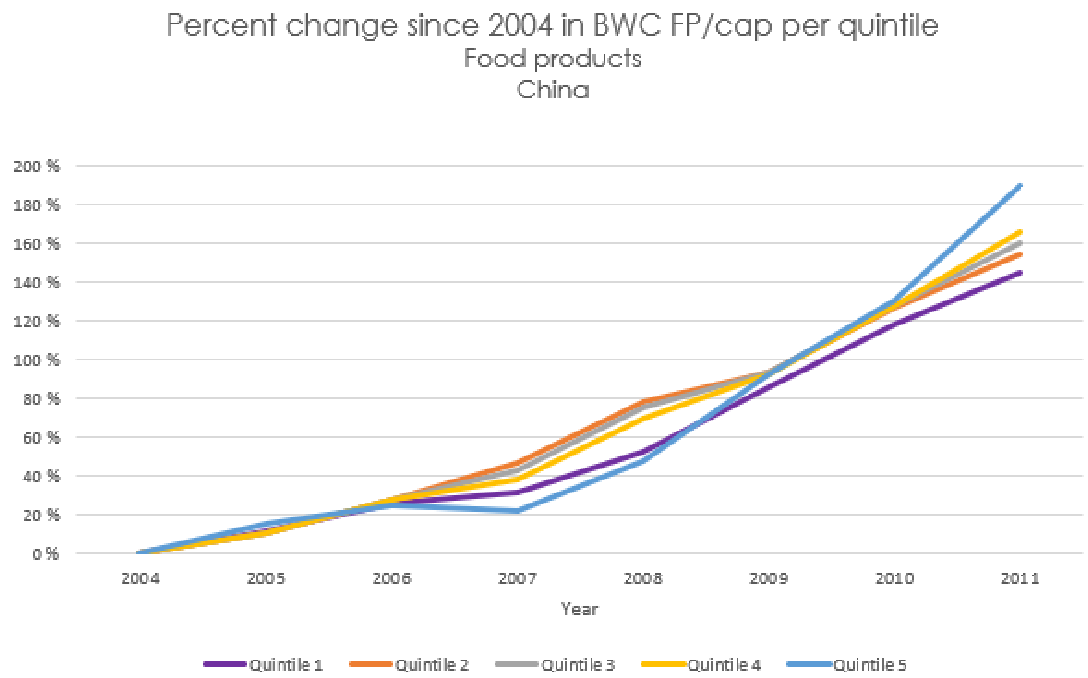

Figure 18: Development in BWC footprint from food consumption per capita from 2004 to 2011 in China, given for each income group. Quintile 1 represents bottom 20%, whereas quintile 5 is the top 20% of income.

In Figure 18 it is observed that the change for the quintiles follow approximately the same pattern. However, it is clear that the top income group stands out as the one experiencing the largest shift from 2004 to 2011 with around 190%, followed by quintile 4. The bottom income group show the smallest change at around 140%, however, this is still a significant shift for an 8-year period. Interestingly, from 2007 to 2008 the positions seem to be switched around, with quintile 5 on the bottom and quintile 2 experiencing the largest change.

Being one of the world's emerging economies, the footprints from China might be expected to rise significantly. In order to illustrate this, one may find it beneficial to compare these finding with the results of the same analysis done on an industrial country, such as United States (Figure 19).

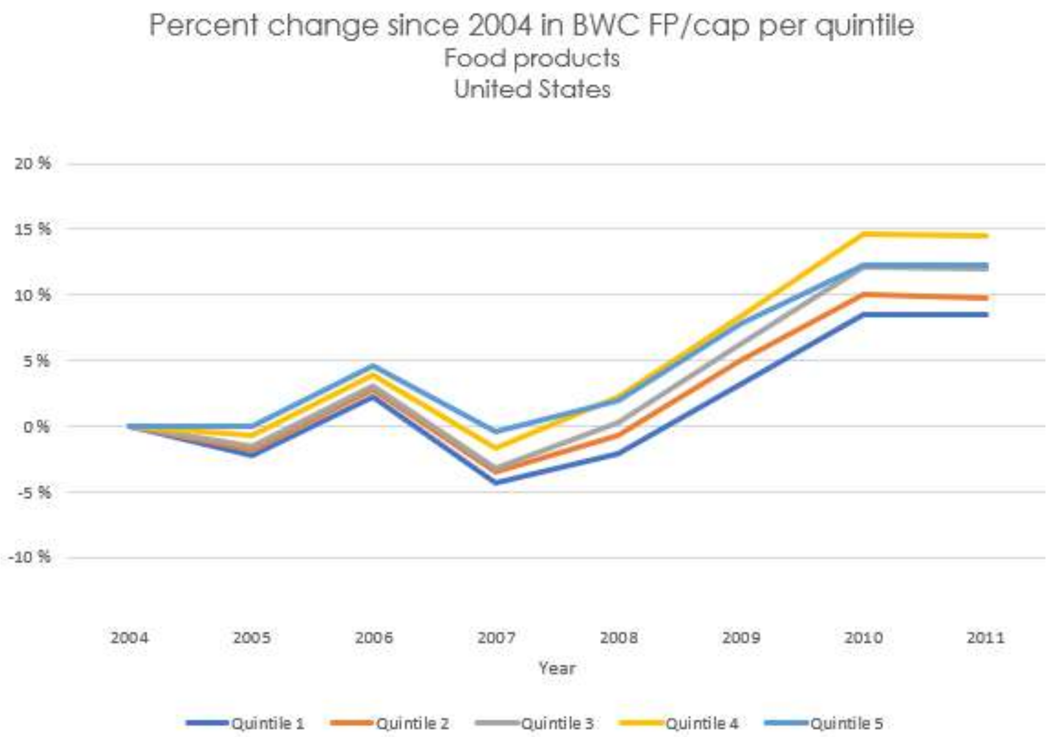

Figure 19: Development in BWC footprint from food consumption per capita from 2004 to 2011 in the United States, given for each income group. Quintile 1 represents bottom 20%, whereas quintile 5 is the top 20% of income.

Examining the results displayed in Figure 19, it becomes clear that the footprint development in the United States is quite dissimilar than what was found for China. Firstly, it is the fourth quintile, and not the top one, that has experienced the largest changes from 2004 to 2011, and secondly this change is conspicuously smaller (~14% change compared to ~190% for China). Thirdly, negative values are observed for the years 2005 and 2007, indicating that the contribution to the footprints in these years were smaller than in 2004.

Importantly, the results displayed in this section has only accounted for the *changes* that have taken place between 2004 and 2011. These are vital findings to understand how the impacts have evolved with time across the quintiles, however, they do not say anything about how the footprints are *actually* distributed, which is what will be the main focus of the next section.

4.2.2 Environmental Gini Coefficients (EGCs)

Table 13: Environmental Gini Coefficients for Global Warming Potential (GWP), Land use (LU) and Blue water consumption (BWC) from 2004 to 2011. The coefficients are given for global footprints from consumption of food, as well as all products. An EGC of 0 represents perfect equality, whereas an EGC of 1 signifies the opposite.

Footprint	Product category	2004	2005	2006	2007	2008	2009	2010	2011
GWP	Only food	0,361	0,367	0,366	0,366	0,366	0,372	0,375	0,379
	All products	0,395	0,400	0,400	0,402	0,404	0,411	0,416	0,423
LU	Only food	0,376	0,382	0,380	0,381	0,381	0,385	0,389	0,389
	All products	0,422	0,428	0,426	0,430	0,428	0,432	0,436	0,436
BWC	Only food	0,356	0,363	0,362	0,362	0,362	0,368	0,369	0,374
	All products	0,378	0,385	0,384	0,386	0,386	0,393	0,394	0,400

The EGCs for GWP, LU and BWC from 2004 to 2011 for global consumption of food and all products are presented in Table 13. Here, it is observed that the footprints from all products are more unevenly distributed than only food, something that is in alignment with the Lorenz curves in section 4.2.3. The highest coefficients are observed for LU for both product categories, and the lowest ones for BWC. A thought-provoking observation is that the coefficients seem to be increasing gradually from 2004 to 2011, indicating that the environmental impacts are growing to become more unequally distributed across income quintiles.

The findings presented until now throughout the result section have shown that regional footprints may differ significantly from global ones, which is why examining the ECGs on a regional level (Table 14) might provide an interesting perspective.

Table 14: Environmental Gini Coefficients for Global Warming Potential (GWP), Land use (LU) and Blue water consumption (BWC) from 2004 to 2011 for selected regions. An EGC of 0 represents perfect equality, whereas an EGC of 1 signifies the opposite.

Footprint	Region	2004	2005	2006	2007	2008	2009	2010	2011
GWP	China	0,437	0,442	0,433	0,412	0,412	0,434	0,436	0,454
	Brazil	0,314	0,310	0,302	0,298	0,291	0,283	0,280	0,278
	Norway	0,242	0,235	0,219	0,217	0,222	0,211	0,210	0,208
	United States	0,338	0,341	0,341	0,344	0,343	0,344	0,342	0,342
	Indonesia	0,331	0,342	0,353	0,362	0,362	0,361	0,379	0,397
	RoW Africa	0,470	0,467	0,463	0,476	0,486	0,499	0,509	0,503
LU	China	0,461	0,465	0,454	0,432	0,430	0,451	0,452	0,469
	Brazil	0,318	0,314	0,306	0,302	0,295	0,287	0,284	0,282
	Norway	0,241	0,234	0,218	0,217	0,221	0,210	0,209	0,208
	United States	0,337	0,340	0,340	0,343	0,343	0,343	0,342	0,342
	Indonesia	0,343	0,359	0,368	0,378	0,377	0,377	0,397	0,416
	RoW Africa	0,455	0,452	0,448	0,462	0,472	0,485	0,495	0,489
BWC	China	0,420	0,426	0,417	0,397	0,399	0,421	0,424	0,442
	Brazil	0,316	0,313	0,305	0,300	0,292	0,284	0,280	0,278
	Norway	0,244	0,237	0,221	0,220	0,224	0,213	0,212	0,211
	United States	0,333	0,337	0,337	0,340	0,339	0,340	0,339	0,339
	Indonesia	0,302	0,311	0,321	0,331	0,333	0,330	0,347	0,365
	RoW Africa	0,407	0,404	0,400	0,413	0,425	0,438	0,449	0,442

According to Table 14, the EGCs vary notably across the regions. For the GWP, the coefficients range from 0.242 in Norway to 0.470 in RoW Africa in 2004, ending at 0.208 and 0.503, respectively, in 2011. Interestingly, some regions have increasing ECGs for GWP from 2004 until 2011, whereas some nations show decreasing values. China, United States, Indonesia and RoW Africa all show rising values, hence growing more unequal with time. On the other hand, Norway and Brazil, tend to lower their EGCs over the timespan.

Comparing the EGCs for GWP and LU, it is observed that their coefficients follow approximately the same patterns. In 2011, RoW Africa again appears to have the most unequal distribution (EGC = 0.489), whereas Norway has the most equal one (EGC = 0.208). Again, China, United States, Indonesia and RoW seems to have growing EGCs, in contrast to Brazil and Norway, where the footprint distribution tends to grow more equal across quintiles.

Furthermore, also the BWC tends to follow the same trends. Yet again, RoW Africa shows EGC of 0.442, sharing the place as the most unequal along with China, whereas

Norway stands out as the most equal one (EGC = 0.211). As was also found for the other two footprints, China, United States, Indonesia and RoW Africa are tending to grow more unequal with time, whereas Brazil and Norway follow the opposite trend.

In general, the LU footprint stands out as the one being most unequally distributed within the regions, however, there are some exceptions. The GWP FP in RoW Africa and the BWC FP in Norway have higher EGCs than for their corresponding LU FPs. The results from food consumption displayed in Table 13 and Table 14 are presented in Figure 20, for visualization purposes.

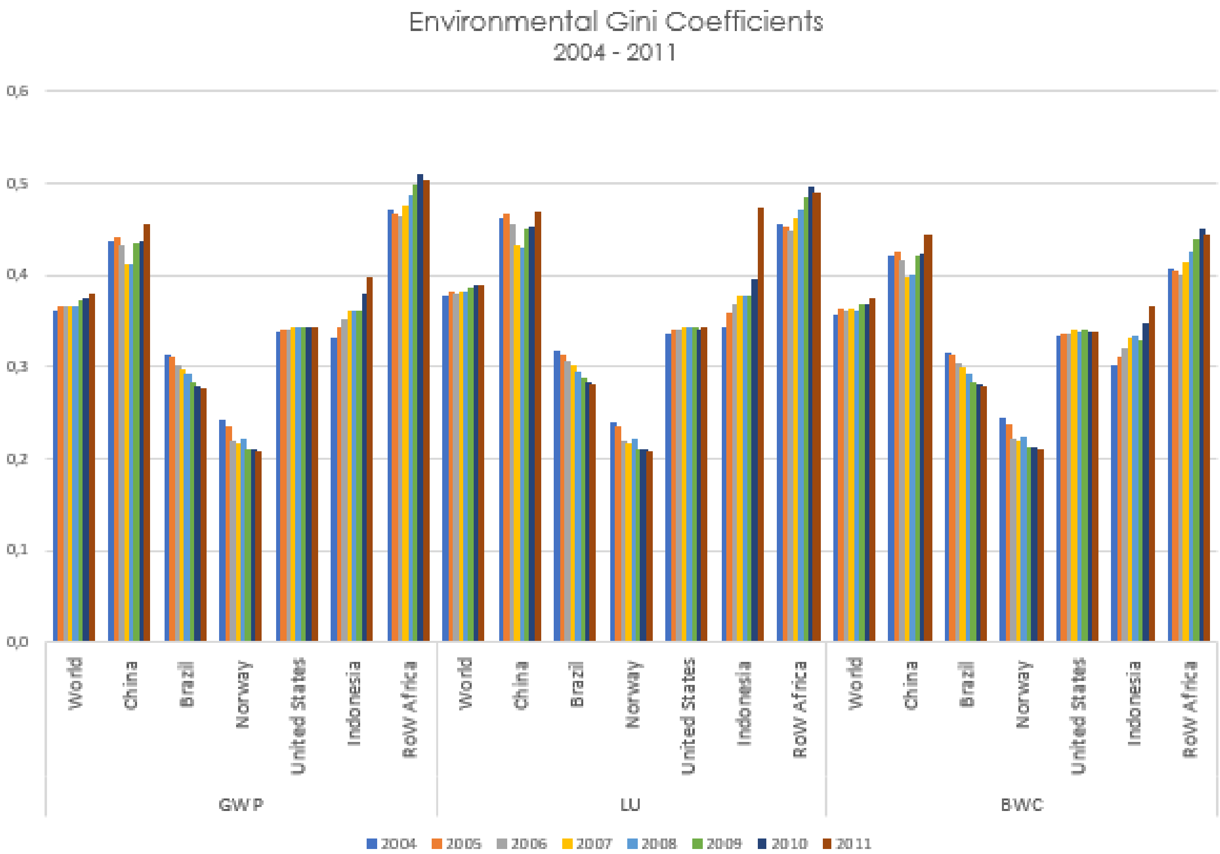

Figure 20: The EGCs for GWP, LU and BWC from food consumption from 2004 to 2011 for World average, China, Brazil, Norway, United States, Indonesia and RoW Africa.

The absolute values of the EGCs in Table 13, Table 14 and Figure 20 provide an important insight into how footprints from food consumption are distributed between quintiles and how this differs from region to region. However, interpreting which regions are experiencing the most changes in distribution from a table might be a challenging task. Therefore, looking at the percent of change in EGC from food consumption since 2004 might open for a deeper understanding of the development (Figure 21, Figure 22 and Figure 23).

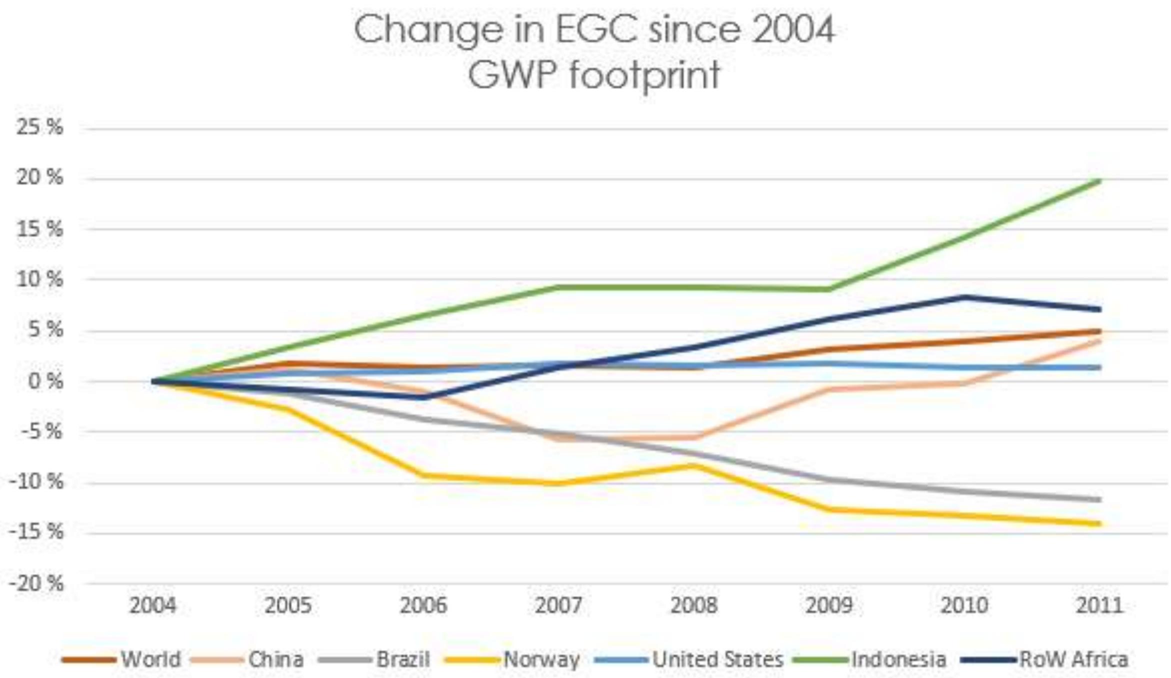

Figure 21: The percent change in the EGC since 2004 for the GWP footprint from food consumption.

As Figure 21 clearly expresses, Indonesia has experienced the most increase of the EGC for GWP with an approximate increase of ~20% from 2004 to 2011, something that is four times larger than the world average (~5%). Among the remaining regions, only RoW Africa beats the world average growth (~7.5%), whereas Norway and Brazil certainly tend to have decreasing EGCs. Undoubtedly, the EGC for United States has increased slightly over the whole timespan, however, this development seems to have been stagnating at around 2008 and slowly been decreasing towards 2011. This is an interesting finding, as it may suggest that the distribution of footprints from the United States are slowly growing to become more equal.

Moving forward, one may find it beneficial to compare the development of the EGCs for the GWP FP to the ones for LU.

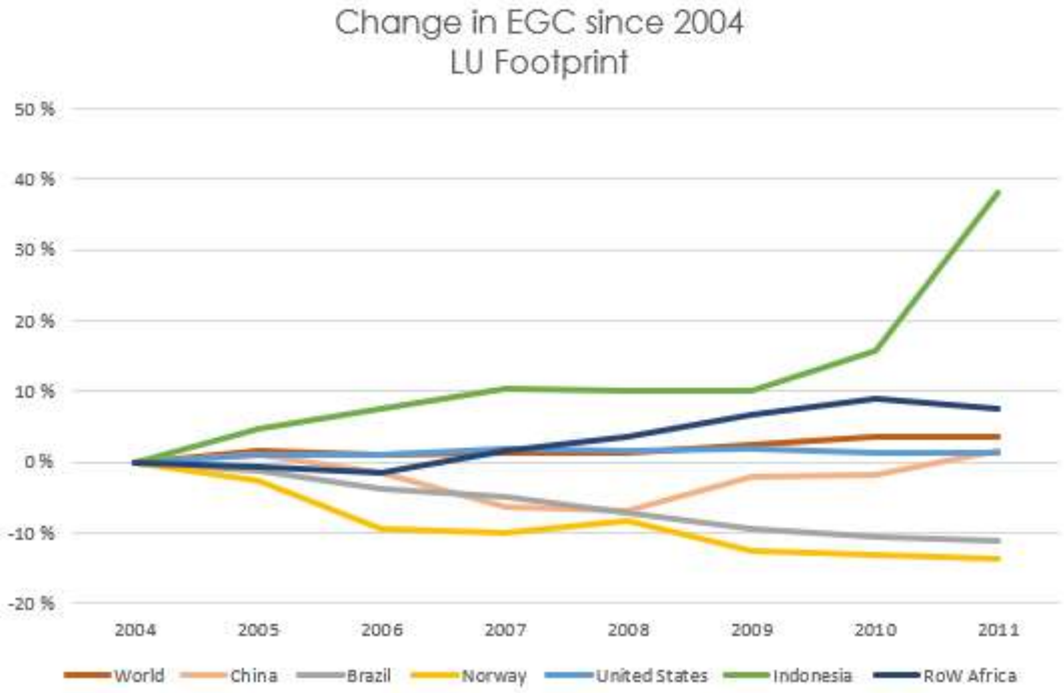

Figure 22: The percent change in the EGC since 2004 for the LU footprint from food consumption

Also, in Figure 22, the EGC for Indonesia seems to be increasing the most, as was also found for GWP. However, the EGC from the LU footprint in the region seems to have been increasing almost twice as much as it did for GWP (~38%). Noticing that this doubling of increase is not taking place in the other regions, one may find this observation for Indonesia highly interesting. Further, the EGCs for the other nations tend to have been changing approximately similarly as for the GWP from 2004 to 2011, with RoW Africa, World average, United States and China increasing at ~8%, ~4%, ~2% and ~2%, respectively. Brazil and Norway, on the other hand, has had declining EGCs for LU at ~11% and ~14%, respectively, something that is very much alike what was displayed in Figure 21.

Interestingly, the same trends are also found for the EGCs from the BWC footprint from food consumption (Figure 23).

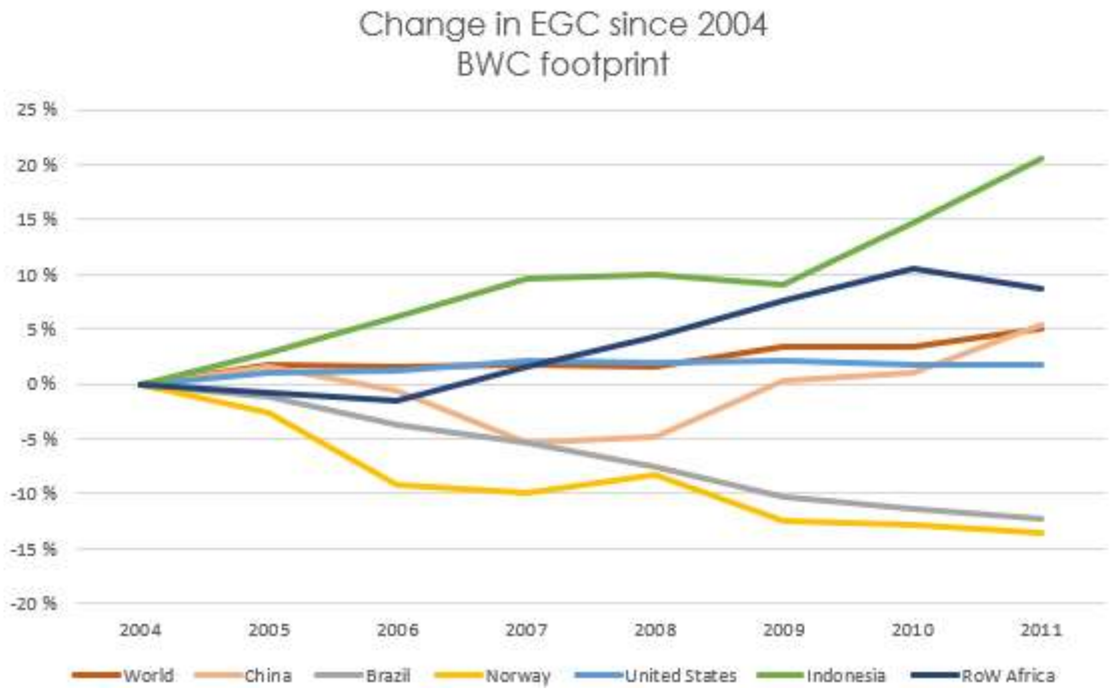

Figure 23: The percent change in the EGC since 2004 for the BWC footprint from food consumption.

Also, in Figure 23, similar tendencies are observed for the different regions. Indonesia seems to be experiencing the largest change at around 21% increase, followed by RoW Africa (~8%), China (~5.5%), World average (~5%) and United States (~3%). As was found for the EGCs for GWP (Figure 21), the United States seems to have slightly declining ECG values from 2008. Further, Brazil and Norway also here show decreasing values at around ~13% and ~14%, respectively.

Clearly, the footprints from the different quintiles presented so far are strongly connected to income, but how is this connected to the level of development (HDI)? In order to answer this question, one might consider looking into the development of the income Gini Coefficients (IGCs) and HDI to gain a more comprehensive perspective on the EGCs.

4.2.3 Footprint distribution

To get an overview over how the footprints are distributed among socioeconomic groups, looking at the Lorenz curves for global impacts for a selected year might be beneficial. Due to it being the closest year to the time of writing (2018), the Lorenz curve from 2011 is selected to illustrate the distribution of global impacts (Figure 24).

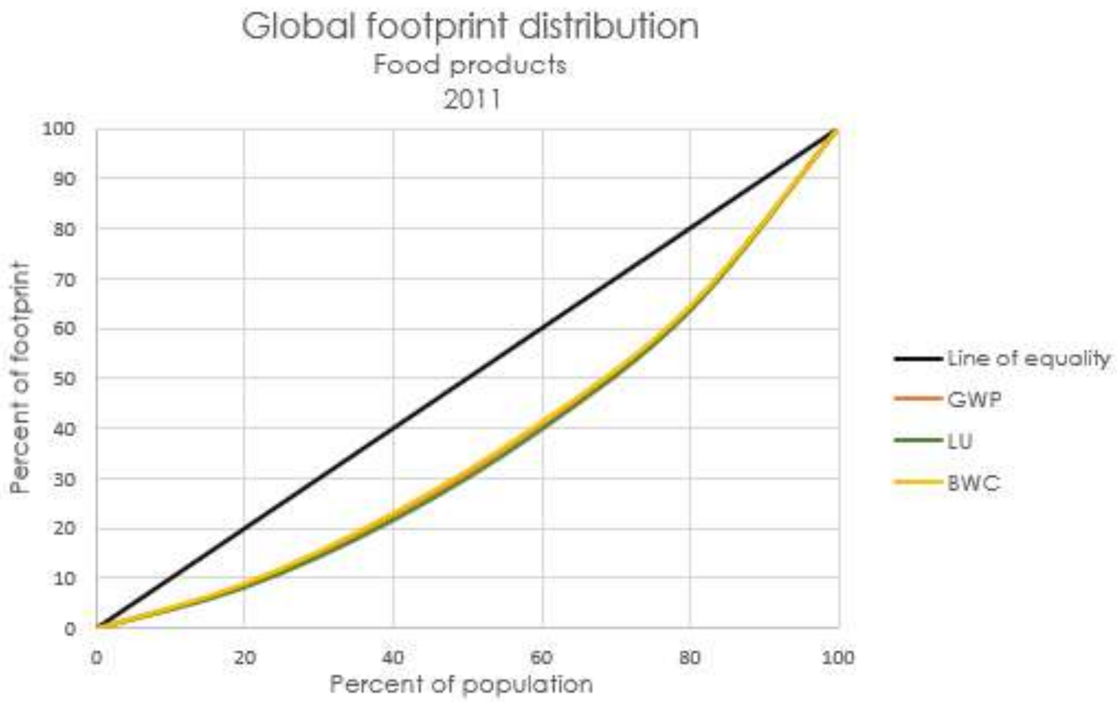

Figure 24: The Lorenz Curve for the global distribution of total footprints from food consumption in 2011. The FPs encompass Global Warming Potential (GWP), Land Use (LU) and Blue Water Consumption (BWC).

As Figure 24 displays, the environmental footprints are clearly not distributed equally across the socioeconomic groups. Interestingly, the colored lines in the curve are situated remarkably close to each other, indicating that the footprints from food consumption are distributed practically evenly unequally. However, the LU seems to be slightly more unequally distributed than GWP and BWC, whose curves tend to be superposing each other.

To gain a wider perspective on the social distribution of impacts, looking at the allocation of the footprints from all products might give an interesting aspect. This curve is presented in Figure 25.

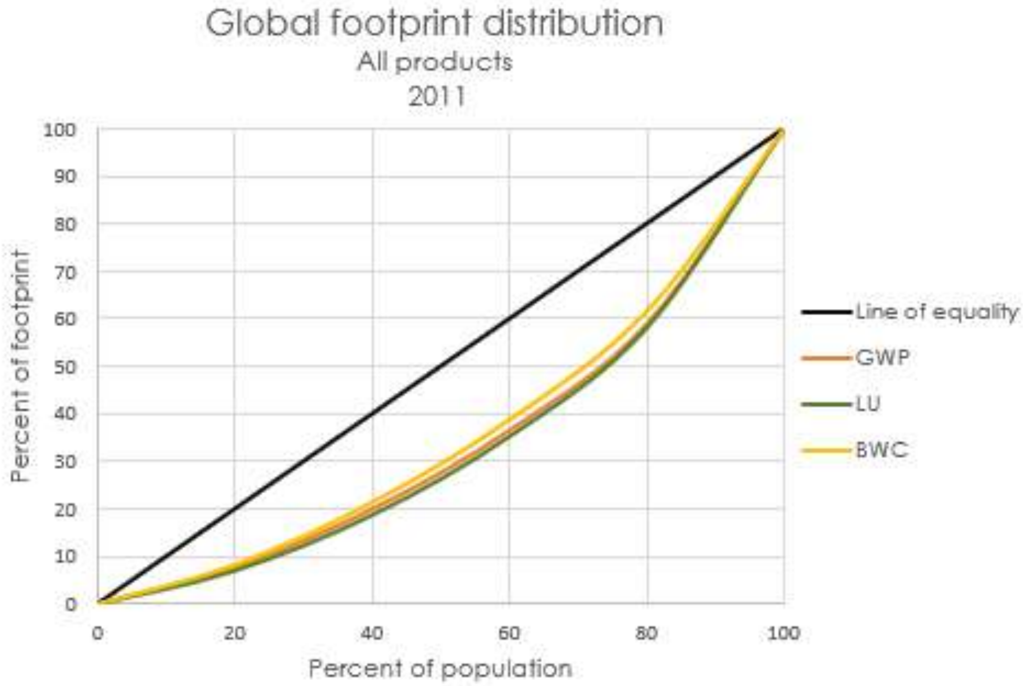

Figure 25: The Lorenz Curve for the global distribution of total footprints from total product consumption in 2011. The FPs encompass Global Warming Potential (GWP), Land Use (LU) and Blue Water Consumption (BWC).

Observing Figure 25, it becomes clear that the distribution of impacts from all products is evidently more disperse than what was presented in Figure 24. The BWC footprint from all products is as unequally distributed as for food consumption, however, LU and GWP seem to be more unequally apportioned between socioeconomic groups than what was found for solely food products. This is an intriguing finding and will be delved further into in the discussion section.

To acquire a deeper insight into the social distribution of footprints and how their allocation has been changing with time, looking at the share of impacts for 2004 and 2011 might provide an interesting viewpoint. This is presented in Figure 26, which consists of six pie charts, each representing one footprint for a selected year.

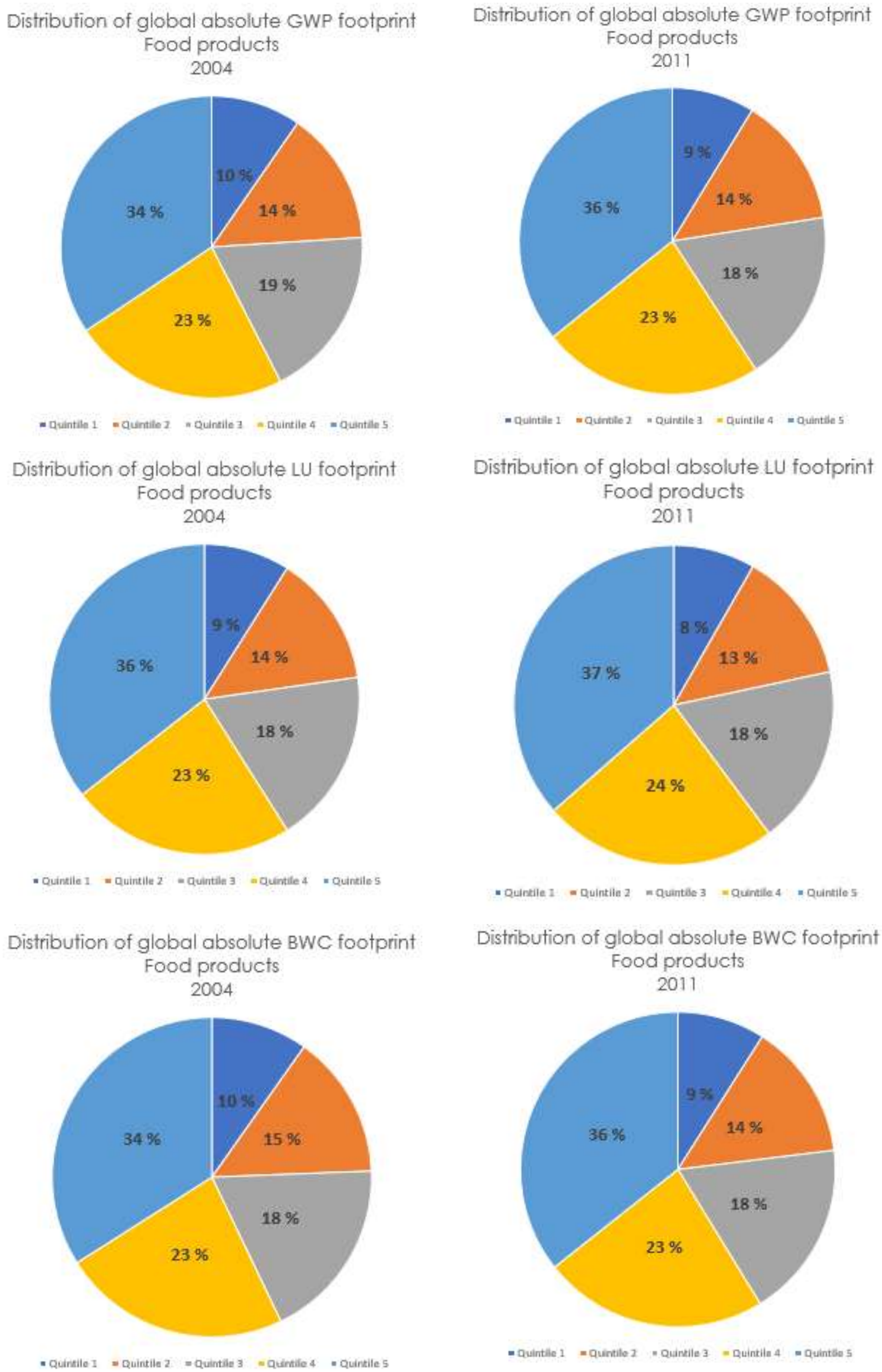

Figure 26: The distribution of global absolute footprints from food consumption across the quintiles. The six pie charts cover GWP, LU and BWC for 2004 and 2011. The share of the total impact is denoted in black inside the charts.

Examining Figure 26, it is observed that there has been a slight change in the allocation of footprints from 2004 to 2011. Please see Appendix H for the distribution on a regional level in 2011. Interestingly, GWP and BWC tend to follow approximately the same patterns, starting at 10% for quintile 1 and 34% for the top income group in 2004, while ending at 9% and 36%, respectively, in 2011. However, the 2% increase for quintile 5 for the two categories has been influencing different income groups. For the GWP, the rising share of the top group has affected quintile 1 (-1%) and quintile 3 (-1%), whereas for the BWC, the two bottom quintiles have been influenced. Furthermore, the LU is slightly more unevenly distributed. Starting in 2004 at a 9% share for the bottom income group and 23% and 36% for quintile 4 and 5, respectively, the impact of the top groups rises to 24% and 37% in 2011, negatively impacting the shares of the two bottom quintiles.

As suggested in the literature review, the Environmental Gini Coefficient (EGC) might provide a valuable insight into the distribution of impacts among people. In order to understand the results presented in Figure 24, Figure 25 and Figure 26 on a deeper level and see them in a larger perspective development-wise, scrutinizing the EGCs might therefore be helpful. The ECGs for the footprints and timespans will be presented in the following chapter.

4.2.4 Income distribution and Human Development index

The absolute values for the Income Gini Coefficients (IGCs) from 2004 to 2011 are presented in Figure 27. As explained in chapter 3.1.3, Madagascar is representing RoW Africa, as no data on this region was available. Further, no data for total global IGCs was accessible.

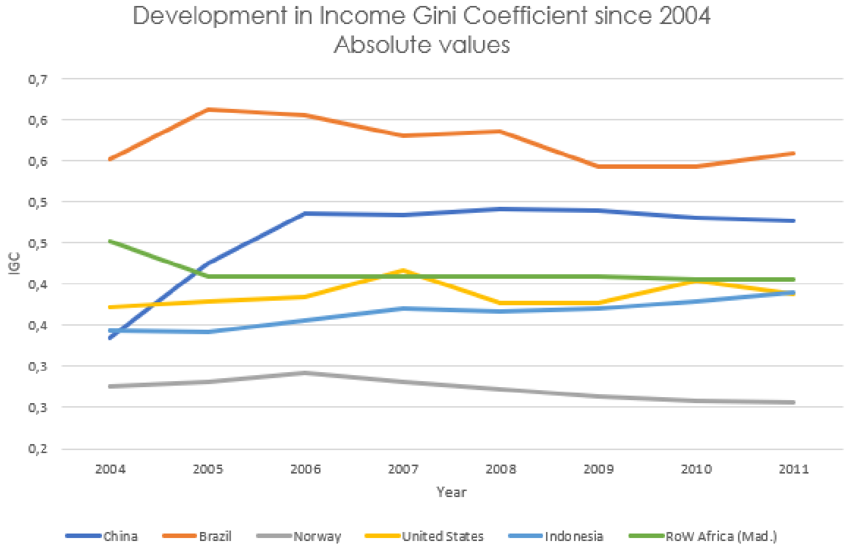

Figure 27: Income Gini Coefficients in absolute values for the selected regions from 2004 to 2011. RoW Africa is represented by Madagascar.

In Figure 27 it is observed that Brazil is the most unequal region in terms of income throughout the whole period, followed by China, where income distribution grew significantly more uneven from 2004 to 2006. Interestingly, the developing country Madagascar (RoW Africa), the emerging economy Indonesia and the industrial nation United States seem to have practically the same income distribution in 2011. Further, Norway stands out as the most equal nation.

The absolute values of IGCs provide a valuable overview of the actual income distribution for certain years, and to widen the perspective on the trends they follow, examining the percent changes with time might be highly beneficial.

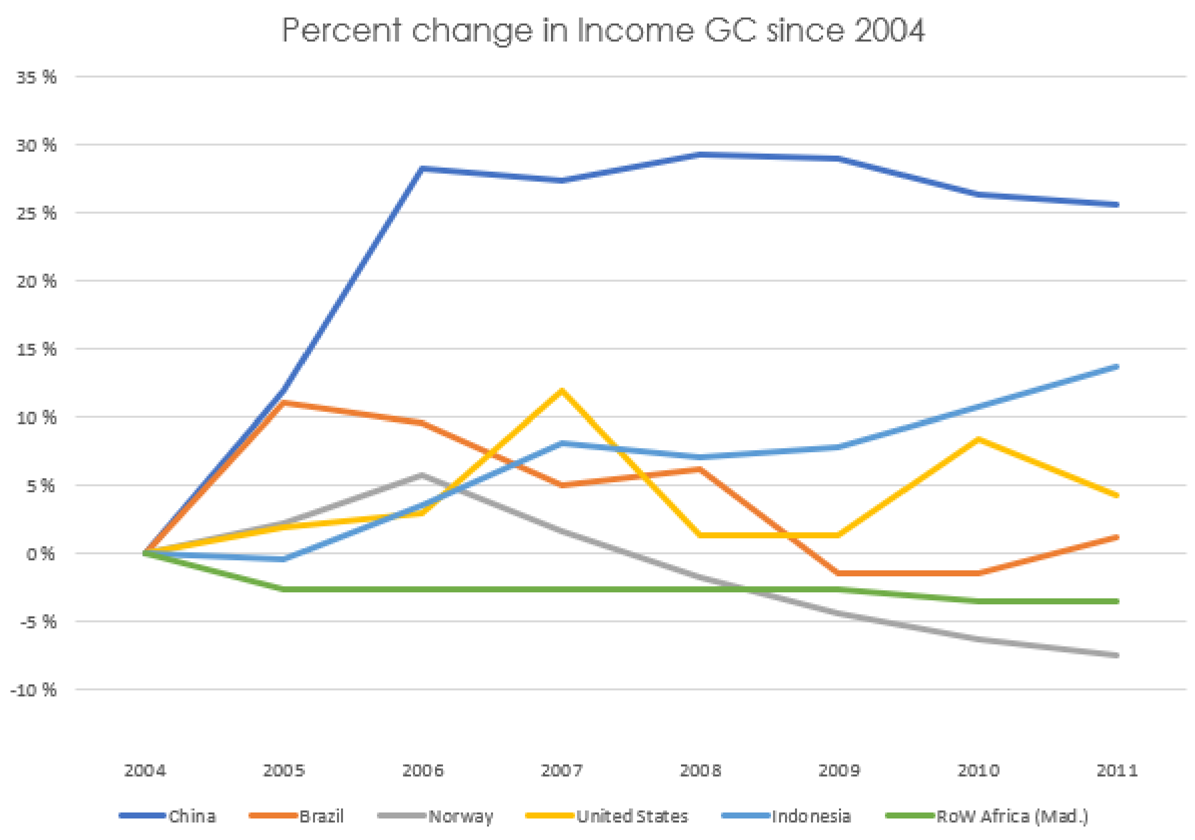

Figure 28: Percent change in Income Gini Coefficient since 2004 for the selected regions. RoW Africa is represented by Madagascar.

According to Figure 28, China certainly stands out as the region that has experienced the largest increase in IGC from 2004 to 2011 (~26%), followed by Indonesia (~14%), United States (~4%) and Brazil (~2%). The finding for China is thought-provokingly large and is discussed further in section 5.2.2.3. Norway appears to have been growing more equal income-wise over the period, with a decline in EGC of ~8%. A rather eye-catching finding is also that the developing country Madagascar also have had a slight decrease in income inequality with ~4%.

Further, one may compare these findings to the changes in the Human Development Index (HDI) in order to seek for a possible correlation between inequality and development.

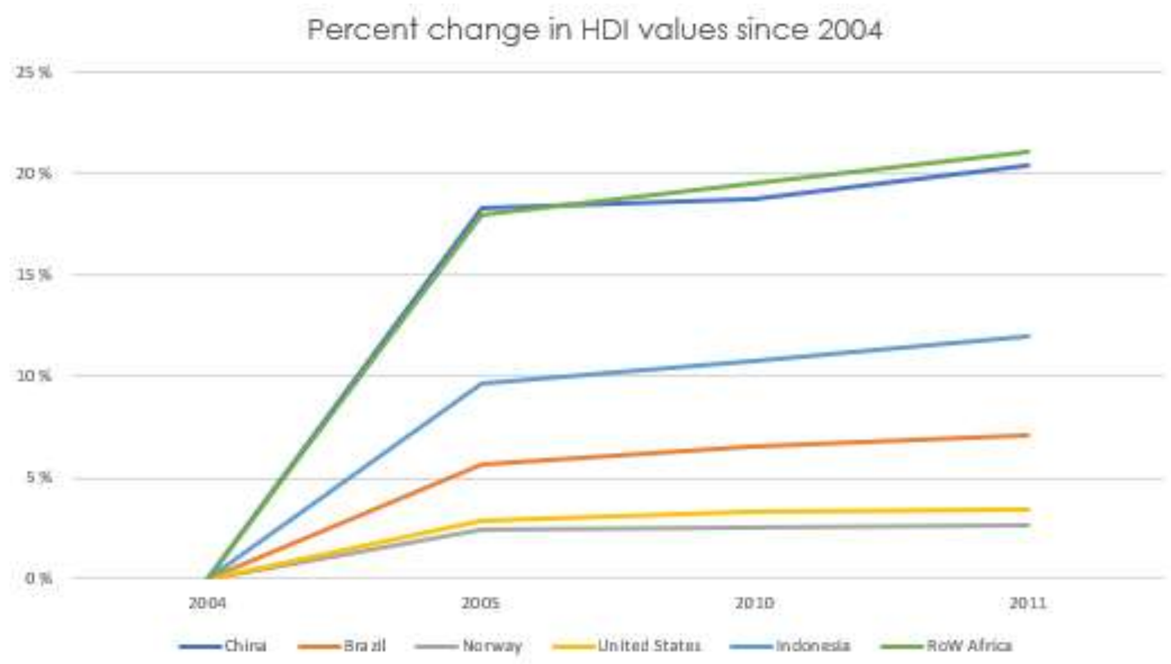

Figure 29: Percent change in HDI values since 2004 in China, Brazil, Norway, United States, Indonesia and RoW Africa.

Here (Figure 29), China and RoW Africa are observed to be the regions to increase their development levels the most from 2004 to 2011 (~21%). Indonesia and Brazil also tend to have had rising HDI since 2004 (~12% and ~7%, respectively), whereas the industrialized countries Norway and United States have experienced smaller changes (~3-4%). Comparing the results from Figure 28 and Figure 29 might provide a thought-provoking insight and is illustrated by Figure 30.

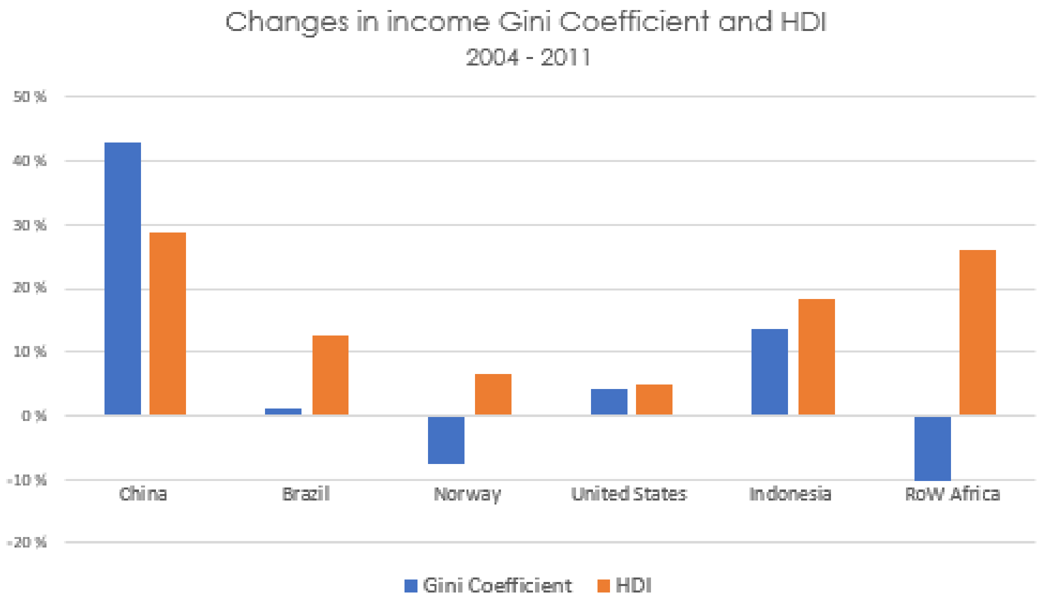

Figure 30: Changes in Income Gini Coefficient and HDI from 2004 to 2011 for China, Brazil, Norway, United States, Indonesia and RoW Africa. The IGC for RoW Africa is represented by the coefficient for Madagascar.

According to Figure 30, the correlation between the HDI and IGC varies notably among the regions. E.g. China and Indonesia both have seemed to increase their HDI over the 8-year timespan, something that is regarded as a positive development, however, on the other hand, inequality has been increasing simultaneously. More positive development patterns are found for Norway and RoW Africa, with increasing HDIs and declining IGCs, though one should keep in mind that the IGC for Madagascar is representing RoW Africa as a whole. Further, Brazil appears to have increased their HDI to a notably larger extent than their IGC, whereas United States seems to have increased these two slightly at the approximate same level.

Until now, results on income distribution and development levels have been presented in order to provide a larger overview on the environmental impacts from food consumption. Further, the underlying causes for these footprints will be examined, in an attempt to provide a fuller perspective on the actual driving forces behind them.

4.3 Expenditure analysis and footprints from food

The global GWP FP/cap from each food product are displayed in Figure 31.

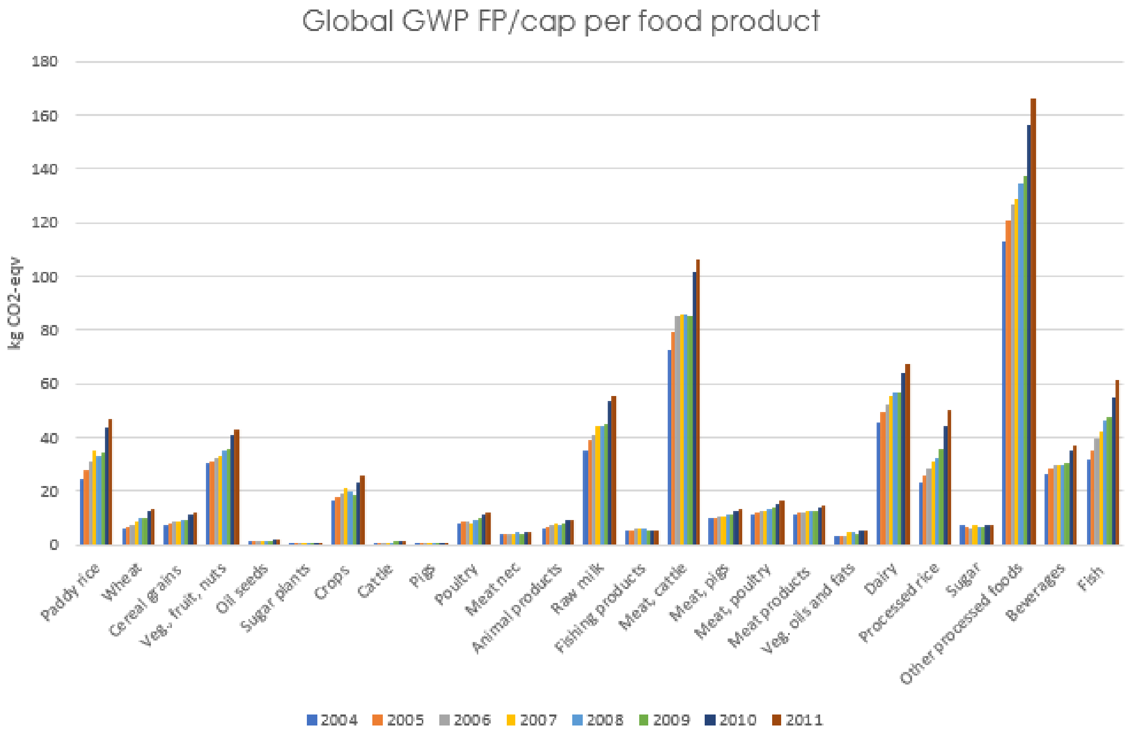

Figure 31: Global GWP footprint per capita per food product from 2004 to 2011, given in kg CO_2-equivalents.

Here (Figure 31), it is observed that nearly every food product has had increasing impacts from 2004 to 2011. Further, some products have significantly larger footprints than others. The product category "Other processed foods" seems have the largest impacts, however, unfortunately, this group consists of processed commodities, thus specifying which food products it involves and in which quantity is a very challenging task. This is further reflected upon in section 5.1. Following this category, comes meat from cattle, dairy and raw milk with significant impacts. Some contribution from paddy rice, processed rice and vegetables, fruits and nuts is also observed.

These findings are quite comparable with the ones found for the LU FP/cap per food product (Figure 32).

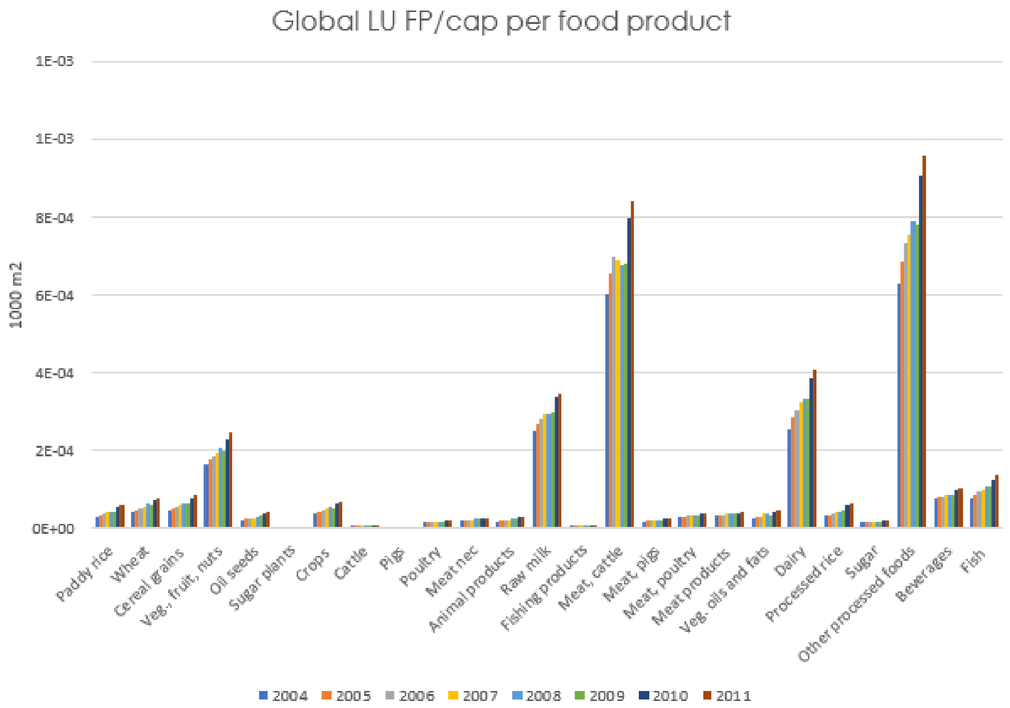

Figure 32: Global LU footprint per capita per food product from 2004 to 2011, given in 1000 m^2 of land.

Also, for the LU FP/cap it is the category "Other processed foods" that has the largest impact (Figure 32), followed by meat from cattle, dairy and raw milk. Vegetables, fruit and nuts also have some impacts. Interestingly, these findings are fairly dissimilar from what was found for the BWC (Figure 33).

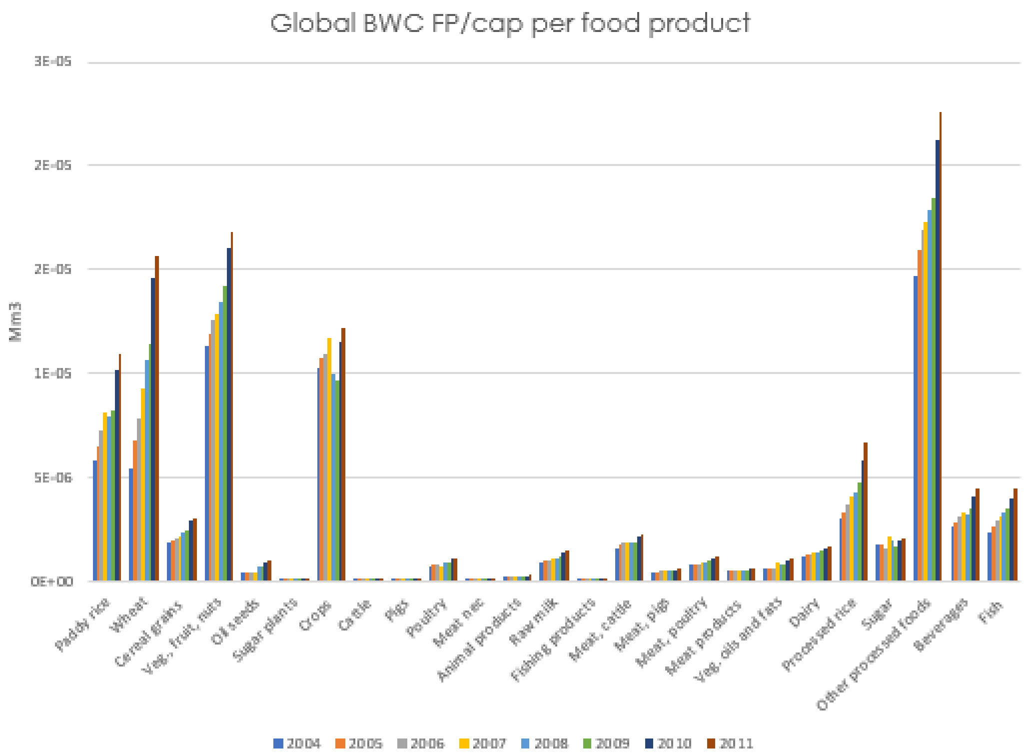

Figure 33: Global BWC footprint per capita per food product from 2004 to 2011, given in Mm^3 .

As Figure 33 suggests, “Other processed foods” is again the most impactful category for the BWC FP. Disregarding this, the products that contribute the largest to the BWC are quite different from what was found for the GWP and LU. Here, vegetables, fruits and nuts, wheat, crops and paddy rice have a certainly larger footprint than animal products, which might be expected due to the importance of blue water for growing plant-foods (see section 2.2.4).

As the basis for these environmental footprints are built on the monetary expenditure on products, examining how much of an impact each product has per unit of expenditure might provide an interesting perspective. Obviously, prices vary with time, something that will affect the results. Therefore, only the impacts from consumption in 2011 will be examined.

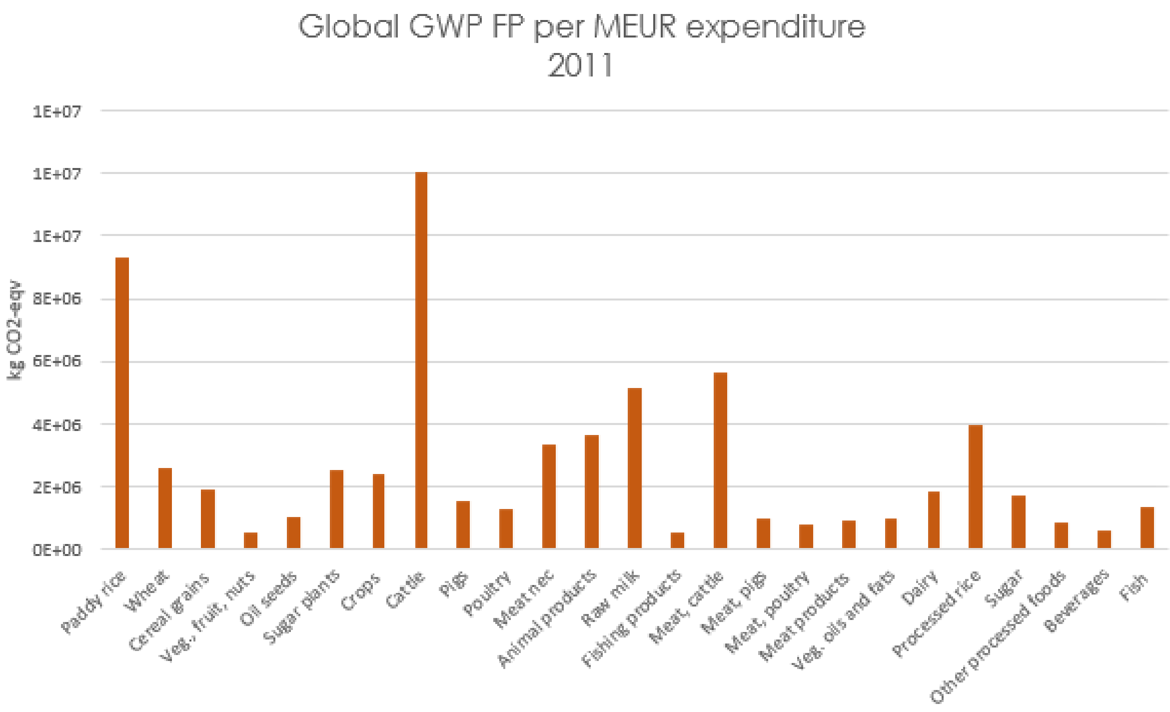

Figure 34: Global GWP FP per MEUR expenditure for each food product in 2011.

According to Figure 34, cattle is having the largest GWP FP per MEUR, closely followed by paddy rice. Notable impacts are also observed for meat from cattle, raw milk and processed rice. These results can be compared with the ones for the LU FP (Figure 35).

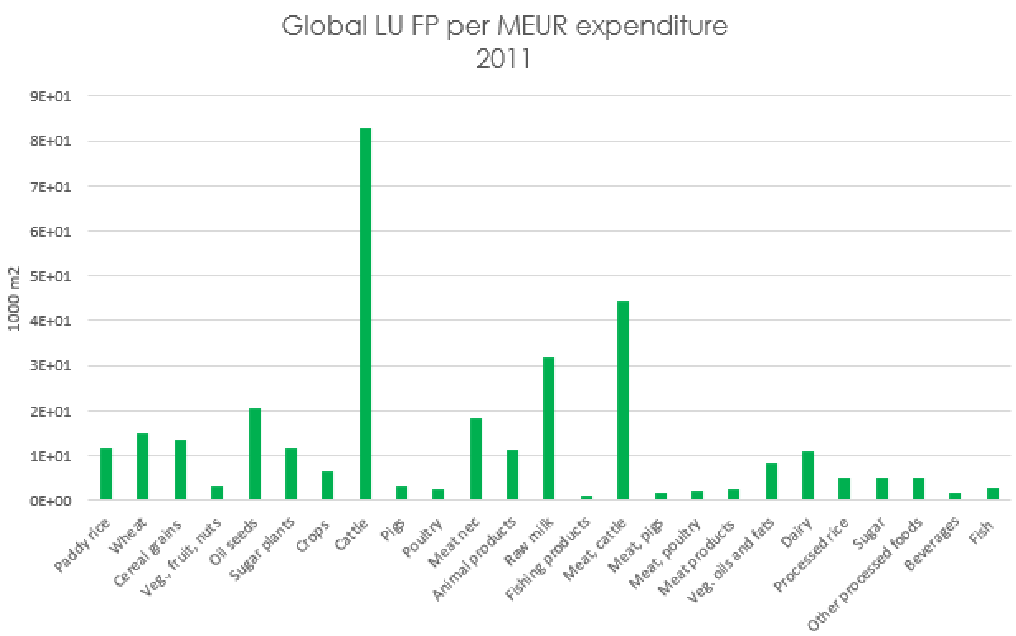

Figure 35: Global LU FP per MEUR expenditure for each food product in 2011.

Also, for the LU FP per MEUR (Figure 35), cattle is clearly having the largest impacts, followed by meat from cattle and raw milk. Oil seeds and meat n.e.c. have some impacts, whereas other plant-based products contribute in small amounts. These findings are quite contrasting to what is found for the BWC footprint (Figure 36). Quite differently from the GWP and LU per MEUR, plant-based foods such as wheat, sugar plants, paddy rice and other crops seems to contribute the most to the BWP FP/MEUR.

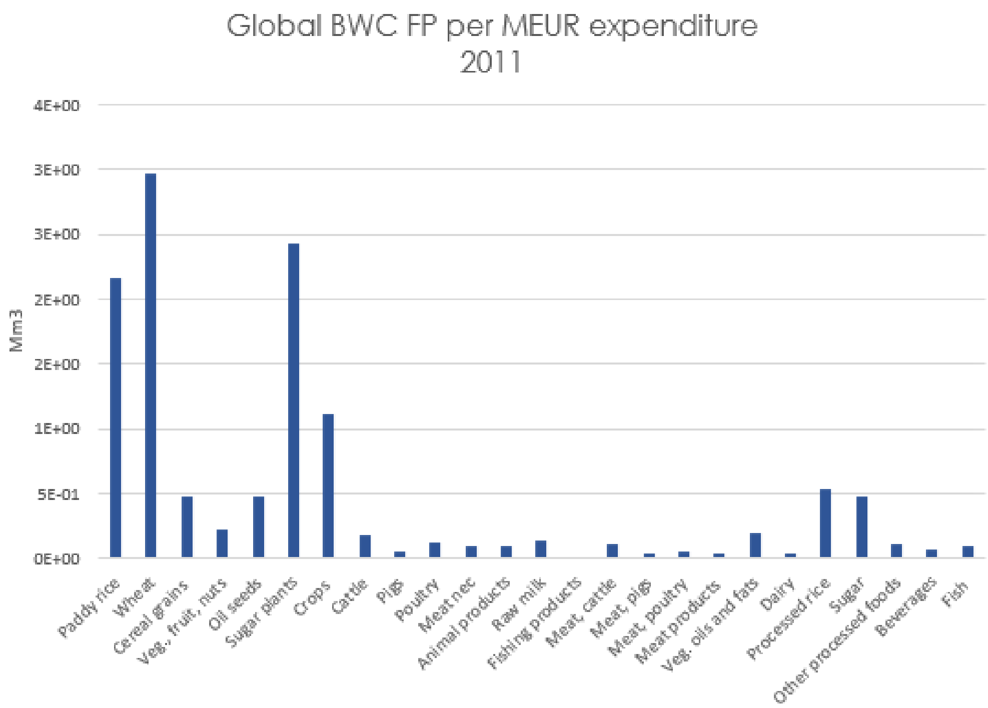

Figure 36: Global BWC FP per MEUR expenditure for each food product in 2011.

Further, one may find it interesting to observe how the expenditure on these products vary between the quintiles globally. These results can be found in Figure 37, and which products are included in the food categories can be found in Table 11 in section 3.2.

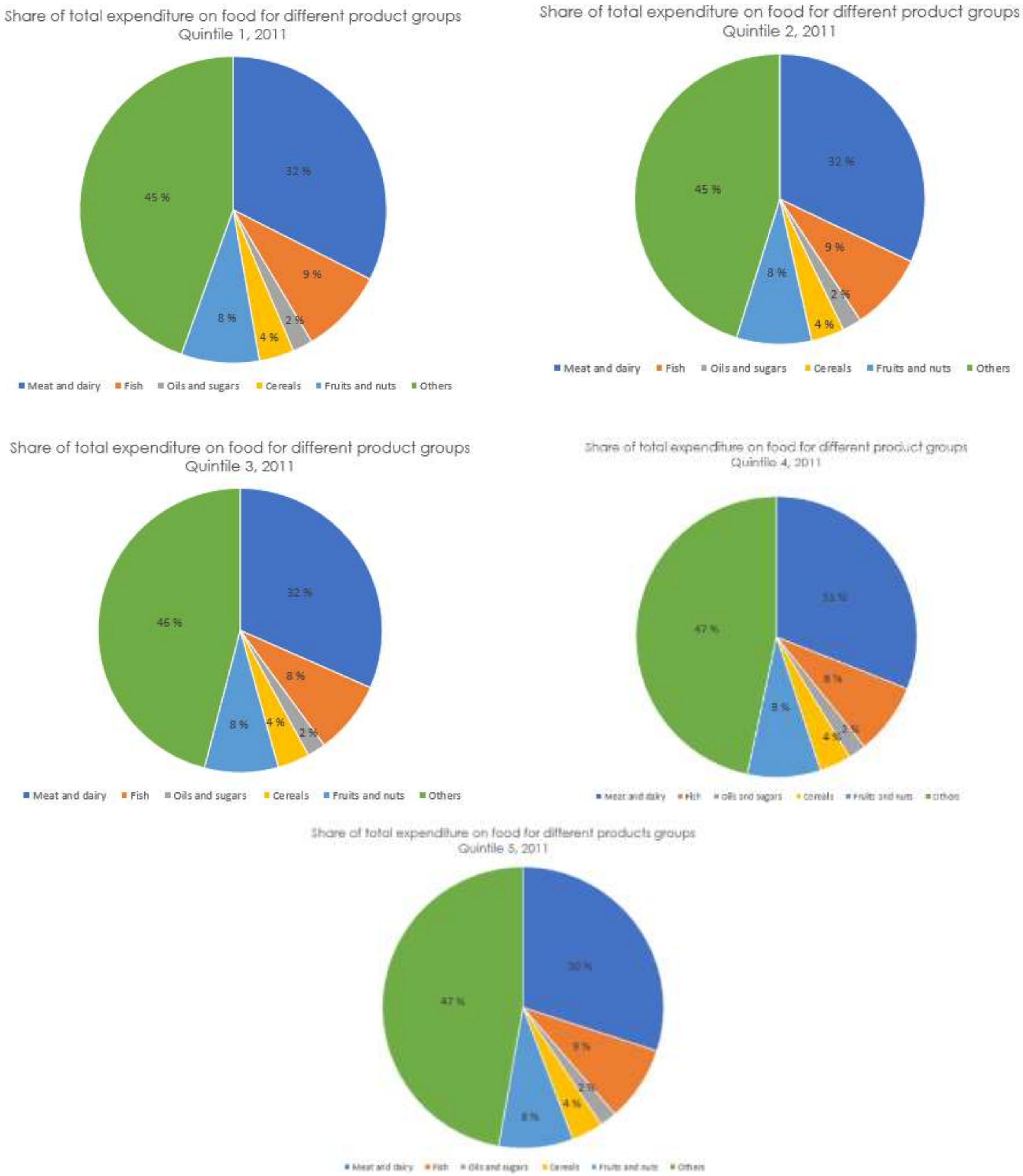

Figure 37: The share of total expenditure on the different food products for the different quintiles globally in 2011. The categories are "Meat and Dairy" (dark blue), "Others" (green), "Fish" (orange), "Fruits and nuts" (light blue), "Cereals" (yellow) and "Oils and sugars" (grey).

In Figure 37, we observe that the category "Others", containing Other processed foods and Beverages clearly have the largest share of total expenditure in all quintiles. Thereafter comes "Meat and Dairy" with around 30-32% share in all income groups, followed by "Fish" and "Fruits and nuts". "Oil and sugars" clearly has the smallest shares in all quintiles at a share of 2%. Thought-provokingly, it is observed that the lowest quintiles (1, 2 and 3) spends a larger share on meat and dairy (32%) and a smaller one on "Others" (45-46%) than the top income groups. The more affluent quintiles (4 and 5) spend a smaller share on meat and dairy (30-31%) and more on "Others" (47%). Another interesting finding is that quintile 4 has a larger share of "Meat and Dairy" (31%) than quintile 5, and the same consumption level of "Others" (47%), which is something that will be discussed in further detail in the discussion section.

In this results section, several findings have been presented. Many of these have been certainly thought-provoking and will be discussed in the following section.

5 Discussion

5.1 Footprints from food products

The drivers behind all FP findings in this study are the various food products available for people's consumption. Therefore, commencing the discussion by taking a deeper look into these might be a natural approach.

For all the footprints, the category "Other processed foods", which encompasses all processed foods, stands out as having the largest effects. This finding may make sense, as food processing has been linked to having significant environmental impacts due to industrial processing and packaging (Kroyer, 1995), though the emission magnitude may vary depending on which type of processing is applied (Pereira and Vicente, 2010). Further, as the category "Other processed foods" will contain the impacts from all commodities included in the products (e.g. meat, dairy, nuts etc.), on top of the effects from processing and packaging, it may make sense that these products have the largest contribution to all footprints from food in this analysis. Notably, this product category is rather complex, due to it consisting of various elements. According to the product definitions in EXIOBASE, "Other processed foods" covers everything processed, from pre-made soups, frozen pizzas and powdered eggs to chocolate, cake doughs and dry cookies. Due to this category being highly intricate, allocating its impacts to specific food products is challenging. If a certain emission number is given for a specified consumption level of “Other processed foods”, one may find it hard to determine whether this was caused by e.g. either dry cookies or frozen pizza, and perhaps even more challenging to determine the impact from their various ingredients. Therefore, the following section will not take these commodities into account and rather focus on the remaining products.

Firstly, “cattle” was found to have the largest effect on the GWP FP per expenditure (Figure 34). This is in alignment with the literature (Gephart et al., 2016; Pradhan et al., 2013; Steinfeld et al., 2006; Westhoek et al., 2014) and with Table 1 in the literature review. Further, “dairy” and “raw milk” are both connected to cattle farming, which also might explain why these are also found to have notable impacts. Interestingly, “paddy rice” also stands out as having a large GWP footprint per MEUR, something that is relatively unexpected, as Tilman and Clark (2014) and Westhoek et al. (2014) both highlight cereals as lower-emission intense food products. However, the category “cereals” contains several grains, such as wheat, maize, rice and rye, which may possibly even out the emissions from paddy rice. On the other hand, according to Nazaries et al. (2013), paddy rice cultivation is responsible for 10% of total anthropogenic emissions. Other studies (Hasegawa and Matsuoka, 2010; Smith et al., 2008) also highlight the significant emissions of GHGs from paddy rice, further stating that this product has one of the greatest emission reduction potentials within in the agricultural sector. Another point is that Figure 34 displays footprints in terms of per expenditure. Therefore, as rice is a relatively cheap product compared to cattle (international market value of 12.5 USD per 100 lbs. for rice and 103.3 USD per lbs. of live cattle in May 2018, according to Trading Economics Data (2018)), the impacts of the product might appear higher in relation to cattle than they would if the FPs were given in terms of e.g. mass. Examining the GWP FP per MEUR per product (Figure 31), paddy rice is observed to have a certainly less significant contribution, something that further underlines the importance of price in Figure 34.

Secondly, for the LU FP in terms of per capita (Figure 32) and per MEUR (Figure 35), it is observed that all products connected to cattle – meat, dairy and raw milk – have the most notable impacts. This is in alignment with the findings of Foley et al., (2011), Gephart et al. (2016), Steinfeld et al. (2006), and Westhoek et al. (2014). However, the numbers in Table 2 in section 2.2.3 indicate that poultry and pork have larger LU footprints per kg than milk, which contradicts the results. As de Vries and de Boer (2010) states in their study, the reason why milk turn out to have a small LU FP in some studies is that it has a large water content.

Therefore, poultry and pork have a larger impact in per kg estimates, but not necessarily in per capita and per expenditure terms.

Lastly, it is observed that wheat, paddy rice, and vegetables, fruits and nuts are having the most significant BWC footprints. As the WF of livestock only consist of around 6.8% blue water (Mekonnen and Hoekstra, 2010), it is expected that plant products has a significantly larger BWC FP. Further, finding that paddy rice and wheat have some of the most significant impacts is in alignment with Mekonnen and Hoekstra (2011), where the researchers state that these two products together are responsible for 45% of the total global BWC footprint. The BWC of the category "vegetables, fruits and nuts" is probably largely driven by nuts, as it has a significant blue water FP (1367 m^3/ton) compared to fruits (147 m^3/ton) and vegetables (43 m^3/ton) (Mekonnen and Hoekstra, 2011). Sugar plants also appears to have a notable BWC FP, something that is interesting regarding that Mekonnen and Hoekstra (2011) declares sugar plants to have the smallest water footprints of all products. However, its notable impact in Figure 35 might be explained by this commodity being relatively affordable compared to other products (international market value of 11.68 USD per 100 lbs. in May 2018) (Trading Economics Data, 2018)).

Clearly, the contribution to the FPs vary significantly from product to product. Thus, the total footprint from each quintile depends heavily on which products people choose to consume. When it is observed that the footprints per capita are rising, this might be an indication of people consuming incrementing amounts of more impacting products, such as cattle, dairy and paddy rice. How the footprints have responded due to consumption of food products will be discussed in the following section.

5.2 Trends and drivers

An unignorable observation that follows many of the results is the tendency of the footprints to be increasing before 2007, declining until around 2009 before rising again towards 2011. This trend does not only apply to global results, but also seem to affect all the selected regions in one way or another. This tendency is likely to be connected to the global financial crisis that started in 2007-2008, before stabilizing at around 2010 (Claessens et al., 2010). Starting in the US around 2007 and spreading internationally the year after, many countries experienced severe drops in GDP (Claessens et al., 2010) in combination with elevated food prices during this time period (Brinkman et al., 2010). Further, Brinkman et al. (2010) found that the level of energy consumption decreased significantly in developing countries between 2006 and 2010, something that expectedly would decrease the footprints as well. Prior to the financial crisis, food prices were steadily inclining, however, in correlation with increasing GDP (United Nations, 2011). After the rapid upsurge in prices and decrease of gross domestic product during the crisis, the prices sunk moderately to almost match pre-crisis levels, before continuing increasing slowly towards 2011 (United Nations, 2011). As the footprints are calculated based on the expenditure on products, it makes sense that the effects of food prices and the financial crisis are reflected in the results that will be discussed in the coming sections.

5.2.1 Total footprints

The outcomes of the simulations on a global scale varies from being expected to thought-provoking. Firstly, the global results for the footprint development from 2004 to 2011 show that GWP/cap, LU/cap and BWC/cap from food consumption have been increasing (Figure 2), something that may not be surprising, as it is in alignment with the literature (Alexandratos and Bruinsma, 2012; Mekonnen and Hoekstra, 2012; Pradhan et al., 2013). Interestingly, the GWP and LU seem to be growing equally, whereas BWC elevates much more. Worldwide, the BWC footprint per capita is certainly higher in dry areas, such as Central Asia and North Africa, Turkmenistan and Iran being the largest consumers per inhabitant (Hoekstra and Mekonnen, 2012). Further, India was responsible for 24% of global BWC in 2005, leaving also consumption habits in this nation to be highly determining for the total global water footprint (Hoekstra and Mekonnen, 2012). According to a recent report from the USDA, the agricultural sector in Iran have recently experienced difficulties due to a 7-year long drought (USDA, 2017). Being one of the world's driest nations, this has put an increasing pressure on ground- and surface water consumption (hence BWC) since 2010, something that has likely affected its neighboring countries, such as Turkmenistan, as well (USDA, 2017). Resulting from this, one might expect the consumption of BWC from food to rise, especially since 92% of the global water footprint is caused by the agricultural sector (Hoekstra and Mekonnen, 2012).

BWC and LU being mainly allocated to agricultural practices presumably explains why the footprint development from all products shows the same development for both these FPs (Figure 3). Interestingly, the GWP seems to have increased more for only food products (55% for food, 51% for all products). Peters et al. (2012) found that carbon emissions from all products grew faster than ever before after the financial crisis, something that is in alignment with the obtained curves in Figure 2 and Figure 3. In their statistical review of 2017, the

World Trade Organization illustrates how world expenditures grew rapidly from 2009 to 2011, the agricultural sector experiencing a slightly larger increase than all industries combined (WTO, 2017). This, in combination with the rapid price elevation of food and severe decline in value of oil and other products during 2007-2009 (United Nations, 2011), might be what is causing the different observations made in Figure 2 and Figure 3.

Comparing global footprints to regional ones, it becomes clear that the development varies notably from place to place. Clearly, there are huge variations among the countries, where China and the United States stand out as having the largest total footprints (Table 12). In per capita terms, China falls to the bottom as one of the smallest contributors, whereas United States, interestingly, still stands as one of the top two emitters, along with Norway (Figure 7, Figure 8 and Figure 9). Fortunately, Brazil and Indonesia appear to experience the largest increases in impacts, and not the countries that have the highest footprints from before. Brazil appearing to experience significant changes in the GWP FP is in alignment with Kearney (2010), which points towards rapid transitions to more meat-based diets in the country. Due to meat from cattle being one of the most impacting products on both GWP and LU (Figure 31 and Figure 32), it is expected that higher consumption of these products will lead to larger footprints. Further, the consumption of ultra-processed foods have increased significantly in the country over the last years, something that also is likely to affect the footprint (Monteiro et al., 2010). Brazil is worldwide known as being one of the largest producers of agricultural products, especially biofuels and soy beans (Hartman et al., 2011; The World Bank, 2008), with one of the highest growth rates of agricultural expansion (FAO, 2017). However, it is important to keep in mind that the footprints are allocated due to consumption and not production. Brazil was one of the world's largest exporter of agricultural products (Mekonnen and Hoekstra, 2012) and meat in 2012 (FAO, 2012), consequently, the footprints from these products will be allocated to the importing countries. One might assume that the changes in environmental impacts in Brazil would have been somewhat larger if they were correlated to production, and not consumption.

Further, Indonesia also show significant changes in the footprints. According to the literature, this country also experienced large transitions from cereal-based diets to consuming more meat, dairy, eggs and processed foods from 1981 to 2005 (The World Bank, 2008). Also, in an attempt to increase local production of rice, one of the main staples in 2/3 of the Indonesian population's diet, the national government introduced a ban on rice import in 2004 (The World Bank, 2008). This ban was still ongoing in 2017 (USDA, 2017), consequently elevating the rice price to unexpected levels (The World Bank, 2008), perhaps forcing people to choose products of other kinds, such as animal products.

Another interesting observation is the large LU FP/cap of Norway (Figure 8). Large amounts of the food production in this country is based on fish farming and livestock (MAF Norway, 2015), where significant parts of the required feed need to be imported. From 2004 to 2013 the imports of soy rose from almost none to 368 000 tons/year, 80% of this coming from Brazil (Lindahl, 2014). Soybean production in Brazil has of lately been in the center of attention internationally, mostly due to its significant impact on land use (Lathuillière et al., 2017), something that might explain the LU FP obtained for Norway.

The global results obviously communicate that the intra-region footprints are not equally distributed, something that is highly anticipated, due to different income levels, climate conditions, culture, and governmental practices on a global scale. The distribution of the inter-region footprints, on the other hand, shows some interesting tendencies that will be discussed in further detail in the coming section.

5.2.2 Footprints by quintiles

5.2.2.1 Development

According to the results from the different quintiles, global GWP and LU (Figure 10 and Figure 11) seem to follow more similar patterns than BWC (Figure 11). For the GWP and LU, it is clear that the financial crisis has had notable effects, as they tend to steadily increase for all years except between 2007 and 2009. Further, an interesting observation is the tendency for the bottom quintile to be changing the most of all the quintiles before the crisis, and the most slowly after. This may indicate that the distribution of impacts was growing towards becoming more equal before 2007, however, the poorer part of the world seems to have suffered the most from the repercussions from the crisis. This has lead the distribution to grow more unequal since 2009, something that is in alignment with recent report from the United Nations (2017b). Further, United Nations (2009) explains how the crisis especially hit those in already more scarce living conditions, due to accelerating food prices, increasing rates of unemployment and the cease of external financing of developing countries. This is also found in the studies by Ravallion and Chen (2010) and Habib et al. (2010), where the latter further elucidate the potential long-term effects on the world’s middle income classes. Interestingly, even though the global economy suffered largely during the crisis, it does not seem to have stopped the constant increase in footprints per capita after 2009. This is likely to be partly related to increased GDP and development levels after 2009 (The World Bank, 2017; UNDP, 2016). Another factor that may have had some additional impact is also the crisis leading to reduced investments in environmental preservation, as well as water and land management, consequently delaying the process towards ensuring sustainable development (United Nations, 2009).

Another interesting observation in the global results on a quintile level for GWP and LU, is that the FPs from quintile 4 seem to be increasing more than for all the other income groups after 2009. This may also be reflected in Figure 37, which shows that quintile 4 and 5 spent the largest shares on processed foods in 2011, compared to the other income groups. Additionally, quintile 4 spent a bigger share on meat and dairy than the top income group. According to Figure 34 and Figure 35, meat, dairy and processed foods have a significant impact on both GWP and LU, which may explain why the FPs from quintile 4 have been increasing the most. Further, as the development for the 4th quintile does not show the largest increases in the non-industrial countries China, Brazil, Indonesia and RoW Africa (section 4.2.1.2), one may expect that the global results are driven by development for industrial countries. However, the driver behind the consumption patterns of quintile 4 may be challenging to pinpoint. Investigating consumption pattern in three cities in the Netherlands, Belgium and Germany, Hupkens et al. (2000) found that middle educated women had a larger consumption of meat, milk, sweets and chips than the highly educated ones, and a smaller intake of these products than those with the lowest education. The middle class consuming less processed foods (sweets and chips) than the lower class in developing countries is not in alignment with the results in Figure 37, however, one must take into account that the paper of Hupkens et al. (2000) was published in 2000 – 11 years before the results in Figure 37, and consumption habits may have changed since then. Further, Kearney (2010) states that consumption of “Functional foods”, i.e. enriched, fortified or enhanced foods, dietary supplements and conventional foods, has increased significantly in the developed world. This is driven by higher life expectancy, acceptance of the interconnection between health and diet and a desire for convenience (Kearney, 2010), and has been most prevalent among higher income groups in developed countries (Childs, 1997; Niva, 2006). Functional foods are a form of processed products, which was found to be associated with higher GWP and LU FPs in this thesis, something that might explain why the top income groups tend to have the most increasing FP from 2009 to 2011. However, due limited amounts of previous studies, exactly determining what is the driver behind the increase for the 4th quintile is challenging, and more research is suggested to be done on this area.

As expected, the development of the GWP FP per quintile differs across the regions (Figure 13, Figure 14 and Figure 15). However, a general trend is observed for them all – the top quintiles are changing their footprints at a much more rapid pace than the lower ones, especially in Indonesia and RoW Africa. This development is also seen for The United States, however, the growth is not as large as for e.g. Indonesia. In the last decade, both Indonesia and RoW Africa have experienced a declining level of regional undernourishment, something that has not happened in the US, due to this not being a significant issue (FAO, IFAD, UNICEF, WFP and WHO, 2017). Driven by globalization, GDP per capita rose notably percentage wise in Indonesia and Sub-Saharan Africa compared to in the US from 2004 to 2011 (The World Bank, 2017), which together with rapidly rising food prices within this time period (FAO, 2017) might explain why these regions experience larger changes than the US. Additionally, Indonesia has experienced an upsurge in cattle meat consumption in the last decade (Asian Insights Office, 2016), which according to the findings in Figure 34 is the product with the largest GWP FP. Further, due to cattle meat being one of the most expensive food products in the country (Asian Insights Office, 2016), one might expect this upsurge in consumption to take place among those who can afford it, hence the upper income classes. This might explain why the top quintiles in the country are the ones experiencing the largest changes.

These findings for the GWP can be compared for the ones for LU. The footprints of the United States (Figure 17) follow approximately the same development as for the GWP, however, this is not the case for Brazil (Figure 16). Interestingly, this nation follows a different pattern, where the lower income groups experience the most noticeable changes. These findings may make sense, as observing the development of the income shares from 2004 to 2011 reveals that the bottom quintiles have risen their shares of total income, whereas those of the top groups have declined. Further, Carvalho et al. (2013) found that the intake of red meat was most prevalent in the Brazilian middle class, something that might explain why the top income group is experiencing smaller changes in GWP FP. However, the study also found the bottom group to consume less meat than the rest of the population, something that will contradict the results obtained. On the other hand, Sans and Combris (2015) points towards a correlation between rising income and meat consumption in Brazil, and as the bottom quintiles have increased their share of total income, the results obtained in this study may make sense. Another interesting finding is that quintile 4, and not the top one, is experiencing the largest increases in GWP FP and LU FP in the United States. In 2017, Zagorsky and Smith (2017) found that the consumption of fast food in the United States rose parallelly with income in bottom- and middle income classes, whereas this was not observed for the highest income group. As fast food belongs to the product category "processed foods" which has the most impact on both GWP and LU (Figure 34 and Figure 35), it might make sense that the highest middle class, quintile 4, is appearing to be increasing the most. Please see section 4.2.1.1 for further elaborations on consumption habits for quintile 4. Further, Kearney (2010) elucidate how the top income groups in some developing countries tend to switch towards diets that are higher in plant-foods, which according to the results, in general have a lower impact on both GWP and LU, something that may explain why the top income group in The United States is not the one experiencing the largest change. Also, Behrens et al. (2017) found that top income countries, such as The United States, have dietary recommendations based on more environmentally friendly food products, which is more likely to be followed by those with higher socioeconomic status (Drewnowski, 2009; Inglis et al., 2005).

Interestingly, the development of the BWC FP from food consumption seems be following a conspicuously different development than the GWP and LU FP. Here, the top quintiles are growing the most rapidly over the whole time-span, and the ratio of change between top- and bottom quintiles is significantly higher for this footprint. This is a thought-provoking finding, as the products affecting the BWC the most (45% of global BWC footprint) are wheat and rice (Mekonnen and Hoekstra, 2011), which are common staple foods in diets of people of lower income in developing countries (Du et al., 2004). Further, Du et al. (2004) also points towards the tendency of people switching their starch-based diets towards animal-based ones as income grows, which may be a result of that these products have become more available in the age of globalization. As animal products in general require mostly green, and not blue water, like plant foods (Mekonnen and Hoekstra, 2012), one might expect that the lowest quintile to experience the largest shifts in BWC, and not the top one. Further, Figure 18 and Figure 19 showing the regional development in China and United States displays the same tendencies: the top quintiles experience the largest change. However, in China, the top income group seems to not have experienced the largest change before after 2009, again suggesting that this group was the one that was able to tolerate the Financial Crisis the best. Importantly, as Hoekstra et al. (2012) commiserate, consumption of blue water vary significantly across regions, as well as by climate conditions. In times with more precipitation, less blue water will be necessary to extract and vice versa. Therefore, the BWC FP might differ from year to year and be difficult to connect directly to food consumption behaviors.

A possible explanation for the outcomes of the analysis of BWC, is that it would be easier for those with a more solid economy to get hold of the products produced using blue water in times when this resource is scarce. This scarcity issue might also explain why the difference between quintile 1 and 5 the three last years is much larger than what was found for LU and GWP (Figure 12). Another explanation could be found by looking into consumption behaviors of different regions. According to the OECD (2015), the regions that consume the most wheat per capita are "Developed Europe (107.7 kg per cap/yr), "Developed Oceania" (87.6 kg per cap/yr) and "North America (80.6 kg per cap/yr). Especially, the first mentioned region has a consumption level in stark contrast to the region "Least developed countries" at 28.4 kg per cap/yr. As wheat is the product with the largest impact on the BWC (Mekonnen and Hoekstra, 2011), the regions consuming this in the largest quantities also would have a significant impact on global BWC. Clearly, the industrial countries have a significantly higher consumption levels than many of the nations in the rest of the world (The World Bank, 2018c). According to the literature (Giskes, 2008; Inglis et al., 2005; Kearney, 2010), a general trend observed in developed countries is that people of higher socioeconomic status consume more plant products and increasingly less animal products. On the other hand, in the developing world, people tend to move away from plant products as socioeconomic status grows (Kearney, 2010). As the largest consumers of wheat, consumption trends impacting the BWC in developed countries may dominate those from lower-income nations. Seen from this perspective, the results obtained for the BWC may make sense – the top quintiles consume increasingly more plant products, which again puts an increasing pressure on the blue water footprint. Importantly, one should keep in mind that rice also has a significant impact, which is, as mentioned, essential in diets of people with lower income (Du et al., 2004), which would be expected to give other outcomes of the analysis. However, looking at the results obtained for the BWC FP per product (Figure 36), it is observed that the impact of wheat is 42% higher than rice. Therefore, one might suspect that the contribution of wheat will dominate that of rice, which will be in alignment with the results obtained in this analysis. However, this is only a supposition and looking further into this in another study is suggested.

5.2.2.2 Distribution

In Figure 24 and Figure 25 it is observed that the footprints from food consumption were approximately distributed equally unequally in 2011 – BWC being slightly closer to the equity line and LU the furthest away. Intriguingly, this was different than for consumption of all products, which appears to be more uneven. According to the literature (Davis et al., 2015;

Foley et al., 2011; Porkka et al., 2013) food production has expanded significantly the last decades, becoming more efficient and producing larger yields. Further, Carr et al. (2016) found that from 1986 to 2011, food availability inequality was reduced by 25-33%, resulting from increased international trade driven by globalization. This finding of reduced food inequality might be contributing to the result of FPs from food being more equally distributed than from all products. However, a factor that is believed to be more determining is the *accessibility* of different products to the world population. Everybody needs food to survive, whether one is living in luxury in Monaco or in extreme poverty on the fields of Mali. Therefore, approximately everyone will have a food footprint to some extent. Other products, such as technical equipment, oil and electricity are important for many, however, neither vital for survival nor always accessible for people that can barely fulfill their daily calorific needs. According to The World Bank (2016), 12.6% of the world population were living without access to electricity in 2016. Further, many people in developing countries live without access to motor vehicles (Our World in Data, 2014). The agricultural sector was responsible for 24% of global GHG emissions in 2010 (IPCC, 2014c), and the remaining 76% must therefore come from other services and products. As many of these are inaccessible to the world’s poor, it makes sense that the footprints from food are more equally distributed on a global level than those stemming from all products. However, one should also keep in mind that the world experienced a food crisis in 2016, causing several countries to fall into severe aliment scarcity (FSIN, 2017), which may indicate that food inequality has risen again to some extent in the years after the selected time-span of this analysis.

The pie charts in Figure 26 show the distribution of the footprints among the quintiles in 2004 and 2011. Here, we observe the trend that was also displayed in the Lorenz’ curves: The LU FP is most unevenly distributed in 2011 with quintile 1 contributing 8%, and quintile 5 having a 37% share. Comparing this to the development of the LU FP per capita in Figure 11, one may expect this distribution to grow even more unequal with time, as the higher income groups are growing more than the lower ones in this figure. The other FPs both have a 9% and 36% share for the two income groups the same year, also pointing towards increasing inequality with their corresponding development results in Figure 10 and Figure 12. Scrutinizing the impact of each food product on the LU FP in Figure 35, it is noticed that the categories “Cattle”, “Meat, cattle” and “Raw milk” are having the biggest effects. This can be compared to the GWP FP, where “Cattle” and “Paddy rice” are the most contributing products. A reason why the latter footprint is more equally distributed might be that rice is a staple product consumed in large quantities in the lowest, as well as the highest quintiles

(Seck et al., 2012). Meat, as mentioned before, is on the other hand more connected to higher incomes in developing countries (Kearney, 2010). This might explain why the LU FP is less equally distributed than the GWP FP. The same principle might be applied to the BWP FP – paddy rice and wheat are impacting this FP significantly; two products that are prevalent amongst people of lower incomes, thus perhaps more equally distributed.

5.2.2.3 Gini Coefficients and HDI

The Environmental Gini Coefficients displayed in Table 13 show that the distribution of all selected footprint categories is growing more unequal over the time-span, both from consumption of food, as well as from all products. The EGCs from all products are higher than the corresponding ones from food, something that was discussed in chapter 5.2.2.2. The global EGC for GWP from all products was found to be 0.423 in 2011, something that is slightly lower than the findings of Teixidó-Figueras et al. (2016) of 0.579. On the other hand, obtained result of 0.436 for LU in 2011 is more in alignment with the findings of the same researchers of 0.423 for LU. Importantly, Teixidó-Figueras et al. (2016) have based their findings on data from 2000, and suggests that their results might not be comparable to years after this, as world economy changed significantly from 2000 to 2015. Further, White (2007) found the EGC for the Ecological Footprint to be 0.446 in 2003, something that is also comparable to the result obtained for the LU FP from all products in this study. Markedly, one should keep in mind that the EF and LU FP are not exactly the same, but still comparable (Galli et al., 2012; Steen-Olsen et al., 2012).

Further, for all the footprints, we observe that the EGC from food consumption has been rising in all regions from 2004 to 2011, except in Norway and Brazil. This is an interesting observation, due to Brazil being the country with the highest Income Gini Coefficient out of the 6 selected regions, and Norway being the one with the lowest (Figure 27). Further, the IGC of Norway seems to be decreasing over the time-period, whereas Brazil shows rising values (Figure 28). When the distribution of income becomes more equal, it may make sense that the share of the total environmental pressure becomes less unequal, as it enables people to consume the same amounts and types of products. However, this seems not to be the case for Brazil. Here, income inequality keeps rising while inequality of environmental impacts from food is declining. As also touched upon in section 5.2.2.1, a possible explanation for this is that the nation has experienced rapid growth in GDP over the time-span (The World Bank, 2017), perhaps strengthening the economy of lower income groups to consume more food products with a higher environmental pressure, such as milk and meat from cattle. This is also in alignment with Kearney (2010), which further explains how this increased income and reduced prices of animal products and processed foods has resulted in obesity being a sign of poverty in Brazil. As these two product groups clearly have large impacts on all the FP categories in every year (Figure 31, Figure 32 and Figure 33), it may make sense that the distribution of footprints is growing more equal in Brazil.

As mentioned in the methods section, the numbers on IGCs were retrieved directly from WIID (UNU-WIDER, 2017). Here, especially China stands out by experiencing a significant increase from 2004 to 2006. In 2013, Li et al. (2013) found that income inequality in this nation rose notably between 2002 and 2007, resulting in this country being the most unequal in the entire Asian continent. The researchers state that this was largely driven by a significantly increasing income-gap between rural and urban populations. Between 2002 and 2007, incomes of the urban population rose considerably compared to that of rural populations, largely driven by implementations of governmental policies that favored urban areas (Li et al., 2013). This might explain the outcomes for the IGC of China in Figure 28. Further, Xie and Zhou (2014) analyzed the IGCs for China from different databases, also using the same data from WIID that was applied in this study. It is observed in their findings that the data from WIID do not always match the data from national surveys and official figures, however, all databases seem to follow the same development trend with significantly increasing IGCs between 2000 and 2010.

A thought-provoking exercise is to compare EGCs, IGCs and HDI for the selected regions and the world average. Globally, the level of development (HDI) has been increasing (UNDP, 2016), something that could be regarded as a positive trend. However, according to the OECD (2011) and the United Nations (2017b), driven by globalization, world income inequality is also increasing, along with the EGCs from food consumption found in this study. The trend of rising values of all EGC, IGC and HDI is also recognized for China, United States and Indonesia (Figure 29 and Figure 30). RoW Africa shows increasing EGC and HDI, as well as decreasing IGC for Madagascar. Importantly, one should keep in mind that Madagascar might not represent all countries in the region. However, according to the UNDP (2017), income inequality declined in Sub-Saharan Africa from 1991 to 2011 by around 3%, though still leaving it to be the most unequal region in the world. Brazil has experienced higher development levels, increasing IGCs, but declining EGCs, something that was discussed in the previous section. Norway, on the other hand, is growing more equally, both income-wise and footprint-wise, while still experiencing rising HDI. The latter country is known to be one of the countries with the highest gender equality (Langvasbråten, 2008;

Terjesen et al., 2015), something that has also been connected to increased environmentalism (Norgaard and York, 2005). However, it might be more likely that the results can be explained by Norway being the region that is the most equal income-wise, thus the poorest part of the population may still have the financial capacity to buy the same food products as the ones in the top quintiles.

5.3 Analysis

The fact that world average trends show that HDI and environmental footprints from food are increasing, whereas footprint and income distributions are growing more unequal, presents an important question; *can we say that increasing environmental footprints are resulting from rising development levels?* In some ways – yes, increased development levels have presumably enabled many to consume more environmentally impacting food products and aliments in larger quantities, consequently rising the FPs. However, according to the findings of this study, the top income group is already responsible for over a third of these, quintile 4 and 5 together having a 59% to 61% share of all total impacts in 2011. Further, all global results indicate that the food FPs from the top quintiles are growing the most. This leaves one with the expectation of a more unequal distribution of FPs from food in the future, even though the HDI has risen. Because of this, one might ask what the driver behind this rise is. Clearly, the lowest quintiles have increased their incomes, however, according to the results, one may suspect that the highest quintiles have risen their incomes even more.

As aforementioned, climate change is most threatening for those with lower incomes. The current development in the age of globalization indicates that the environmental damage from food consumption will be increasingly caused by those with larger purchasing power. This might be perceived as an unfair trend, where the rich part of the world increasingly damages the environment that especially hits the poorer world, perhaps consequently increasing inequality even more. This is a trend observed alongside rising HDI levels, and one may therefore ask if this indicator is suitable for fully reflecting development levels after all. This current development contravenes the ambitions to reach the Sustainable Development Goals. Increased GDP has lifted millions out of hunger, however, consumption habits – especially among those of higher incomes – negatively affects both climate and world inequality, where climate changes might affect inequality even more. Therefore, to answer the question whether increasing footprints are linked to rising development levels, one might reply yes *and* no – lifting people out of poverty have certainly allowed them to increasingly consume more products, consequently affecting the climate. However, the largest portion of the rising FPs are believably caused by those who were not in need to increase their consumption habits in the first place, i.e. people in higher income quintiles.

Importantly, the upper income classes have the most increasing footprints solely after the financial crisis for LU and GWP. Before this time, the lower income quintiles were dominating the development, thus tending to further equalize the footprint distribution. This demonstrates the sensibility of inequality development to financial changes, but also that having a development that grows towards more equality footprint-wise is possible. By 2050, world population is expected to have risen from 6.9 billion in 2010 to 9.15 billion, consequently significantly increasing world food demand (Alexandratos and Bruinsma, 2012). Decreasing the total impacts from food consumption in general might be highly beneficial, perhaps especially for decreasing inequality, due to the sensitivity to climate change for lower income groups. This is not necessarily done by decreasing food intake, but rather by switching away from diets heavy in meat, milk and dairy to diets higher in plant-based products, as the results obtained suggests. However, this might only be applying to those who can already fulfill their nutritional needs while eating differently. In some of the poorest parts of the world, animal products may play an important part in poverty alleviation (Randolph et al., 2007), thus decreasing consumption might be more damaging than beneficial.

To be able to ensure future food security for all and reduced inequality, working towards achieving a fairer footprint development as it was before 2007 for LU and GWP might be favorable. However, as explained in the literature, this might become increasingly difficult in this age of globalization. Policies aiming at reducing inequality may be highly beneficial (Schmitt, 2009), as well as informing the commons of the environmental impacts of different food products. However, encouraging people to consume more environmentally friendly products might require more available information on how to manage a diet transition (Lea et al., 2006a, 2006b).

6 Conclusion

With globalization rapidly changing world consumption patterns, several million people living in food insecurity and poverty, as well as quickly increasing population numbers, the food production sector is undoubtedly of significant importance. To ensure a future without food scarcity, world agricultural production needs to be expanded significantly in the years to come. Importantly, a problem arising from this is the environmental impacts such an expansion will cause. Former studies have pointed towards correlations between increased

HDI and environmental footprints, however, these have been based on average development levels for a specific region. This study attacked the issue at a deeper level, by investigating how the footprints were affected by five different income quintiles on a global as well as a regional level. Globally, the GWP, LU and BWC FPs have all increased in every quintile from 2004 to 2011. For global warming and land use, the bottom quintiles grew the most before 2007, whereas the top income groups were changing the most after 2009. Globally, the fifth quintile had the largest increase in BWC FP over the whole time-period, whereas the fourth quintile had the largest increases in GWP FP and LU FP. Further, the global GWP FP and LU FP were found to be decreasing during The Global Financial Crisis around 2008, where the footprints from the poorest quintiles were found to be the most sensitive to the economic changes caused by the crisis. Environmental Gini Coefficients for the FPs were found to be steadily increasing from 2004 to values of 0.379 (GWP), 0.389 (LU) and 0.374 (BWC) in 2011. The top income group was found to be responsible for 36-37% of the FPs, whereas the bottom quintile had a share of 8-9%. Thus, as the top quintiles had the most increasing FPs, this indicated that world inequality in terms of food footprints has been growing. Regionally, China, United States, Indonesia and RoW Africa were found to experience increasing footprint inequality, whereas Norway and Brazil were growing more equal. Regional factors, such as policies and food consumption culture largely determine national FP distributions.

Rising the HDI and lifting people out of poverty does lead to some impacts due to elevated food consumption, however, the largest increases in footprints are observed among those who presumably were not poor in the first place. Therefore, in order to attain the SDGs of ensuring food for all, declined inequality and less climate change simultaneously, one might consider focusing on the top income groups when introducing mitigation policies. Also, the demand side may lower their GWP and LU impacts by consuming less meat from cattle, milk and dairy, whereas BWC may be lowered by reducing intake of wheat and paddy rice.

If available data, further research could address the footprint development for more recent years, as world economy is volatile and expected to have changed since 2011. Furthermore, including grey and green water in addition to blue water, as well as including more impact categories might provide an interesting perspective. Also, more research could address the upper middle class (4^{th} quintile) in the developed world to further explore the drivers behind their consumption patterns. Acquiring a full overview of the footprints from food consumption may be complicated, obtaining the complete picture on a socioeconomic level even more so. However, understanding environmental footprints on this level might be highly important for future policy making, and is something that may be anticipated to increase in relevance in the decades to come.

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APPENDIX A

This code was used to collect and sort the data on quintile demand for 2010 from EXIOBASE.

```
%Creating matrix for using for quintile calculations

load('EXIOBASE_2010_HHFD_split_by_income_quintile.mat');

y1= Household_Final_Demand_split.IO_2010.AT.Household_FD_BasicPrice_pq;
y2= Household_Final_Demand_split.IO_2010.BE.Household_FD_BasicPrice_pq;
y3= Household_Final_Demand_split.IO_2010.BG.Household_FD_BasicPrice_pq;
y4= Household_Final_Demand_split.IO_2010.CY.Household_FD_BasicPrice_pq;
y5= Household_Final_Demand_split.IO_2010.CZ.Household_FD_BasicPrice_pq;
y6= Household_Final_Demand_split.IO_2010.DE.Household_FD_BasicPrice_pq;
y7= Household_Final_Demand_split.IO_2010.DK.Household_FD_BasicPrice_pq;
y8= Household_Final_Demand_split.IO_2010.EE.Household_FD_BasicPrice_pq;
y9= Household_Final_Demand_split.IO_2010.ES.Household_FD_BasicPrice_pq;
y10= Household_Final_Demand_split.IO_2010.FI.Household_FD_BasicPrice_pq;
y11= Household_Final_Demand_split.IO_2010.FR.Household_FD_BasicPrice_pq;
y12= Household_Final_Demand_split.IO_2010.GR.Household_FD_BasicPrice_pq;
y13= Household_Final_Demand_split.IO_2010.HR.Household_FD_BasicPrice_pq;
y14= Household_Final_Demand_split.IO_2010.HU.Household_FD_BasicPrice_pq;
y15= Household_Final_Demand_split.IO_2010.IE.Household_FD_BasicPrice_pq;
y16= Household_Final_Demand_split.IO_2010.IT.Household_FD_BasicPrice_pq;
y17= Household_Final_Demand_split.IO_2010.LT.Household_FD_BasicPrice_pq;
y18= Household_Final_Demand_split.IO_2010.LU.Household_FD_BasicPrice_pq;
y19= Household_Final_Demand_split.IO_2010.LV.Household_FD_BasicPrice_pq;
y20= Household_Final_Demand_split.IO_2010.MT.Household_FD_BasicPrice_pq;
y21= Household_Final_Demand_split.IO_2010.NL.Household_FD_BasicPrice_pq;
y22= Household_Final_Demand_split.IO_2010.PL.Household_FD_BasicPrice_pq;
y23= Household_Final_Demand_split.IO_2010.PT.Household_FD_BasicPrice_pq;
y24= Household_Final_Demand_split.IO_2010.RO.Household_FD_BasicPrice_pq;
y25= Household_Final_Demand_split.IO_2010.SE.Household_FD_BasicPrice_pq;
y26= Household_Final_Demand_split.IO_2010.SI.Household_FD_BasicPrice_pq;
y27= Household_Final_Demand_split.IO_2010.SK.Household_FD_BasicPrice_pq;
y28= Household_Final_Demand_split.IO_2010.GB.Household_FD_BasicPrice_pq;
y29= Household_Final_Demand_split.IO_2010.US.Household_FD_BasicPrice_pq;
y30= Household_Final_Demand_split.IO_2010.JP.Household_FD_BasicPrice_pq;
y31= Household_Final_Demand_split.IO_2010.CN.Household_FD_BasicPrice_pq;
y32= Household_Final_Demand_split.IO_2010.CA.Household_FD_BasicPrice_pq;
y33= Household_Final_Demand_split.IO_2010.KR.Household_FD_BasicPrice_pq;
y34= Household_Final_Demand_split.IO_2010.BR.Household_FD_BasicPrice_pq;
y35= Household_Final_Demand_split.IO_2010.IN.Household_FD_BasicPrice_pq;
y36= Household_Final_Demand_split.IO_2010.MX.Household_FD_BasicPrice_pq;
y37= Household_Final_Demand_split.IO_2010.RU.Household_FD_BasicPrice_pq;
y38= Household_Final_Demand_split.IO_2010.AU.Household_FD_BasicPrice_pq;
y39= Household_Final_Demand_split.IO_2010.CH.Household_FD_BasicPrice_pq;
y40= Household_Final_Demand_split.IO_2010.TR.Household_FD_BasicPrice_pq;
y41= Household_Final_Demand_split.IO_2010.TW.Household_FD_BasicPrice_pq;
y42= Household_Final_Demand_split.IO_2010.NO.Household_FD_BasicPrice_pq;
y43= Household_Final_Demand_split.IO_2010.ID.Household_FD_BasicPrice_pq;
y44= Household_Final_Demand_split.IO_2010.ZA.Household_FD_BasicPrice_pq;
y45= Household_Final_Demand_split.IO_2010.WA.Household_FD_BasicPrice_pq;
y46= Household_Final_Demand_split.IO_2010.WL.Household_FD_BasicPrice_pq;
y47= Household_Final_Demand_split.IO_2010.WE.Household_FD_BasicPrice_pq;
y48= Household_Final_Demand_split.IO_2010.WF.Household_FD_BasicPrice_pq;
y49= Household_Final_Demand_split.IO_2010.WM.Household_FD_BasicPrice_pq;
```

```
y_prod_2010_2 = cat(3, y1, y2, y3, y4, y5, y6, y7, y8, y9, y10, y11, y12,
y13, y14,y15,y16, y17, y18,y19, y20, y21, y22, y23, y24, y25, y26, y27,
y28, y29, y30, y31, y32,y33,y34, y35, y36, y37, y38, y39, y40, y41, y42,
y43, y44, y45, y46, y47, y48, y49);
```

APPENDIX B

This code was applied to calculate the quintile demand for all the years from 2004 to 2011, using the data from 2010.

```
saveYs = '\\129.241.160.207\kristimt\Master\Results\FP_results_new';

M_Create2010Data(); %putting data from 2010 together (quintiles)

IncomeData = xlsread('IncomeData .xlsx', 'SortedIncome', 'M3:T247');

tot_exp_quin_10 = permute(sum(y_prod_2010_2, 1), [2 3 1]);

end_year = 2011;
start_year =2004;

tot_cons_pr_quin = zeros(5, 49, 8); %5quin, 49 reg, 8 years
pop_reg = zeros(49, 8); %matrix of all populations per region per year
for i = start_year:1:end_year

    year = num2str(i); %converting the numbers to letters
    year_sim = i - 2003; %for use in matrices etc.

   load(['IOT_', year,'_pxp.mat'])

   y_hhld_prod = reshape(sum(IO.Y(:, 1:7:end), 2), 200, 49); %(total
consumption of 200 prods in 49 regions)
   y_hhld_tot = sum(y_hhld_prod, 1); %(Total consumption in euros of all
products, 1x49 reg)

   Income_reshaped = reshape(IncomeData(:, year_sim), 5, 49); %(reshaping
for easier calculations. 5 quintiles in 49 countries)

   pop_reg(:, year_sim) = table2array(IO.pop(:, 3));

   %finding consumption per quintile for every region in the specific year
   %of the loop
   cons_pr_quintile= zeros(5, 49);
   for quin = 1:5
   cons_pr_quintile(quin, :) = (y_hhld_tot.*Income_reshaped(quin, :))./100;
   end

   tot_cons_pr_quin(:, :, year_sim) = cons_pr_quintile; %collecting
everything into a matrix. total consumption per quintile per reg per year
end
%
% %Finding the change per quintile in MEuro in relation to 2010 values (NOT
MR_HFFD)

change_pr_quin = zeros(5, 49, 8);

for i = 1:8
    change_pr_quin(:, :, i) = tot_cons_pr_quin(:, :,
i)./tot_cons_pr_quin(:, :, 7);
end
```

```
estimating the expenditure for every quintile in every country every year.
exp_quin_expected = zeros(5, 49, 8);
for j = 1:8
    exp_quin_expected(:, :, j) = change_pr_quin(:, :, j) .*
tot_exp_quin_10; %(5*49*8)
end

 exp_quin_expected_sum = permute(sum(exp_quin_expected, 1), [2 3 1]); %(49
reg * 8 years)
%--------rescaling -----------


y1 = reshape(sum(MR_HHFD_byQuintile.data.MR_HHFD_byQuintile(:, 1:5:end),
2), 200, 49); %(200 x 49)
y2 = reshape(sum(MR_HHFD_byQuintile.data.MR_HHFD_byQuintile(:, 2:5:end),
2), 200, 49); %(200 x 49)
y3 = reshape(sum(MR_HHFD_byQuintile.data.MR_HHFD_byQuintile(:, 3:5:end),
2), 200, 49); %(200 x 49)
y4 = reshape(sum(MR_HHFD_byQuintile.data.MR_HHFD_byQuintile(:, 4:5:end),
2), 200, 49); %(200 x 49)
y5 = reshape(sum(MR_HHFD_byQuintile.data.MR_HHFD_byQuintile(:, 5:5:end),
2), 200, 49); %(200 x 49)
y_comb = cat(3, y1,y2, y3, y4, y5);

%y_prod_2010 = permute(y_comb, [1 3 2]); %200*5*49
 y_prod_2010 = y_prod_2010_2;

exp_quin_rescaled = zeros(5, 49, 8);

for i = start_year:1:end_year

    year = num2str(i); %converting the numbers to letters
    year_sim = i - 2003; %for use in matrices etc.

   load(['IOT_', year,'_pxp.mat'])

   y_hhld_prod = reshape(sum(IO.Y(:, 1:7:end), 2), 200, 49); %(total
consumption of 200 prods in 49 regions)
   y_hhld_tot = sum(y_hhld_prod, 1)'; %(Total consumption in euros of all
products, 49*1 reg)

   knownExp_vs_expectedExp = (y_hhld_tot ./ exp_quin_expected_sum(:,
year_sim))'; %real exp vs expected exp (1*49)

   for quin = 1:5
   exp_quin_rescaled(quin, :, year_sim) = exp_quin_expected(quin, :,
year_sim) .* knownExp_vs_expectedExp;
   end
end

%test to check whether the rescaled one matces the real output
exp_quin_rescaled_sum = permute(sum(exp_quin_rescaled, 1), [2 3 1]);

 exp_quin_rescaled_perm = permute(exp_quin_rescaled, [2 1 3]);


%Estimating expenditure by quintiles for every year
```

```
for i = start_year:1:end_year

    year = num2str(i); %converting the numbers to string
    year_sim = i - 2003; %for use in matrices etc.

   load(['IOT_', year,'_pxp.mat'])

   q_pop = IO.pop(:, 3); %collecting population information
   q_pop = table2array(q_pop)'./5;

   y_hhld_prod = reshape(sum(IO.Y(:, 1:7:end), 2), 200, 49); %(total
consumption of 200 prods in 49 regions)
   y_prod_year = zeros(200, 5, 49);

for reg = 1:49

   y_new = y_prod_2010_2(:, :, reg);

    for r = 1:1000

        scalerows =  y_hhld_prod(:, reg)./sum(y_new, 2);
        %Problem: 0/number == NaN, Number/0 == Inf
        %0/number--> product is consumed in e.g. 2011 but not 2010
        %Number/0 --> Product was consumed in 2010 but not in e.g. 2011
        scalerows(isinf(scalerows)) = 0;
        scalerows(isnan(scalerows)) = 0;

        y_new = diag(scalerows) * y_new;
%
        scalecols = exp_quin_rescaled_perm(reg, :, year_sim)./sum(y_new,
1);
         scalecols(isinf(scalecols)) = 0;
        scalecols(isnan(scalecols)) = 0;

        y_new = y_new * diag(scalecols);

        y_new(isnan(y_new)) = 0;

    end
     %200 * 5 * 49
    y_prod_year(:, :, reg) = y_new;
end


QuinData = struct();
QuinData.y_prod_year = y_prod_year;
QuinData.q_pop = q_pop;

save(fullfile(saveYs,['DemandPerQuin_' year '.mat']),'QuinData')
 end

%
```

APPENDIX C

This code was applied to calculate the footprints using the results from the code in Appendix B.

```
start_year = 2004;
end_year = 2011;
saveFPs = '\\129.241.160.207\kristimt\Master\Results\FP_results_new';
 for n = start_year:1:end_year

    year = num2str(n); %converting the numbers to letters
    year_sim = n - 1994; %for use in matrices etc.

   load(['DemandPerQuin_', year,'.mat'])
   %load('MR_HHFD_2010_byQuintile.mat');


  y1 = reshape(QuinData.y_prod_year(:, 1, :), 9800, 1); %reshaping for
making diagonalization easier
  y2 = reshape(QuinData.y_prod_year(:, 2, :), 9800, 1);
  y3= reshape(QuinData.y_prod_year(:, 3, :), 9800, 1);
  y4= reshape(QuinData.y_prod_year(:, 4, :), 9800, 1);
  y5= reshape(QuinData.y_prod_year(:, 5, :), 9800, 1);


q1_prod_fp_by_region_land=reshape((IO.char(124,:)*IO.S*inv(eye(size(IO.A))-
IO.A)*diag(y1)), 200, 49); %200 prods * 49 regions, quintile 1

q2_prod_fp_by_region_land=reshape((IO.char(124,:)*IO.S*inv(eye(size(IO.A))-
IO.A)*diag(y2)), 200, 49);

q3_prod_fp_by_region_land=reshape((IO.char(124,:)*IO.S*inv(eye(size(IO.A))-
IO.A)*diag(y3)), 200, 49);

q4_prod_fp_by_region_land=reshape((IO.char(124,:)*IO.S*inv(eye(size(IO.A))-
IO.A)*diag(y4)), 200, 49);

q5_prod_fp_by_region_land=reshape((IO.char(124,:)*IO.S*inv(eye(size(IO.A))-
IO.A)*diag(y5)), 200, 49);
%
 q1_prod_fp_by_region_gwp=reshape((IO.char(9,:)*IO.S*inv(eye(size(IO.A))-
IO.A)*diag(y1)), 200, 49);
 q2_prod_fp_by_region_gwp=reshape((IO.char(9,:)*IO.S*inv(eye(size(IO.A))-
IO.A)*diag(y2)), 200, 49);
 q3_prod_fp_by_region_gwp=reshape((IO.char(9,:)*IO.S*inv(eye(size(IO.A))-
IO.A)*diag(y3)), 200, 49);
 q4_prod_fp_by_region_gwp=reshape((IO.char(9,:)*IO.S*inv(eye(size(IO.A))-
IO.A)*diag(y4)), 200, 49);
 q5_prod_fp_by_region_gwp=reshape((IO.char(9,:)*IO.S*inv(eye(size(IO.A))-
IO.A)*diag(y5)), 200, 49);
%
 q1_prod_fp_by_region_wc=reshape((IO.char(119,:)*IO.S*inv(eye(size(IO.A))-
IO.A)*diag(y1)), 200, 49);
 q2_prod_fp_by_region_wc=reshape((IO.char(119,:)*IO.S*inv(eye(size(IO.A))-
IO.A)*diag(y2)), 200, 49);
 q3_prod_fp_by_region_wc=reshape((IO.char(119,:)*IO.S*inv(eye(size(IO.A))-
IO.A)*diag(y3)), 200, 49);
```

```
 q4_prod_fp_by_region_wc=reshape((IO.char(119,:)*IO.S*inv(eye(size(IO.A))-
IO.A)*diag(y4)), 200, 49);
 q5_prod_fp_by_region_wc=reshape((IO.char(119,:)*IO.S*inv(eye(size(IO.A))-
IO.A)*diag(y5)), 200, 49);
%
 %combining the fp's from the quintiles together in 200*49*5 matrices
 combine_gwp_fp = cat(3, q1_prod_fp_by_region_gwp,
q2_prod_fp_by_region_gwp, q3_prod_fp_by_region_gwp,
q4_prod_fp_by_region_gwp, q5_prod_fp_by_region_gwp);
 combine_land_fp = cat(3, q1_prod_fp_by_region_land,
q2_prod_fp_by_region_land, q3_prod_fp_by_region_land,
q4_prod_fp_by_region_land, q5_prod_fp_by_region_land);
 combine_wc_fp = cat(3, q1_prod_fp_by_region_wc, q2_prod_fp_by_region_wc,
q3_prod_fp_by_region_wc, q4_prod_fp_by_region_wc, q5_prod_fp_by_region_wc);
%
 Final_fp_gwp = permute(combine_gwp_fp, [3, 1, 2]); %(5*200*49);
 Final_fp_land = permute(combine_land_fp, [3, 1, 2]); %(5*200*49);
 Final_fp_wc = permute(combine_wc_fp, [3, 1, 2]); %(5*200*49);
%
 file_char ='classification and description of products_Kristin.xlsx';
 %food_products = xlsread(file_char, 'Classification', 'F3:F202'); %only
for all food products
%
% %Adjusting to only 25 food groups
%
% %trans_food = food_products'; %transposing food_products for the for loop
% %trans_food is a vector of 200 numbers of 1's and 0's, 1 for food, 0 for
% %non-foods
 Final_FP_food_gwp = zeros(5, 25, 49); %allocating space for the final
footprints
 Final_FP_food_land = zeros(5, 25, 49);
 Final_FP_food_wc = zeros(5, 25, 49);
%
 Aggregation = xlsread(file_char, 'Aggregation', 'A1:Y200');
for in = 1:49
    Final_FP_food_gwp (:, :, in) = squeeze(Final_fp_gwp(:, :, in)) *
Aggregation;
    Final_FP_food_land (:, :, in) = squeeze(Final_fp_land(:, :, in)) *
Aggregation;
    Final_FP_food_wc(:, :, in) = squeeze(Final_fp_wc(:, :, in)) *
Aggregation;
end

%per cap values
Final_fp_gwp_cap = zeros(5, 200, 49);
Final_fp_land_cap= zeros(5, 200, 49);
Final_fp_wc_cap= zeros(5, 200, 49);
Final_FP_food_gwp_cap= zeros(5, 25, 49);
Final_FP_food_land_cap= zeros(5, 25, 49);
Final_FP_food_wc_cap= zeros(5, 25, 49);
q_pop1 = permute(q_pop,[1 3 2]);

for quin = 1:5
    for prod = 1:200
    Final_fp_gwp_cap(quin, prod, : ) = Final_fp_gwp(quin, prod, :)./q_pop1;
    Final_fp_land_cap(quin, prod, : ) = Final_fp_land(quin, prod,
:)./q_pop1;
    Final_fp_wc_cap(quin, prod, : ) = Final_fp_wc(quin, prod, :)./q_pop1;
    end

    for food = 1:25
```

```
        Final_FP_food_gwp_cap(quin, food, :) = Final_FP_food_gwp(quin,
food, :)./q_pop1;
        Final_FP_food_land_cap(quin, food, :) = Final_FP_food_land(quin,
food, :)./q_pop1;
        Final_FP_food_wc_cap(quin, food, :) = Final_FP_food_wc(quin, food,
:)./q_pop1;
    end

end

q_Final_FPs = struct();
%absolute values
q_Final_FPs.Final_FP_food_gwp = Final_FP_food_gwp; %(5*25*49)
q_Final_FPs.Final_FP_food_land = Final_FP_food_land; %5*25*49
q_Final_FPs.Final_FP_food_wc = Final_FP_food_wc; %5*25*49

q_Final_FPs.Final_fp_gwp = Final_fp_gwp; %5*200*49
q_Final_FPs.Final_fp_land = Final_fp_land; %5*200*49
q_Final_FPs.Final_fp_wc = Final_fp_wc; %5*200*49

%per cap values
q_Final_FPs.Final_FP_food_gwp_cap = Final_FP_food_gwp_cap; %(5*25*49)
q_Final_FPs.Final_FP_food_land_cap = Final_FP_food_land_cap; %5*25*49
q_Final_FPs.Final_FP_food_wc_cap = Final_FP_food_wc_cap; %5*25*49

q_Final_FPs.Final_fp_gwp_cap = Final_fp_gwp_cap; %5*200*49
q_Final_FPs.Final_fp_land_cap = Final_fp_land_cap; %5*200*49
q_Final_FPs.Final_fp_wc_cap = Final_fp_wc_cap; %5*200*49

 save(fullfile(saveFPs,['Footprints3_' year '.mat']),'q_Final_FPs')
 disp(['Done with year ' year])
 end
```

APPENDIX D

The following code was used to treat the results from the code in Appendix C. Here, the footprints for all products and solely food products for all quintiles and years are organized into different matrices.

```
w_sum_food_gwp = zeros(5, 8);
w_sum_food_land = zeros(5, 8);
w_sum_food_wc = zeros(5, 8);

w_sum_prod_gwp = zeros(5, 8);
w_sum_prod_land = zeros(5, 8);
w_sum_prod_wc = zeros(5, 8);

w_sum_food_gwp_cap = zeros(5, 8);
w_sum_food_land_cap = zeros(5, 8);
w_sum_food_wc_cap = zeros(5, 8);

w_sum_prod_gwp_cap = zeros(5, 8);
w_sum_prod_land_cap = zeros(5, 8);
w_sum_prod_wc_cap = zeros(5, 8);

gwp_by_food = zeros(25, 8); %gwp FP per food prod
land_by_food = zeros(25, 8); %land FP per food prod
wc_by_food = zeros(25, 8); %wc FP per food prod

pos = 3;
width = 3;     % Width in inches
height = 3;    % Height in inches
alw = 0.75;    % AxesLineWidth
fsz = 11;      % Fontsize
lw = 1.5;      % LineWidth
msz = 8;        %markerSize

for year1 = sim_years %looping over 8 years

    year2 = num2str(year1);
    year3 = year1 - 2003;

    load(['Footprints3_', year2,'.mat']) %gathering the footprints each
year

    %absolute values

    r_sum_food_gwp = permute(sum(q_Final_FPs.Final_FP_food_gwp, 2), [1 3
2]); %total food gwp fp per q and reg (5*49)
    r_sum_food_land = permute(sum(q_Final_FPs.Final_FP_food_land, 2), [1 3
2]);
    r_sum_food_wc = permute(sum(q_Final_FPs.Final_FP_food_wc, 2), [1 3 2]);

    temp_sum_food_gwp = sum(r_sum_food_gwp, 2); %total food fp per q (5 *
1);
    temp_sum_food_land = sum(r_sum_food_land, 2);
    temp_sum_food_wc = sum(r_sum_food_wc, 2);
```

```
    r_sum_prod_gwp = permute(sum(q_Final_FPs.Final_fp_gwp, 2), [1 3 2]);
%total gwp fp per q and reg (5*49), all prods
    r_sum_prod_land = permute(sum(q_Final_FPs.Final_fp_land, 2), [1 3 2]);
    r_sum_prod_wc = permute(sum(q_Final_FPs.Final_fp_wc, 2), [1 3 2]);

    temp_sum_prod_gwp = sum(r_sum_prod_gwp, 2);  %total fp per q (5*1)
    temp_sum_prod_land = sum(r_sum_prod_land, 2);
    temp_sum_prod_wc = sum(r_sum_prod_wc, 2);

    w_sum_food_gwp(:, year3) = temp_sum_food_gwp; %yearly development of
food fp (5*17)
    w_sum_food_land(:, year3) = temp_sum_food_land;
    w_sum_food_wc(:, year3) = temp_sum_food_wc;

    w_sum_prod_gwp(:, year3) = temp_sum_prod_gwp; %yearly development of
all prod fp (5*17)
    w_sum_prod_land(:, year3) = temp_sum_prod_land;
    w_sum_prod_wc(:, year3) = temp_sum_prod_wc;

    %per cap values

    r_sum_food_gwp_cap = permute(sum(q_Final_FPs.Final_FP_food_gwp_cap, 2),
[1 3 2]); %total food gwp fp per q and reg (5*49)
    r_sum_food_land_cap = permute(sum(q_Final_FPs.Final_FP_food_land_cap,
2), [1 3 2]);
    r_sum_food_wc_cap = permute(sum(q_Final_FPs.Final_FP_food_wc_cap, 2),
[1 3 2]);

    temp_sum_food_gwp_cap = sum(r_sum_food_gwp_cap, 2); %total food fp per
q (5 * 1);
    temp_sum_food_land_cap = sum(r_sum_food_land_cap, 2);
    temp_sum_food_wc_cap = sum(r_sum_food_wc_cap, 2);

    r_sum_prod_gwp_cap = permute(sum(q_Final_FPs.Final_fp_gwp_cap, 2), [1 3
2]); %total gwp fp per q and reg (5*49), all prods
    r_sum_prod_land_cap = permute(sum(q_Final_FPs.Final_fp_land_cap, 2), [1
3 2]);
    r_sum_prod_wc_cap = permute(sum(q_Final_FPs.Final_fp_wc_cap, 2), [1 3
2]);

    temp_sum_prod_gwp_cap = sum(r_sum_prod_gwp_cap, 2);  %total fp per q
(5*1)
    temp_sum_prod_land_cap = sum(r_sum_prod_land_cap, 2);
    temp_sum_prod_wc_cap = sum(r_sum_prod_wc_cap, 2);

    w_sum_food_gwp_cap(:, year3) = temp_sum_food_gwp_cap; %yearly
development of food fp (5*17)
    w_sum_food_land_cap(:, year3) = temp_sum_food_land_cap;
    w_sum_food_wc_cap(:, year3) = temp_sum_food_wc_cap;

    w_sum_prod_gwp_cap(:, year3) = temp_sum_prod_gwp_cap; %yearly
development of all prod fp (5*17)
    w_sum_prod_land_cap(:, year3) = temp_sum_prod_land_cap;
    w_sum_prod_wc_cap(:, year3) = temp_sum_prod_wc_cap;

    gwp_by_food_reg = permute(sum(q_Final_FPs.Final_FP_food_gwp, 1), [2 3
1]); %temporary matrix, 25 foods in 49 reg (25*49)
    gwp_by_food(:, year3) = sum(gwp_by_food_reg, 2); %gwp fp per prod per
year (25*8)
```

```
    land_by_food_reg = permute(sum(q_Final_FPs.Final_FP_food_land, 1), [2 3
1]); %temporary matrix, 25 foods in 49 reg (25*49)
    land_by_food(:, year3) = sum(land_by_food_reg, 2); %land fp per prod
per year (25*8)

    wc_by_food_reg = permute(sum(q_Final_FPs.Final_FP_food_wc, 1), [2 3
1]); %temporary matrix, 25 foods in 49 reg (25*49)
    wc_by_food(:, year3) = sum(wc_by_food_reg, 2); %wc fp per prod per year
(25*8)

end
```

APPENDIX E

This code extracts the footprints for different regions, creating matrices solely concerning one region.

```
FPnames = {'GWP','Blue water consumption', 'Land use'};
FPunits = {'Kg CO2-eq','Mm3', 'km2'};
stressors = [9, 119, 124];
sim_years = 2004:1:2011; %vector of all simutalted years
qNames = {'Quintile 1', 'Quintile 2', 'Quintile 3', 'Quintile 4', 'Quintile
5'};


file = 'AllQuintileResults236.xlsx';
reg_saveFPs = '\\129.241.160.207\kristimt\Master\Results\Reg_results';

china_FP_food_gwp_cap = zeros(5, 8);
brazil_FP_food_gwp_cap = zeros(5, 8);
norway_FP_food_gwp_cap = zeros(5, 8);
us_FP_food_gwp_cap = zeros(5, 8);
ind_FP_food_gwp_cap = zeros(5, 8);
africa_FP_food_gwp_cap = zeros(5, 8);

china_FP_food_land_cap = zeros(5, 8);
brazil_FP_food_land_cap = zeros(5,8);
norway_FP_food_land_cap = zeros(5, 8);
us_FP_food_land_cap = zeros(5, 8);
ind_FP_food_land_cap = zeros(5, 8);
africa_FP_food_land_cap = zeros(5, 8);

china_FP_food_wc_cap = zeros(5,8);
brazil_FP_food_wc_cap = zeros(5, 8);
norway_FP_food_wc_cap = zeros(5, 8);
us_FP_food_wc_cap = zeros(5, 8);
ind_FP_food_wc_cap = zeros(5, 8);
africa_FP_food_wc_cap = zeros(5, 8);

for year1 = sim_years %looping over 8 years

    year2 = num2str(year1);
    year3 = year1 - 2003;

    load(['Footprints3_', year2,'.mat']) %gathering the footprints each
year

    %everything here is in per cap values
    sum_FP_food_gwp = permute(sum(q_Final_FPs.Final_FP_food_gwp_cap, 2), [1
3 2]); %5 quintiles, 49 reg for that specific year
    sum_FP_food_land = permute(sum(q_Final_FPs.Final_FP_food_land_cap, 2),
[1 3 2]); %5 quintiles, 49 reg for that specific year
    sum_FP_food_wc = permute(sum(q_Final_FPs.Final_FP_food_wc_cap, 2), [1 3
2]); %5 quintiles, 49 reg for that specific year

    %extracting columns for the selected countries
    china_FP_gwp = sum_FP_food_gwp(:, 31);
    brazil_FP_gwp = sum_FP_food_gwp(:, 34);
```

```
    norway_FP_gwp = sum_FP_food_gwp(:, 42);
    us_FP_gwp = sum_FP_food_gwp(:, 29);
    ind_FP_gwp = sum_FP_food_gwp(:, 43);
    africa_FP_gwp = sum_FP_food_gwp(:, 48);

    china_FP_land = sum_FP_food_land(:, 31);
    brazil_FP_land = sum_FP_food_land(:, 34);
    norway_FP_land = sum_FP_food_land(:, 42);
    us_FP_land = sum_FP_food_land(:, 29);
    ind_FP_land = sum_FP_food_land(:, 43);
    africa_FP_land = sum_FP_food_land(:, 48);

    china_FP_wc = sum_FP_food_wc(:, 31);
    brazil_FP_wc = sum_FP_food_wc(:, 34);
    norway_FP_wc = sum_FP_food_wc(:, 42);
    us_FP_wc = sum_FP_food_wc(:, 29);
    ind_FP_wc = sum_FP_food_wc(:, 43);
    africa_FP_wc = sum_FP_food_wc(:, 48);

    %putting everything into the final matrices
    china_FP_food_gwp_cap(:, year3) = china_FP_gwp;
    brazil_FP_food_gwp_cap(:, year3) = brazil_FP_gwp;
    norway_FP_food_gwp_cap(:, year3) = norway_FP_gwp;
    us_FP_food_gwp_cap(:, year3) = us_FP_gwp;
    ind_FP_food_gwp_cap(:, year3) = ind_FP_gwp;
    africa_FP_food_gwp_cap(:, year3) = africa_FP_gwp;

    china_FP_food_land_cap(:, year3) = china_FP_land;
    brazil_FP_food_land_cap(:, year3) = brazil_FP_land;
    norway_FP_food_land_cap(:, year3) = norway_FP_land;
    us_FP_food_land_cap(:, year3) = us_FP_land;
    ind_FP_food_land_cap(:, year3) = ind_FP_land;
    africa_FP_food_land_cap(:, year3) = africa_FP_land;

    china_FP_food_wc_cap(:, year3) = china_FP_wc;
    brazil_FP_food_wc_cap(:, year3) = brazil_FP_wc;
    norway_FP_food_wc_cap(:, year3) = norway_FP_wc;
    us_FP_food_wc_cap(:, year3) = us_FP_wc;
    ind_FP_food_wc_cap(:, year3) = ind_FP_wc;
    africa_FP_food_wc_cap(:, year3) = africa_FP_wc;

end

xlswrite(file, china_FP_food_gwp_cap , 'RegionalCalculations', 'D6')
xlswrite(file, brazil_FP_food_gwp_cap , 'RegionalCalculations', 'D26')
xlswrite(file, norway_FP_food_gwp_cap , 'RegionalCalculations', 'D46')
xlswrite(file, us_FP_food_gwp_cap , 'RegionalCalculations', 'D66')
xlswrite(file, ind_FP_food_gwp_cap , 'RegionalCalculations', 'D86')
xlswrite(file, africa_FP_food_gwp_cap , 'RegionalCalculations', 'D106')

xlswrite(file, china_FP_food_land_cap , 'RegionalCalculations', 'D11')
xlswrite(file, brazil_FP_food_land_cap , 'RegionalCalculations', 'D31')
xlswrite(file, norway_FP_food_land_cap , 'RegionalCalculations', 'D51')
xlswrite(file, us_FP_food_land_cap , 'RegionalCalculations', 'D71')
xlswrite(file, ind_FP_food_land_cap , 'RegionalCalculations', 'D91')
xlswrite(file, africa_FP_food_land_cap , 'RegionalCalculations', 'D111')

xlswrite(file, china_FP_food_wc_cap , 'RegionalCalculations', 'D16')
xlswrite(file, brazil_FP_food_wc_cap , 'RegionalCalculations', 'D36')
xlswrite(file, norway_FP_food_wc_cap , 'RegionalCalculations', 'D56')
```

```
xlswrite(file, us_FP_food_wc_cap , 'RegionalCalculations', 'D76')
xlswrite(file, ind_FP_food_wc_cap , 'RegionalCalculations', 'D96')
xlswrite(file, africa_FP_food_wc_cap , 'RegionalCalculations', 'D116')


region_fps = struct();
region_fps.china_FP_food_gwp_cap = china_FP_food_gwp_cap;
region_fps.brazil_FP_food_gwp_cap = brazil_FP_food_gwp_cap;
region_fps.norway_FP_food_gwp_cap = norway_FP_food_gwp_cap;
region_fps.us_FP_food_gwp_cap = us_FP_food_gwp_cap;
region_fps.ind_FP_food_gwp_cap = ind_FP_food_gwp_cap;
region_fps.africa_FP_food_gwp_cap = africa_FP_food_gwp_cap;

region_fps.china_FP_food_land_cap = china_FP_food_land_cap;
region_fps.brazil_FP_food_land_cap = brazil_FP_food_land_cap;
region_fps.norway_FP_food_land_cap = norway_FP_food_land_cap;
region_fps.us_FP_food_land_cap = us_FP_food_land_cap;
region_fps.ind_FP_food_land_cap = ind_FP_food_land_cap;
region_fps.africa_FP_food_land_cap = africa_FP_food_land_cap;

region_fps.china_FP_food_wc_cap = china_FP_food_wc_cap;
region_fps.brazil_FP_food_wc_cap = brazil_FP_food_wc_cap;
region_fps.norway_FP_food_wc_cap = norway_FP_food_wc_cap;
region_fps.us_FP_food_wc_cap = us_FP_food_wc_cap;
region_fps.ind_FP_food_wc_cap = ind_FP_food_wc_cap;
region_fps.africa_FP_food_wc_cap = africa_FP_food_wc_cap;

save(fullfile(reg_saveFPs,['Reg_FP' year2 '.mat']),'region_fps')
```

APPENDIX F

This code aims at processing some of the findings and writing them to excel, where they were further analyzed and presented in graphs.

```
%Writing data to excel file

file = 'AllQuintileResults238.xlsx';
load('Footprints3_2004.mat')

r_sum_food_gwp = permute(sum(q_Final_FPs.Final_FP_food_gwp, 2), [1 3 2]);
%total food gwp fp per q and reg (5*49)
r_sum_food_land = permute(sum(q_Final_FPs.Final_FP_food_land, 2), [1 3 2]);
r_sum_food_wc = permute(sum(q_Final_FPs.Final_FP_food_wc, 2), [1 3 2]);
r_sum_food_1 = cat(1, r_sum_food_gwp, r_sum_food_land, r_sum_food_wc);

r_sum_prod_gwp = permute(sum(q_Final_FPs.Final_fp_gwp, 2), [1 3 2]); %total
gwp fp per q and reg (5*49), all prods
r_sum_prod_land = permute(sum(q_Final_FPs.Final_fp_land, 2), [1 3 2]);
r_sum_prod_wc = permute(sum(q_Final_FPs.Final_fp_wc, 2), [1 3 2]);
r_sum_prod_1 = cat(1, r_sum_prod_gwp, r_sum_prod_land, r_sum_prod_wc);

r_sum_food_gwp_cap = permute(sum(q_Final_FPs.Final_FP_food_gwp_cap, 2), [1
3 2]); %total food gwp fp per q and reg (5*49)
r_sum_food_land_cap = permute(sum(q_Final_FPs.Final_FP_food_land_cap, 2),
[1 3 2]);
r_sum_food_wc_cap = permute(sum(q_Final_FPs.Final_FP_food_wc_cap, 2), [1 3
2]);
r_sum_food_1_cap = cat(1, r_sum_food_gwp_cap, r_sum_food_land_cap,
r_sum_food_wc_cap);

r_sum_prod_gwp_cap = permute(sum(q_Final_FPs.Final_fp_gwp_cap, 2), [1 3
2]); %total gwp fp per q and reg (5*49), all prods
r_sum_prod_land_cap = permute(sum(q_Final_FPs.Final_fp_land_cap, 2), [1 3
2]);
r_sum_prod_wc_cap = permute(sum(q_Final_FPs.Final_fp_wc_cap, 2), [1 3 2]);
r_sum_prod_1_cap = cat(1, r_sum_prod_gwp_cap, r_sum_prod_land_cap,
r_sum_prod_wc_cap);

xlswrite(file, r_sum_food_1, 'FootprintDistributions', 'D5')
xlswrite(file, r_sum_prod_1, 'FootprintDistributions', 'D42')
xlswrite(file, r_sum_food_1_cap, 'FootprintDistributions', 'D82')
xlswrite(file, r_sum_prod_1_cap, 'FootprintDistributions', 'D120')

load('Footprints3_2011.mat')

r_sum_food_gwp = permute(sum(q_Final_FPs.Final_FP_food_gwp, 2), [1 3 2]);
%total food gwp fp per q and reg (5*49)
r_sum_food_land = permute(sum(q_Final_FPs.Final_FP_food_land, 2), [1 3 2]);
r_sum_food_wc = permute(sum(q_Final_FPs.Final_FP_food_wc, 2), [1 3 2]);
r_sum_food_1 = cat(1, r_sum_food_gwp, r_sum_food_land, r_sum_food_wc);

r_sum_prod_gwp = permute(sum(q_Final_FPs.Final_fp_gwp, 2), [1 3 2]); %total
gwp fp per q and reg (5*49), all prods
r_sum_prod_land = permute(sum(q_Final_FPs.Final_fp_land, 2), [1 3 2]);
r_sum_prod_wc = permute(sum(q_Final_FPs.Final_fp_wc, 2), [1 3 2]);
```

```
r_sum_prod_1 = cat(1, r_sum_prod_gwp, r_sum_prod_land, r_sum_prod_wc);

r_sum_food_gwp_cap = permute(sum(q_Final_FPs.Final_FP_food_gwp_cap, 2), [1
3 2]); %total food gwp fp per q and reg (5*49)
r_sum_food_land_cap = permute(sum(q_Final_FPs.Final_FP_food_land_cap, 2),
[1 3 2]);
r_sum_food_wc_cap = permute(sum(q_Final_FPs.Final_FP_food_wc_cap, 2), [1 3
2]);
r_sum_food_1_cap = cat(1, r_sum_food_gwp_cap, r_sum_food_land_cap,
r_sum_food_wc_cap);

r_sum_prod_gwp_cap = permute(sum(q_Final_FPs.Final_fp_gwp_cap, 2), [1 3
2]); %total gwp fp per q and reg (5*49), all prods
r_sum_prod_land_cap = permute(sum(q_Final_FPs.Final_fp_land_cap, 2), [1 3
2]);
r_sum_prod_wc_cap = permute(sum(q_Final_FPs.Final_fp_wc_cap, 2), [1 3 2]);
r_sum_prod_1_cap = cat(1, r_sum_prod_gwp_cap, r_sum_prod_land_cap,
r_sum_prod_wc_cap);

xlswrite(file, r_sum_food_1, 'FootprintDistributions', 'D23')
xlswrite(file, r_sum_prod_1, 'FootprintDistributions', 'D61')
xlswrite(file, r_sum_food_1_cap, 'FootprintDistributions', 'D100')
xlswrite(file, r_sum_prod_1_cap, 'FootprintDistributions', 'D138')

%writing world total values
xlswrite(file, w_sum_food_gwp, 'TotalFPs', 'D7');
xlswrite(file, w_sum_food_land, 'TotalFPs', 'D12');
xlswrite(file, w_sum_food_wc, 'TotalFPs', 'D17');
xlswrite(file, w_sum_prod_gwp, 'TotalFPs', 'D27');
xlswrite(file, w_sum_prod_land, 'TotalFPs', 'D32');
xlswrite(file, w_sum_prod_wc, 'TotalFPs', 'D37');

xlswrite(file, w_sum_food_gwp_cap, 'TotalFPs', 'D45');
xlswrite(file, w_sum_food_land_cap, 'TotalFPs', 'D50');
xlswrite(file, w_sum_food_wc_cap, 'TotalFPs', 'D55');
xlswrite(file, w_sum_prod_gwp_cap, 'TotalFPs', 'D63');
xlswrite(file, w_sum_prod_land_cap, 'TotalFPs', 'D68');
xlswrite(file, w_sum_prod_wc_cap, 'TotalFPs', 'D73');



%writing pop values
xlswrite(file, sum_pop_val, 'TotalFPs', 'V31');

%collecting data on tot world FP per quin per year to use for Gini
%Calculations

start_year = 2004;
end_year = 2011;

tot_FPs_food = zeros(15, 8); %5 quintiles, 3 FPs, 8 years
tot_FPs_prod = zeros(15, 8); %5 quintiles, 3 FPs, 8 years
 for n = start_year:1:end_year

    year = num2str(n); %converting the numbers to letters
    year_sim = n - 2003; %for use in matrices etc.

   load(['Footprints3_', year,'.mat'])
```

```
    gwp_food_prod_sum = sum(q_Final_FPs.Final_FP_food_gwp, 3);
    gwp_food_sum = sum(gwp_food_prod_sum, 2);

    land_food_prod_sum = sum(q_Final_FPs.Final_FP_food_land, 3);
    land_food_sum = sum(land_food_prod_sum, 2);

    wc_food_prod_sum = sum(q_Final_FPs.Final_FP_food_wc, 3);
    wc_food_sum = sum(wc_food_prod_sum, 2);

    tot_FPs_food(1:5, year_sim) =  gwp_food_sum;
    tot_FPs_food(6:10, year_sim) = land_food_sum;
    tot_FPs_food(11:15, year_sim)= wc_food_sum;

    %prods

    gwp_prod_prod_sum = sum(q_Final_FPs.Final_fp_gwp, 3);
    gwp_prod_sum = sum(gwp_prod_prod_sum, 2);

    land_prod_prod_sum = sum(q_Final_FPs.Final_fp_land, 3);
    land_prod_sum = sum(land_prod_prod_sum, 2);

    wc_prod_prod_sum = sum(q_Final_FPs.Final_fp_wc, 3);
    wc_prod_sum = sum(wc_prod_prod_sum, 2);

    tot_FPs_prod(1:5, year_sim) =  gwp_prod_sum;
    tot_FPs_prod(6:10, year_sim) = land_prod_sum;
    tot_FPs_prod(11:15, year_sim)= wc_prod_sum;

end
```

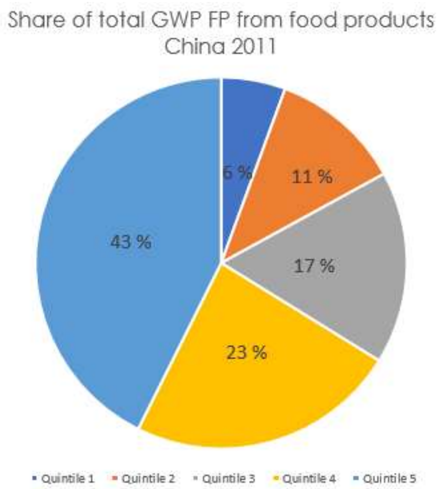
APPENDIX G

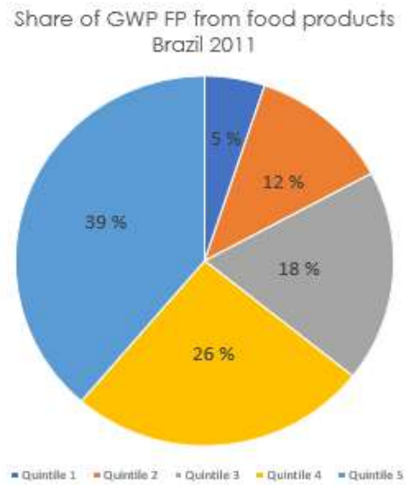
The official EXIOBASE names and the applied abridgements for the food products are listed in this section.

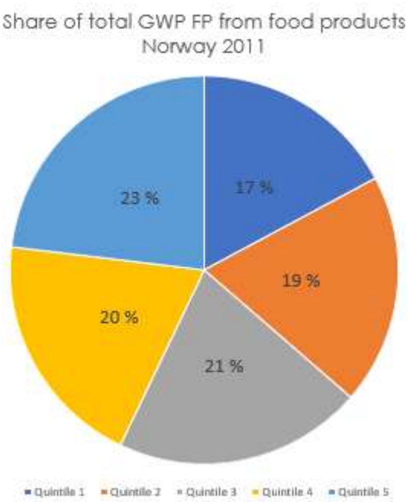
Abridgement	Official EXIOBASE name
Paddy rice	Paddy rice
Wheat	Wheat
Cereal grains	Cereal grains nec
Veg., fruit, nuts	Vegetables, fruit, nuts
Oil seeds	Oil seeds
Sugar plants	Sugar cane, sugar beet
Crops	Crops nec
Cattle	Cattle
Pigs	Pigs
Poultry	Poultry
Meat nec	Meat animals nec
Animal products	Animal products nec
Fish products	Fish products
Raw milk	Raw milk
Fishing products	Fish and other fishing products; services incidental of fishing
Meat, cattle	Products of meat cattle
Meat, pigs	Products of meat pigs
Meat, poultry	Products of meat poultry
Meat products	Meat products nec
Veg. oils and fats	products of Vegetable oils and fats
Dairy	Dairy products
Processed rice	Processed rice
Sugar	Sugar
Other processed foods	Food products nec
Beverages	Beverages

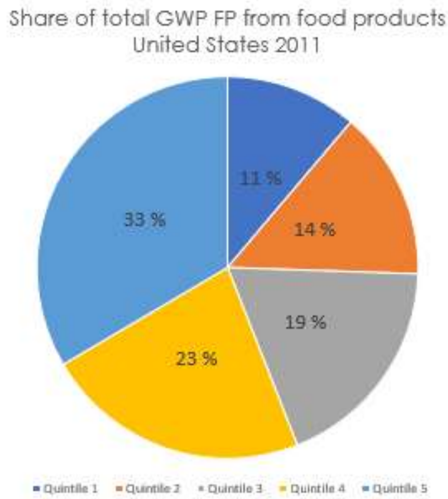
APPENDIX H

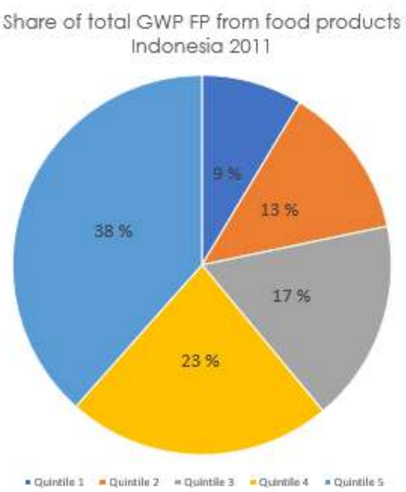
The pie charts in this appendix display the share of total FPs in terms of GWP, LU and BWC in 2011 for the five quintiles in the the six selected regions.

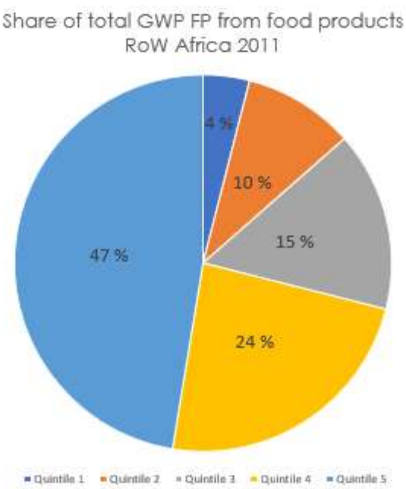


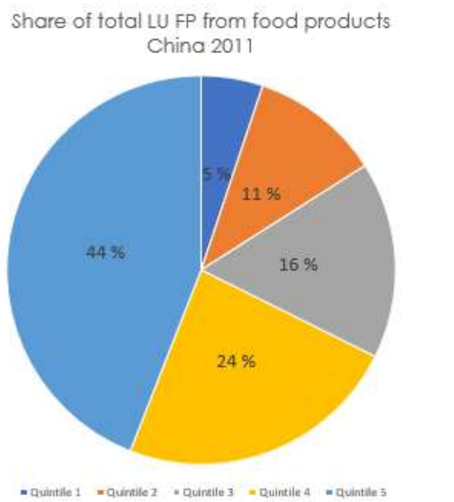


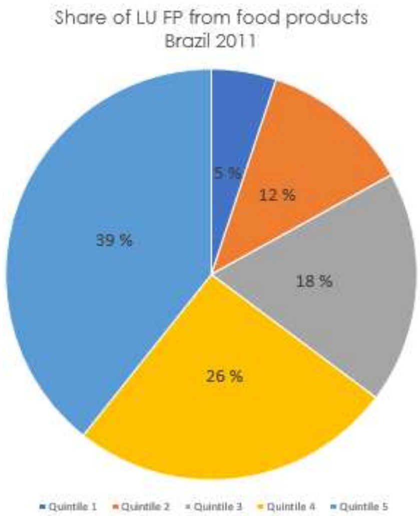


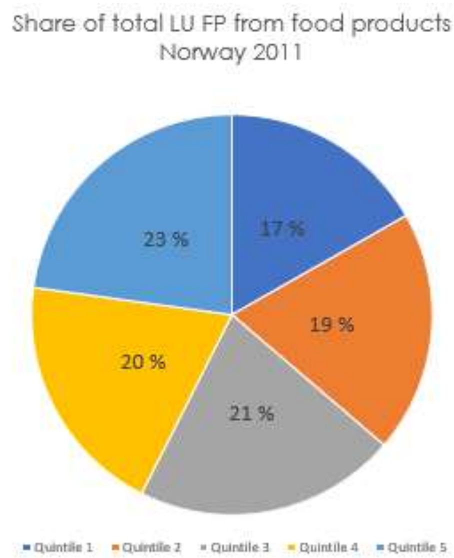


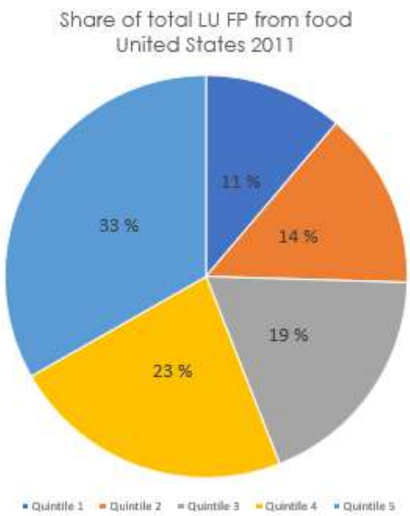


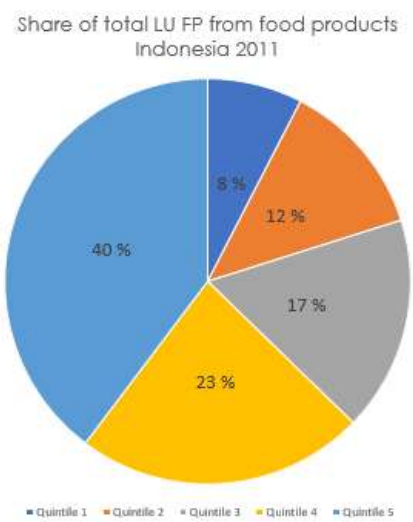


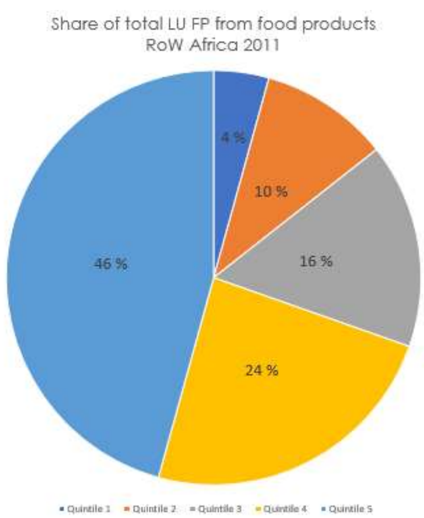

Share of total LU FP from food products
China 2011
5 %
11 %
16 %
24 %
44 %
Quintile 1
Quintile 2
Quintile 3
Quintile 4
Quintile 5

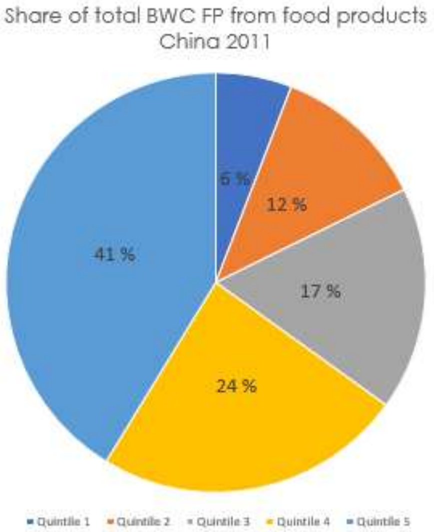

Share of LU FP from food products
Brazil 2011
5 %
12 %
18 %
26 %
39 %
Quintile 1
Quintile 2
Quintile 3
Quintile 4
Quintile 5

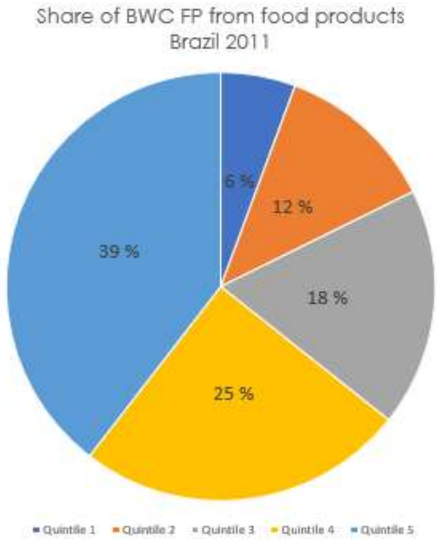

Share of total LU FP from food products
Norway 2011
17 %
19 %
21 %
20 %
23 %
Quintile 1
Quintile 2
Quintile 3
Quintile 4
Quintile 5

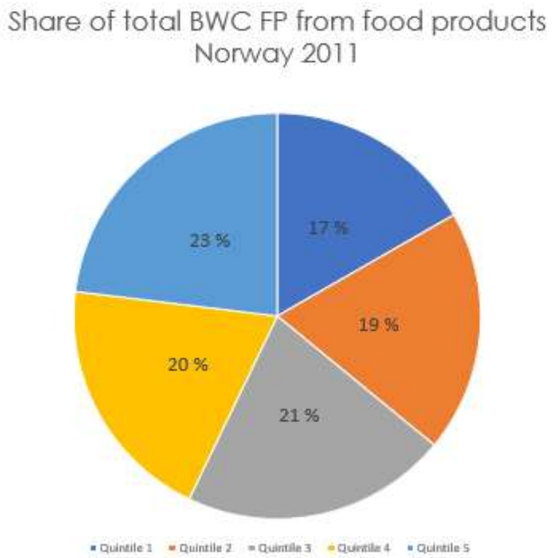

Share of total LU FP from food
United States 2011
11 %
14 %
19 %
23 %
33 %
Quintile 1
Quintile 2
Quintile 3
Quintile 4
Quintile 5

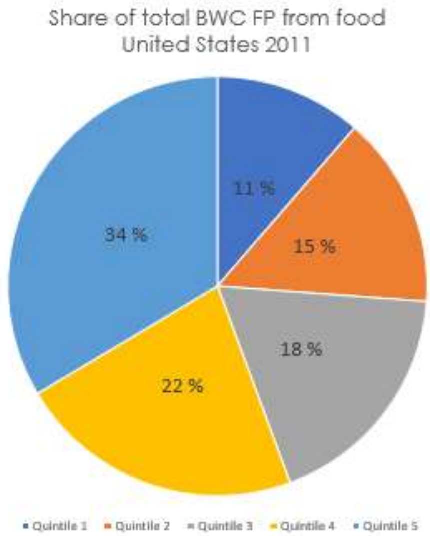

Share of total LU FP from food products
Indonesia 2011
8 %
12 %
17 %
23 %
40 %
Quintile 1
Quintile 2
Quintile 3
Quintile 4
Quintile 5

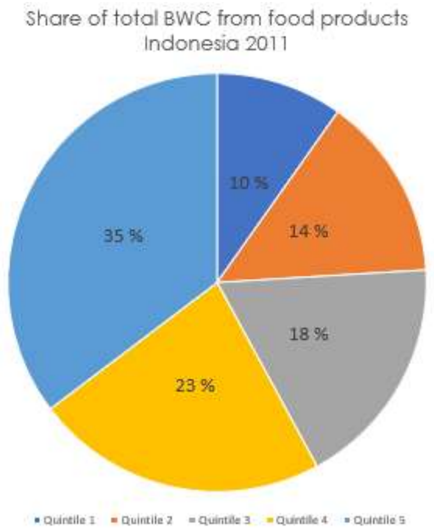

Share of total LU FP from food products
RoW Africa 2011
4 %
10 %
16 %
24 %
46 %
Quintile 1
Quintile 2
Quintile 3
Quintile 4
Quintile 5

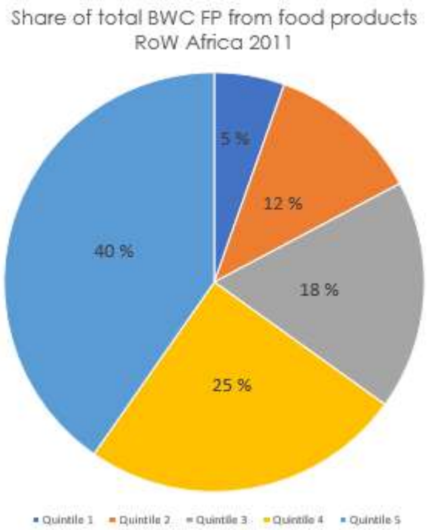

Share of total BWC FP from food products
China 2011
6 %
12 %
17 %
24 %
41 %
Quintile 1
Quintile 2
Quintile 3
Quintile 4
Quintile 5


Share of BWC FP from food products
Brazil 2011
6 %
12 %
18 %
25 %
39 %
Quintile 1
Quintile 2
Quintile 3
Quintile 4
Quintile 5


Share of total BWC FP from food products
Norway 2011
17 %
19 %
21 %
20 %
23 %
Quintile 1
Quintile 2
Quintile 3
Quintile 4
Quintile 5


Share of total BWC FP from food
United States 2011
11 %
15 %
18 %
22 %
34 %
Quintile 1
Quintile 2
Quintile 3
Quintile 4
Quintile 5


Share of total BWC from food products
Indonesia 2011
10 %
14 %
18 %
23 %
35 %
Quintile 1
Quintile 2
Quintile 3
Quintile 4
Quintile 5


Share of total BWC FP from food products
RoW Africa 2011
5 %
12 %
18 %
25 %
40 %
Quintile 1
Quintile 2
Quintile 3
Quintile 4
Quintile 5