Greenhouse Gas Emission Footprints across Agricultural Commodities, Countries, and Global Trade Routes

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Abstract

Globally, agriculture is a critical sector for achieving greenhouse gas (GHG) reduction targets. However, systematic cross-country comparisons for specific crops or livestock activities and benchmark data on emission intensities for traded agricultural products remain scarce, but are important to accurately understand direct and indirect carbon footprints from agriculture and food systems. Using emissions intensity data compiled from eight different sources, this paper aims to provide production-based GHG emissions metrics for country-commodity pairs along with an analysis of variance (ANOVVA) of emissions intensities embodied in trade and consumption in support of trade-related strategies for reducing GHG emissions from the food system. We find significant emissions intensity disparities across commodities, countries, and data sources and that strategies to mitigate emissions through enhanced productivity, trade optimization, and dietary shifts, can all be achieved through international trade. These findings have important implications when it comes to designing effective policy recommendations to promote environmental sustainability in agricultural production and trade.

Keywords: Agriculture, Sustainability, Greenhouse Gas (GHG) Emissions, CO2 equivalents

JEL: Q56, Q17, F64

1. INTRODUCTION

The Paris agreement, signed by 196 Parties at the UN Climate Change Conference (COP21), calls for action to reduce global carbon dioxide (CO_2) emissions by 45 percent by 2030 to hold "the increase in the global average temperature to well below 2 Celsius degrees above pre-industrial levels." A key new outcome from last year's COP28 summit in Dubai was to focus on climate action for agriculture and food systems with funds and pledges aimed at transforming the global food system to achieve the goals of "sustainable agriculture". Indeed, the global agri-food industry is a significant contributor to greenhouse gas (GHG) emissions (Lamb et al., 2021), being responsible for up to one-third of total anthropogenic GHG emissions (Crippa et al., 2021). Therefore, the food system plays a critical role in mitigating climate change and to achieve GHG emissions reduction targets.

Reducing agricultural emissions from field crops and animal production is an important component to achieving decarbonization. According to the US Environmental Protection Agency (EPA, 2024), annual GHG emissions from crop and animal output in 2022 constituted 10 percent of total US emissions. Key agricultural GHG emissions include carbon dioxide (CO_2), nitrous oxide (N_2O), and methane (CH_4). To evaluate GHG emission footprints, nitrous oxide and methane can be converted to "carbon dioxide equivalent" (CO_2e) based on their global warming potential (GWP) impacts on climate change. However, agricultural GHG emissions are more difficult to measure than emissions based on burning fossil fuels. Methane emissions are primarily from livestock digestion (i.e., enteric fermentation), the way in which livestock manure is managed, and from food waste. Nitrous oxide emissions result from agricultural fertilizer application to soils, which varies widely across countries and climate zones, and from manure management. Finally, direct CO_2 emissions come from increased decomposition crop residues in soils and from converting natural vegetation to agricultural activity.[1]

Moreover, an accurate understanding of a country's emissions footprint in the food system should account for emissions embodied in agricultural trade (Foong et al., 2022). Trade affords food deficit regions the ability to increase consumption levels through imports without putting pressure on domestic resources and increasing GHG emission footprints locally. For food surplus countries, however, increased exports can drive GHG emissions and cropland expansion that is unrelated to domestic consumption levels. Very little benchmark data calculating the emission intensities for traded agricultural products is available to compare emission intensities across countries and decompose trade-adjusted GHG emission footprints from future scenarios where new trade policy measures are being considered or erected to prevent CO_2 and non-CO_2 leakage. Specifically, the lack of global climate policy coordination has raised questions about the relationship between national climate measures to reduce greenhouse gas emissions on the domestic market and international trade where domestic emission reductions could be offset by increases in "imported" emissions from other countries through international trade (Felder and Rutherford, 1993; Copeland and Taylor, 1994; Bohringer, Carbone and Rutherford, 2016).

In this context, identifying key drivers of farm-level agricultural emission footprints across countries is important to improve production practices and enable more effective GHG mitigation strategies and policies. Further, translating farm-level emissions to emission footprints embodied in international trade of agricultural products provides a more complete picture of GHG emissions in consumption vis a vis international trade, particularly for food deficit and emerging market countries who are experiencing rapid dietary transitions. While many federal agencies, private

[1] CO_2 emissions can also be partially offset by increased crop residues and plant matter stored in cropland soils.

thinktank and modeling organizations, and academic studies have evaluated GHG footprints of crop and livestock production, comparisons across countries for a given crop or livestock activity has not been systematically explored. Similarly, within the global modeling community policies to curb future agricultural GHG emissions are based on differing baselines and reference years, product aggregations, projection periods and time horizons, and assumptions by which market forces and agricultural production, consumption and trade generate GHG emissions.

What does the current data tell us about the level of GHG emission footprints across countries? How much do GHG emissions intensities vary across countries for a given crop or livestock product? To what extent do differing modeling frameworks and baselines lead to differing emissions intensities across countries? To this end, many initiatives exploiting different methods and models based on various databases have led to different GHG emissions estimates from the food system (e.g., Crippa et al., 2021; Tubiello et al., 2021), which can cause fragmentation in reporting GHG emissions from sectors and activities, thereby generating unnecessary costs for stakeholders (Deconinck et al., 2023). To fill this gap in the literature, this paper pursues two main objectives. The first is to provide granular GHG emissions metrics for country-commodity pairs while broadening perspectives on the current range of emissions intensities across countries, products, and data and modeling sources. Hong et al., (2021) introduce global land-use emissions and intensity metrics for products or countries over 57 years mainly using the FAOSTAT database and bookkeeping models. Poore & Nemecek (2018) illustrate environmental impact indicators including GHG emissions from the food system by an in-depth meta-analysis of 570 studies, estimating global GHG emissions within and between products. Second, we analyze three major strategies for reducing GHG emissions from agriculture and food systems, presenting the current state of carbon footprints embodied in trade and consumption, which provides evidence on the role of trade in reducing GHG emissions from agriculture and food systems.

To do so, we build a database for the farm gate emissions intensities across agricultural commodities, countries, and data sources with collected data from 8 different sources, exploiting a life-cycle analysis (LCA) based (Agri-footprint), three formula-based (Food and Agriculture Organization Statistics, FAOSTAT; Comprehensive Accounting of Land-Use Emissions, CALUE; International Food Policy Research Institute, IFPRI), and four model-based (Aglink-Cosimo; Global Change Analysis Model, GCAM; Global Biosphere Management Model, GLOBIOM; Global Trade Analysis Project, GTAP) data sources.

Using the comprehensive database established, we *(i)* present the current state of emissions intensities in a highly disaggregated way, by country, by product, by data source, and where possible, by GHG emissions source, focusing on the main producing countries across major agricultural products, *(ii)* examine the factors contributing to the variation in emissions intensities, *(iii)* extrapolate the implications of the variability in emissions intensities, and *(iv)* estimate the emissions intensity embodied in trade and consumption to link production-based emissions intensities to trade-based and consumption-based emissions intensity to shape how GHG emissions are embodied in trade and consumption, which takes a considerable share in total GHG emissions.

The emissions intensities of major agricultural products vary significantly, with livestock generally having higher emissions intensity than crops. Beef has the highest emissions intensity, vastly exceeding that of crops like rice, maize, and soybean. Among livestock, chicken has the lowest emissions intensity, even lower than rice, which has the highest emissions among crops. The cross-country and cross-data source variation account for the variation of emissions intensities.

Country-specific factors such as yield, agricultural practices, and fertilizer application rates make differences in emissions intensity. The analysis further reveals that different data sources account for emissions intensities through the scope of farm gate emissions and estimation methods, adding to the complexity of comparing intensities. Varying emissions intensities have economic implications, especially when considering the social cost of carbon. The study suggests strategies to reduce agricultural emissions through improved productivity and the sourcing of agricultural products through trade, highlighting the role of international trade in shifting consumption patterns towards lower carbon footprint products and countries.

The rest of the paper proceeds as follows. Section 2 reviews literature on GHG emissions estimates in agriculture and the relationship between trade and the environment. Section 3 demonstrates the data collection process from multiple data sources to define the scope of the database. Section 4 analyzes the farm gate emissions intensities based on production, consumption, and trade. Section 5 concludes with policy implications.

2. LITERATURE REVIEW

The importance of the food system including agricultural production has been emphasized in mitigating climate change and achieving the goals of the Paris Agreement (Borsellino et al., 2020; Clark et al., 2020; Fanzo et al., 2021; Garnett, 2011; Rosenzweig et al., 2020; Vermeulen et al., 2012; Zurek et al., 2022). The NDC reports submitted to the UNFCCC Secretariat every five years document each party's plans and targets across sectors including agriculture to meet the ends of the Paris Agreement and economists strive to estimate the environmental impacts of particular environmental policies, trade measures, and sectors (Arndt et al., 2022; Korpar et al., 2023; Parlasca & Qaim, 2022). Plans and results depend on GHG emissions estimates. Previous studies (see for e.g., Crippa et al., 2021; Tubiello et al., 2021) have shed considerable light on the emission footprints of the agri-food system and Hong et al. (2022), especially, examined the land use emissions embodied in international trade using emissions data from FAO and trade data from GTAP. However, specific agricultural product (crop and livestock)-country combinations have not been examined rigorously. The main results of the papers vary. For example, the total GHG emissions from the food system are varying: 14.6 gigatons (Gt) of CO2 eq to 16 Gt to 18 Gt (Crippa et al., 2021; Hong et al., 2021; Tubiello et al., 2021, respectively). Moreover, Friedlingstein et al. (2023) reports the 2023 carbon flux from land use, land-use change, and forestry (LULUCF) emissions ranging from 2.4 Gt to 6.6 Gt of CO2 per year from a total of 26 different models.[2]

Earlier research on trade and the environment provides important implications for our study though studies are centered on manufacturing sector. Firstly, more productive plants present lower emissions intensity (Shapiro and Walker, 2018). Related to the relationship between productivity and emissions intensity, emissions intensities are varying across countries (Copeland et al., 2022). Emissions embodied in trade take substantial part of total GHG emissions (Copeland et al., 2022; Eaton et al., 2016). Trade have impacts on the environment through scale, technique, and composition effects (Copeland and Taylor, 1994). Among those effects, the technique effect refers to reducing emissions intensity through the adoption of environmentally friendly technologies. The decomposition of changes in emissions reveal that the technique effect by environmental regulations accounts for a larger share in the changes (Antweiler et al., 2001; Cherniwchan, 2017; Levinson, 2015; Shapiro and Walker, 2018).

In agricultural production, countries demonstrate varying levels of GHG emissions per unit of land area or per unit of food energy (Hong et al., 2021). Varying emissions intensities at the

[2] The Global Carbon Budget (2023) includes 3 bookkeeping models, 3 peat emissions models, and 20 dynamic global vegetation models.

farm gate present opportunities for reducing GHG emissions, particularly in countries with high emissions. Two effective strategies are the adoption of technologies to produce less GHG emissions per equivalent production and the achievement of productivity gains. The technique effect aligns with the first strategy. Cleaner technologies and best management practices, such as precision agriculture and crop rotation, have been shown to decrease emissions intensity by minimizing the use of inputs like fertilizers, which are major sources of GHG emissions in crop production. Trade openness can facilitate the transfer of such technologies and pratices across borders, enabling countries to produce agricultural goods more sustainably (Copeland & Taylor, 2004). Moreover, reduction of GHG emissions at the farm gate can be achieved by the improvement of productivity through a channel of intermediate input trade. Yield gains lead to lower emissions intensity in agricultural production. Reductions in trade cost of agricultural inputs are found to help close the productivity gap between countries (Farrokhi & Pellegrina, 2023).

3. DATA

We created an extensive database of mass-based farm-gate emissions intensities of four major crops (maize, wheat, soybean, and rice) and four livestock (beef, chicken, pork, and milk) in top-producing countries with eight data sources (Aglink-Cosimo, Agri-footprint, CALUE, FAOSTAT, GCAM, GLOBIOM, GTAP, and IFPRI). Table 1 presents the overview of data sources in key aspects. Depending on data sources, different sets of data (total GHG emissions, production quantity, and/or emissions intensities) were extracted. We calculated the emissions intensity of a product by the ratio of total GHG emissions and production quantity.

Where emissions intensities are available, we used the emissions intensity data without any modification. In cases where no production quantity is available from a given data source, we used the country-product specific production quantity from FAOSTAT. However, depending on data availability, broader product categories including individual products (e.g., cereals including maize, oil seeds including soybean) were used to represent the emissions intensity of an individual product. Three GHG, CH4, CO2, and N2O, were extracted to capture farm-gate emissions. Most data sources provided GHG emissions data in CO2 equivalents, using various Global Warming Potentials (GWPs) for conversion. When emissions were given as CH4 or N2O, we converted them to CO2 equivalents using the specified GWP in the data source documentation.

We extracted top-producing countries – taking at least 80 percent of world production in crops and 60 percent in livestock – in each agricultural product, considering comparability across data sources, the importance of top-producing countries in the total GHG emissions, and the issues of outliers.[3] Thus, a different number of countries are assigned to each product: maize (9 countries), soybean (3), rice (8), wheat (15), beef (9), chicken (10), pork (4), and milk (12). The year 2017 was selected as the reference year for comparison in the database given its wide availability across data sources. Due to a lack of availability, the year 2020 was selected for two data sources, GCAM and GLOBIOM.

Land use change (LUC) emissions are excluded from the database. It is complex to estimate LUC emissions due to their long-lasting characteristics and complicated observation. Emissions by deforestation last more than a year and capturing how lands are being assigned to agricultural products is not easily observable and trackable. Thus, we exclude the LUC emissions in our database due to a lack of availability across data sources and difficulty in distributing aggregated LUC emissions into individual products.

[3] The production quantity is based on the average value (2017-2020) from the FAOSTAT.

Table 2 presents the descriptive statistics for the emissions intensities of eight products. Overall, the median and mean emissions intensities of crops are, by and large, not as high as those of livestock. The median emissions intensity of beef is almost 19 times that of rice, showing the highest emissions intensity, 95 times that of maize and wheat, and 190 times that of soybean. Chicken, showing the least median emissions intensity in livestock, however, presents lower mean and median emissions intensities in comparison with rice, the greatest emissions intensity in crops. Even in conversion to the calorie-based emissions intensity, chicken (1,220 kcal per kg) shows a relatively smaller mean and median emissions intensity compared to rice (2,800 kcal per kg). Among crops, rice shows the highest mean (1.40 kg of CO2 eq per 1 kg of rice) and median (1.21) emissions intensity; soybean has the lowest mean (0.19) and median (0.10) values.

4. EMPIRICAL ANALYSIS

With the database established from eight different data sources based on specific criteria, we begin by i) presenting the range of emissions intensities for eight major agricultural products across countries and data sources, ii) implementing a variance analysis to examine the contribution of data sources and countries to the variation of emissions intensities, iii) examining the factors for the cross-country and cross-data source variation, and iv) extending the range of emissions intensities across data sources to SCC to capture the varying costs of negative externalities by agricultural GHG emissions.

4.1. Cross-country variation of emissions intensities

The global maize production in 2021 was 1.2 gigatons. The top-producing country was the United States (383 MMT), followed by China (273 MMT) and Brazil (88 MMT). A total of 196 MMT of production was traded. China was the largest importer with 33 MMT, followed by Mexico (18 MMT) and Japan (15 MMT). Yield and synthetic fertilizer use are the critical factors to varying emissions intensities across countries. GHG emissions from the application of synthetic fertilizers take up the largest part of total GHG emissions from maize production. First of all, according to Fertilizer Use by Crop (FUBC, 2022), China has the highest synthetic fertilizer application rate (189.6 kg/ha) among the top-producing countries; Argentina has the lowest rate (48.7 kg/ha).[4] In maize production, top-producing countries show large productivity gaps. Per hectare, maize production in the United States exceeded that of Brazil by 138 percent.[5] Among the top-producing countries, the United States, Ukraine, Argentina, and China show higher yields while Brazil, Mexico, and India present lower productivity. These differences in the application rate of fertilizers and productivity yield the cross-country variation in the maize emissions intensity.

The global soybean production in 2021 was 373 MMT. The top-producing countries were Brazil (135 MMT), the United States (122 MMT), and Argentina (46 MMT), consisting of more than 80% of the global production. More than 80% of soybean was exported to another place from where it was produced in 2021. China, the largest importer, imported around 96.5 MMT of soybean in 2021 and the second largest importer, Argentina, imported a much smaller amount of 4.9 MMT of soybean. Imported soybean in China is used for both food and feed; feed use is modestly larger than food use. Over time, the soybean yields from three countries have increased at similar rates. Different levels of GHG emissions from nitrogen fertilizer use account for the cross-country variation in emissions intensities. According to Fertilizer Use by Crop (FUBC), soybean

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[4] China (1,896 kg/ha), USA (1,576), Mexico (1,234), Indonesia (1,171), Ukraine (1,068), India (1,042), South Africa (1,000), Brazil (685), and Argentina (487). Data are based on FAOSTAT.

[5] Per hectare, the United States produced 11,089.5 kg, followed by Ukraine (7,681.8), Argentina (7,429.6), China (6,291.0), Indonesia (5,695.7), South Africa (5,426.1), Brazil (4,649.7), Mexico (3,852.2), and India (3,199.3) in 2021. Data are based on FAOSTAT.

production, generally, requires less amount of N fertilizers compared to other crops such as maize and wheat. Brazil applied 8.78 kg of N fertilizers per hectare while the United States and Argentina used 5.34 and 3.49 kg/ha, respectively. Given similar productivity across top-producing countries, the amount of N fertilizers applied to soils is a key factor in the cross-country variation of emissions intensities in soybean.

Rice is the most important staple food in terms of food security as rice feeds more than half of the global population. According to FAOSTAT, China produced 213 MMT in 2021, followed by India (194 MMT), Bangladesh (56 MMT), Indonesia (54 MMT), Viet Nam (44 MMT), and Thailand (33 MMT). CH4 emissions from organic matter in the flooded rice paddy fields take the largest portion of the total GHG emissions in rice production. Owing to this additional emission source, rice cultivation, the overall farm-gate emissions intensity of rice are higher than those of maize, wheat, and soybean. In the top eight rice-producing countries, taking 80 percent of global rice production, the mean emissions intensities are highly variable across countries, which is illustrated in figure 1. The Philippines, the 6th in global rice consumption, presents the highest mean emissions intensity, followed by Thailand and Indonesia among the top rice-producing countries.[6] The higher emissions intensities of the three countries stem from higher seasonally integrated CH4 emission factors for rice cultivation - 27.5 gram per m^2 for the Philippines, 16 for Thailand, 18 for Indonesia, and 15.7 for the average of Asian countries - in the flooded rice paddy fields given universal scaling factor for the rainfed rice and upland rice and correction factor for organic amendments. In addition to emission factors, the Philippines and Thailand also present low rice yields compared to other Asian countries, which leads to high rice emissions intensities.

[6] The rank is based on food use in rice products in 2021 from FAOSTAT.

The rice emissions intensity varies regionally as the main source, rice cultivation, in the rice emissions intensity depends on the agricultural practices (Qian et al., 2023).

Beef is one of the key products in reducing GHG emissions owing to its high emissions intensity compared to other agricultural products. The United States is the largest beef producer in the world with 12.7 MMT in 2021, followed by Brazil (9.8), China (7.0), Argentina (3.0), Mexico (2.1), Australia (1.9), Russia (1.7), France (1.4), and Canada (1.3). A key feature of figure 2 is that countries in Latin America show higher and wider beef emissions intensities across data sources compared to other major beef-producing countries. Two explanations account for this pattern. CH4 emissions from enteric fermentation, a digestive process in ruminant and non-ruminant (to a much lesser degree), are the largest emission source from beef production. The IPCC Guidelines on emission factors for enteric fermentation vary across regions due to differences in typical animal size, animal diet, and the level of activity animals do. For example, the emission factor for beef in Latin America (56 kg of CH4 per head per year) is larger than that of countries in North America (53 kg of CH4 per head per year).[7] The age at slaughter ("time to market") contributes significantly to the total emissions associated with each kg of product. The time to market can vary significantly across countries (reference). Another important factor is the carcass weight at the time of slaughter. Each country produces beef in different ways: production system (pasture-fed and grain-fed), cattle type (temperate or tropical), herd size (small to large), and breeding (degree of breeding intensity). There are yield gaps in beef production across countries; developed countries generally show higher productivity.[8] Heavier carcass weight per head leads to a lower emissions intensity. There

[7] IPCC 2006, Volume 4, Chapter 10, Table 10.11. In 2019 Refinement to the 2006 IPCC Guidelines, the emission factors for enteric fermentation presented updated values – 64 kg of CH4 per head per year in North America and 56 kg of CH4 per head per year in Latin America – which are different from the 2006 values. Many data sources in our database are based on the IPCC 2006 Guidelines.

[8] According to FAOSTAT, in 2021, per head, the US produced 370 kg, Canada 363 kg, France 320 kg, Australia 300 kg, Mexico 249 kg, Brazil 243 kg, Argentina 230 kg, Russia 214 kg, and China 148 kg.

is a variation in the carcass weight across countries. Overall, the carcass weight of Argentina (230 kg per head in 2021) and Brazil (360 kg) is lower than that of Canada (420 kg) and the United States (370 kg).[9] Breed, physiological characteristics (e.g., gestation length), feed type and intake, and management practices (e.g., grazing management, housing, etc.) make these differences in the carcass weight ratio. Productivity-related factors account for the cross-country variation.

4.2. Cross-data source variation of emissions intensities

Different sets of emission sources across data sources can account for the variation of emissions intensities across data sources. For crops, crop residues, burning of crop residues, rice cultivation, and application of synthetic fertilizers are the standard set of emission sources across data sources. Some data sources, however, use additional emission sources. Agri-footprint includes GHG emissions from the application of organic fertilizers (manure), lime use, and energy use. Similarly, GTAP also contains the GHG emissions from energy use on farms. IFPRI additionally includes the GHG emissions from pesticide use. To investigate the role of additional emission sources, where available, we disaggregate the emissions intensity by emission source. Table 5 demonstrates the emission intensity of agricultural products by emission source. Agri-footprint includes additional emission sources, energy use, lime, and manure, which present a meaningful magnitude in the total emissions intensity. The mean of maize emissions intensity in Agri-footprint is 0.26 kg of CO2 equivalent per kg of maize, which is composed of crop residues (0.04), energy use (0.06), lime (0.03), manure (0.01), and synthetic fertilizers (0.12). Along with crop residues and synthetic fertilizers, other additional emission sources take 40 percent of the mean of maize emissions intensity in Agri-footprint. IFPRI contains the GHG emissions from pesticide use. It takes a small

[9] The carcass weight ratio is calculated using stocks and production quantity from FAOSTAT.

share (8%) but is still bigger than the share of crop residues burning (6%). When defining the farm-gate emissions, the scope of emission sources accounts for the variation of emissions intensities across data sources.

The Global Warming Potential (GWP) presents a framework for conversion rates for GHG gases, especially CH4 and N2O gases, to the reference gas, CO2. Most data sources in our database used the GWP values adopted in the IPCC Assessment Reports (AR) while Agri-footprint is based on the EF 3.0 made by the European Commission. For the same amount of CH4 and N2O gases, different GWPs result in different estimates of CO2 equivalent gas. For example, the conversion rates of 1 kg of CH4 gas range from 21 to 36.8 kg of CO2. 1 MMT of CH4 gas in IFPRI using the AR2 GWP (21 kg of CO2 equivalent for 1 kg of CH4) is converted to 21 MMT of CO2 equivalent gases while the same amount of CH4 in Agri-footprint (36.8) is translated into 36.8 MMT. Even within the same AR report, there is variation in the GWPs. CALUE and FAO adopt the GWPs from the IPCC Fifth Assessment Report in converting non-CO2 emissions into CO2 equivalent emissions; however, CALUE uses the AR5 with the climate-carbon feedback and FAO does the AR5 without the feedback. The AR5 with climate-carbon feedback provides higher conversion rates for CH4 and N2O: 34 kg of CO2 equivalent with feedback and 28 without feedback for CH4 and 295 with feedback and 265 without feedback for N2O. 6 kg of difference for 1kg of CH4 gas in conversion to CO2 equivalent emissions seems marginal but it can lead to a drastic gap in total GHG emissions.

4.3. Analysis of Variance by country and data source

We implement a two-way Analysis of Variance (ANOVA) to investigate the extent to which cross-country and data-source variations contribute to the variation in emissions intensities.[10] Table 3 presents the results from analysis for the variation of emissions intensities by country and data source. A relatively greater value of sum of squares (SS) compared to another indicates more attribution to the variation of emissions intensities for a given product. However, we need to use caution when interpreting the SS values in explaining the variation of emissions intensities as it is highly likely to have a higher SS value with more observations given the SS formula. To address this issue, we use the mean squares (MS) to determine which source is more attributed to the variation of emissions intensities. The column of MS and Share reveal that the cross-country variation is more attributed to the variation of emissions intensities in rice, beef, chicken, and pork while the cross-data source variation is more attributed to the variation in maize, wheat, and milk. There is no noticeable difference between the variables in soybean. Overall, we find that depending on commodities, the cross-country or cross-data source variation is more pronounced in accounting for the variation of emissions intensities while no single commodity exhibits overwhelming dominance over the others in accounting for this variation.

4.4. Variation of emissions intensity in total GHG emissions and social cost

In Table 6, we report the extremes (min and max) of emissions intensities for country-product pairs and estimate differences in the GHG emissions and social cost of carbon for the pairs. Across products, the Brazil-beef pair shows the largest gap in total GHG emissions. Depending on data sources, Brazil can produce 238 MMT of CO2 equivalent gases to as much as 508 MMT of CO2

[10] As we are mainly interested in the sum of squares for each variable instead of implementing post-hoc statistical tests and selecting the best model, the interaction term between countries and data sources is excluded and the tests for normality and homogeneous variance are not performed here.

equivalent gases in beef production. Across data sources, China and the United States also present substantial gaps in total GHG emissions from beef production. The ranges of total GHG emissions for the two countries in beef production are 107 and 103 MMT of CO2 eq, respectively. Along with beef, the top rice-producing countries, China and India, show huge differences in GHG emissions in rice production depending on data sources. The gaps in the China-Rice and India-Rice pairs are 120 MMT and 108 MMT of CO2 equivalent gases.

Climate change accelerated by GHG emissions induces negative externalities throughout the economy. The social cost of carbon (SCC) measures the economic cost of an additional amount of CO2 emissions, capturing the marginal effects of climate change. Beyond presenting the variation of emissions intensities across data sources and estimating the range of related GHG emissions, we link the variation of GHG emissions to the economic cost, using estimates from Ricke et al. (2018).[11] As documented in Table 6, China, India, and the United States indicate high SCCs over 100 dollars per ton of CO2: 188.61, 173.61, and 111.71 dollars per ton of CO2, respectively. While the Brazil-beef pair presents the widest range of GHG emissions (269 MMT of CO2 eq), the India-milk pair does the widest range of SCCs (29 billion dollars). It is noteworthy that, even in a relatively low production quantity, the combination of a large gap in emissions intensities across data sources and a high SCC can lead to larger SCC values in the end. For example, China produces almost half of the US beef production; however, due to a wider gap in emissions intensities (2.5 times the gap in the US) and high SCC (around 70% higher than the US),

[11] Depending on the selection of methodologies and assumptions, the CSCC can vary. We chose median CSCC values simulated from a specification based on Burke, Hsian, and Miguel (2015) long-run model with 5 lags, central damage parameters, central climate projection parameters, SSP1 (shared socioeconomic pathway) based on low challenges to mitigation and adaptation, rcp60 (representative concentration pathway), fixed prtp (pure rate of time preference), eta (elasticity of marginal utility), and the fixed discount rate of 3. Please see Ricket et al. (2018) for details.

the SCC gap (20.2 billion dollars) for the China-beef pair is almost twice as the SCC gap (11.5 billion dollars) of the US-beef pair.

4.5. The role of agricultural trade in reducing GHG Emissions

The previous sections analyzed production-based emissions intensities across countries and data sources. In this section, we examine production-based emissions embodied in international trade and the role of agricultural trade as a potential mitigation channel by which to reduce imported carbon footprints. Specifically, we link emissions intensity data to international trade on country-by-product basis and assess border-related strategies to reduce of GHG emissions from the food system. Three main strategies have been suggested to achieve this reduction: (i) improving (i.e., lowering) production-based emissions intensity, (ii) shifting the sourcing of production vis a vis imports to countries with lower carbon footprints, and (iii) shifting consumption to products with lower carbon footprints.

The first strategy is to reduce GHG emissions at farm gate. By investigating the carbon footprint associated with the production of major agricultural products in key countries, it becomes evident that there are gaps in emissions intensity across countries. In other words, there is significant potential to enhance production-based emissions intensity in countries with high carbon footprints in agricultural production. One effective approach is to increase productivity. Figure 3 shows the relationship between emissions intensity and yield across major agricultural products. We find that higher yields are associated with lower emissions intensities across commodities.[12] As observed in the previous section, productivity gaps exist between countries. By addressing

[12] Only soybean presents a different pattern, demonstrating a positive relationship between emissions intensity and yield. When trend lines are drawn by continent (e.g., Asia, Africa, Europe, etc.), Europe and Africa show positive slopes, while other continents exhibit negative slopes. Further research is needed to understand why these two continents display different patterns.

these disparities, countries can improve their production efficiency, that is, lower emissions intensity, which, in turn, contribute to a more sustainable agricultural sector. Thus, technology adoption can play an important role in achieving productivity gains. For example, Farrokhi and Pellegrina (2023) find that reductions in trade costs on imported agricultural inputs help close the productivity gap between countries. Moreover, trade openness can facilitate the transfer of cleaner technologies and best management practices across borders, enabling countries to produce agricultural goods more sustainably (Copeland and Taylor, 2004).

Moreover, efforts should not be confined to the supply side alone. As highlighted by Poore and Nemecek (2018), interventions can be made on the consumption side as well. Given increasing population, few countries can fully meet their demand for food through domestic production alone, which has led to significant increases in agricultural trade over time. Along with the growth in agricultural trade, there has been shifts in the trade composition. For example, in the early 2000s, the United States was the dominant player in the global soybean market, holding the largest share of both production and exports. However, in recent years, Brazil has emerged as a major competitor, even surpassing the US due to increasing export to China. The increasing share of Brazil in the global soybean market have important implications for GHG emissions embodied in soybean trade. All else equal, had the composition of 2000 in soybean trade maintained in 2021 the total GHG emissions from soybean would be reduced by 32 million tons (MMT).[13]

To present the current state of consumption regarding GHG emissions, we use the emissions intensity embodied in total consumption encompassing domestic production and import. The metric is a weighted average of emissions intensities of exporting countries and an importing country. The export shares and domestic production share are weights. Figure 4 presents the

[13] Estimates are calculated from a scenario analysis, based on the share of individual countries in the crop trade market in 2000 and the import volume and emissions intensities of individual countries in 2021.

amount of GHG emissions embodied in 1 kg of beef consumption in major importing countries. For the top three importing countries, we plot the emissions intensities of key exporting countries, the emissions intensity of an importing country, and the emissions intensity embodied in consumption. Across data sources, the emissions intensity of domestic production (green plus sign) in Japan and the United States is lower than that of major exporting countries (navy circle, blue rhombus, and yellow square). As a result, the emissions intensity embodied in consumption (gray cross sign) exceeds that of domestic production. In this context, expanding domestic production could mitigate GHG emissions by reducing beef imports from countries with higher carbon footprints associated with beef production. However, this expansion may face challenges due to various land and pasture constraints in the domestic market. Alternatively, shifting beef imports from high to low GHG emitting countries could reduce the GHG emissions embodied in imports and subsequently lower the emissions intensity embodied in consumption.

Lastly, it has been argued that shifting dietary preferences can reduce GHG emissions (Aleksandrowicz et al., 2016; Godfray et al., 2018; Poore and Nemecek 2018). As emphasized in the previous section, beef is the most carbon-intensive, largely due to methane emissions from enteric fermentation. Pork production emits less GHG emissions compared to beef but more than chicken, mainly from manure management. Meat is a rich source of protein, which is an essential to appropriate body functioning. According to the Food Composition Tables (FAO), beef contains more protein compared to chicken and pork per equivalent amount.[14] However, beef is still associated with the highest GHG emissions compared to chicken and pork in terms of equivalent protein consumption. Figure 5 shows the emissions intensity of meat consumption per protein per

[14] Beef contains 185 grams of protein per 1 kg of beef, 123 grams for chicken, and 110 grams for pork.

capita for selected countries. In developed countries, the emissions intensity of protein consumption ranges between 20-40 kg of CO2 equivalent per kilogram of protein per capita.

5. CONCLUSION AND POLICY IMPLICATIONS

Given the importance of agriculture and food systems in an effort to mitigate climate change, numerous emissions estimates have been estimated with varying methods and techniques. The fragmentation of fast-growing emission estimates from various formulas and methods adopted by numerous institutions or organizations hinders coherent decision-making at the global level (Deconinck et al., 2023; Zurek et al., 2022). Due to data limitations, accurate and granular product-level carbon intensity metrics are inadequate (OECD, 2024). For accurate and complete understanding of the current state of carbon footprints at a granular level in agricultural production, our work provides country-by-commodity emissions intensities estimated from comprehensive data sources. It demonstrates that the cross-country variation is more pronounced than the cross-data source variation while both remain significant. Even minimal variations in emissions intensities can lead to massive differences in total GHG emissions and the social cost of carbon. Granular emissions intensity database for country-by-commodity pairs provide evidence to support three strategies – improving production-based emissions intensity, shifting to countries with lower carbon footprints, and shifting to commodities with lower carbon footprints – for reducing GHG emissions from agriculture and food systems. And trade plays a crucial role in implementing those strategies through a channel of the adoption of cleaner technologies, advanced intermediate inputs, and import diversification.

In a broad view of mitigating climate change, top-producing countries are important as they take a considerable share of the total production. All top-producing countries present stable estimates within a reasonable range in our database. However, we find wider gaps in the emissions intensities of developing countries across data sources. In Table 7, we estimate the standard deviation across products by economic status. Larger standard deviations in developing countries suggest that achieving consensus on country-specific development pairs is challenging. There are possibly numerous reasons why developing countries show a wider range of emissions compared to developed countries. Lack of resources to generate data for developing countries, which is needed for various models, varying model parameters given this lack of data for developing countries, and limited responses to national surveys or censuses can affect the accuracy of official estimates resulting in high variability of GHG emission estimates of developing countries.

Table 1. The overview of data sources in key aspects

		Aglink-Cosimo	Agri-footprint	CALUE	FAO	GCAM	GLOBIOM	GTAP	IFPRI
Crop	Maize	✓	✓	Cereals including wheat and rice	✓	✓	✓	Cereals	Cereals
	Wheat	✓	✓		✓	✓	✓	✓	✓
	Rice	✓	✓		✓	✓	✓	✓	✓
	Soybean	✓	✓	Oil seeds	-	✓	✓	Oil seeds	Oil seeds
Livestock	Beef	✓	✓	✓	✓	✓	✓	Ruminant	Ruminant
	Milk	✓	✓	Dairy	✓	-	✓	✓	✓
	Chicken	✓	✓	✓	✓	✓	✓	Non-ruminant	Non-ruminant
	Pork	✓	✓	✓	✓	✓	✓		
Data		Emissions Production	Emissions Intensity	Emissions Production	Emissions Production	Emissions Production	Emissions Intensity	Emissions	Emissions
Country		35	52	192	195	14	160	139	198
Year		1990-2040	2017	1961-2017	1961-2021	2010-2060 (quinquennial)	2000-2060 (decennial)	2004	2016-2018
GWP		AR4	EF 3.0	AR5+	AR5	AR5	AR4	AR2	AR2
Methodology		PEM	LCA	FM	FM	PEM	PEM	CGEM	FM
Emission source Data availability		✓	✓	✓	✓	-	-	-	✓
Availability		Confidential	Subscription	Public	Public	Public	Public	Confidential	Confidential

Note: GWP refers to the Global Warming Potential. The AR2 is the GWP from the IPCC the second Assessment Report; the AR4 from the IPCC the fourth Assessment Report; the AR5 from the IPCC the fifth Assessment Report; the AR5+ the GWP with the climate-carbon feedback from the IPCC the fifth Assessment Report; the EF 3.0 from the Environmental Footprint 3.0. LCA is a data source based on a life cycle analysis; FM indicates the formula-based data source; CGEM and PEM indicate the computational general equilibrium or partial equilibrium model-based data source. Confidential data is provided upon an individual request.

Table 2. Emissions intensities across data sources and countries, kg of CO2 eq. per kg of product

Product		N	Mean	Median	SD	Min	Max	Max-Min
Crop	Maize	62	0.21	0.20	0.15	0.03	1.07	1.04
	Wheat	93	0.24	0.21	0.19	0.06	1.57	1.51
	Soybean	24	0.19	0.10	0.18	0.06	0.82	0.76
	Rice	45	1.40	1.21	0.68	0.65	3.75	3.09
Livestock	Beef	60	21.85	19.04	10.35	8.35	53.16	44.81
	Chicken	53	0.65	0.38	0.73	0.13	3.81	3.68
	Pork	19	2.47	2.48	1.04	1.04	5.29	4.25
	Milk	64	1.00	0.85	0.61	0.10	3.89	3.79

Notes: The emissions intensities of cereals and oil seeds are used for those of maize and soybean in the GTAP and IFPRI. The emissions intensity of ruminant animals represents the emissions intensity of beef in the GTAP and IFPRI.

Table 3. ANOVA by data source and country

Product	Variable	DF	SS	MS	Share
Maize	Data source	6	0.34	0.06	0.60
	Country	8	0.33	0.04	0.40
Wheat	Data source	6	0.45	0.07	0.54
	Country	14	0.81	0.06	0.46
Soybean	Data source	7	0.27	0.04	0.50
	Country	2	0.07	0.04	0.50
Rice	Data source	6	4.86	0.81	0.37
	Country	7	9.50	1.36	0.63
Beef	Data source	6	1681.52	280.25	0.38
	Country	8	3709.76	463.72	0.62
Chicken	Data source	5	4.97	0.99	0.37
	Country	9	15.30	1.70	0.63
Pork	Data source	5	5.68	1.14	0.30
	Country	3	7.94	2.65	0.70
Milk	Data source	5	9.59	1.92	0.76
	Country	11	6.74	0.61	0.24

Note: DF is the degrees of freedom; SS the partial sum of squares; MS the mean squares; Share is the ratio of the MS by each variable in the total SS by variables.

Table 4. Emissions intensity by data source, kg of CO2 eq. per kg of product

Product	Data source	N	Mean	Median	SD	Min	Max
Maize	Aglink-Cosimo	9	0.19	0.20	0.05	0.12	0.26
	Agri-footprint	9	0.26	0.23	0.11	0.13	0.44
	FAOSTAT	9	0.08	0.06	0.04	0.05	0.15
	GCAM	8	0.17	0.21	0.08	0.03	0.24
	GLOBIOM	9	0.32	0.24	0.31	0.07	1.07
	GTAP	9	0.26	0.27	0.08	0.17	0.39
	IFPRI	9	0.20	0.17	0.07	0.12	0.34
Wheat	Aglink-Cosimo	13	0.21	0.24	0.05	0.12	0.28
	Agri-footprint	13	0.31	0.26	0.12	0.21	0.60
	FAOSTAT	15	0.11	0.08	0.07	0.07	0.30
	GCAM	7	0.33	0.25	0.27	0.07	0.90
	GLOBIOM	15	0.32	0.19	0.39	0.06	1.57
	GTAP	15	0.20	0.19	0.06	0.12	0.30
	IFPRI	15	0.25	0.27	0.08	0.14	0.42
Soybean	Aglink-Cosimo	3	0.08	0.08	0.02	0.07	0.11
	Agri-footprint	3	0.23	0.24	0.03	0.21	0.25
	CALUE	3	0.11	0.08	0.06	0.07	0.18
	FAOSTAT	3	0.07	0.06	0.01	0.06	0.08
	GCAM	3	0.35	0.18	0.41	0.07	0.82
	GLOBIOM	3	0.24	0.15	0.23	0.07	0.50
	GTAP	3	0.31	0.24	0.16	0.20	0.49
	IFPRI	3	0.08	0.08	0.01	0.08	0.09
Rice	Aglink-Cosimo	6	2.22	2.04	0.94	1.31	3.75
	Agri-footprint	5	1.13	1.01	0.32	0.85	1.67
	FAOSTAT	8	1.21	1.10	0.57	0.67	2.42
	GCAM	3	1.10	0.95	0.34	0.87	1.49
	GLOBIOM	8	1.38	1.20	0.66	0.91	2.97
	GTAP	7	1.55	1.39	0.70	0.99	3.03
	IFPRI	8	1.12	0.92	0.45	0.65	1.96
Beef	Aglink-Cosimo	8	25.36	22.94	10.99	14.26	43.97
	CALUE	9	15.60	16.52	5.47	8.35	24.95
	FAOSTAT	9	25.16	23.63	10.30	13.98	41.50
	GCAM	7	17.07	12.81	7.18	10.95	26.58
	GLOBIOM	9	22.37	23.34	7.74	11.46	34.42
Chicken	Aglink-Cosimo	10	0.74	0.44	0.70	0.17	2.23
	Agri-footprint	4	1.34	1.35	0.21	1.13	1.52
	CALUE	10	0.74	0.39	0.85	0.14	2.71
	FAOSTAT	10	0.79	0.35	1.14	0.13	3.81
	GCAM	9	0.29	0.33	0.12	0.15	0.43
	GLOBIOM	10	0.40	0.27	0.28	0.23	1.12
Pork	Aglink-Cosimo	2	1.76	1.76	0.99	1.06	2.46
	Agri-footprint	3	3.06	3.06	0.23	2.82	3.29
	CALUE	4	2.16	2.22	0.83	1.22	3.00
	FAOSTAT	4	1.81	1.86	0.68	1.04	2.48
	GCAM	2	3.33	3.33	0.04	3.30	3.35
	GLOBIOM	4	2.92	2.36	1.68	1.66	5.29
Milk	Aglink-Cosimo	9	0.66	0.53	0.22	0.46	1.09
	Agri-footprint	7	1.43	1.31	0.33	1.07	2.01
	FAOSTAT	12	0.85	0.76	0.31	0.53	1.41
	GLOBIOM	12	1.17	1.19	0.52	0.63	2.47
	GTAP	12	0.50	0.54	0.28	0.10	1.01
	IFPRI	12	1.49	1.19	0.90	0.70	3.89

Table 5. Emissions intensities for maize by emission source, kg of CO2 eq per kg of product

Product	Data source	Emission source	N	Mean	Median	SD	Min	Max
Maize	Aglink-Cosimo	Burning	9	0.02	0.02	0.01	0.01	0.03
		Crop residues	9	0.05	0.05	0.01	0.04	0.06
		Synthetic fertilizers	9	0.13	0.13	0.05	0.06	0.19
		Total	9	0.19	0.20	0.05	0.12	0.26
	Agri-footprint	Crop residues	9	0.04	0.04	0.00	0.04	0.04
		Energy use	9	0.06	0.06	0.04	0.01	0.12
		Lime	9	0.03	0.03	0.01	0.01	0.06
		Manure	9	0.01	0.01	0.01	0.00	0.04
		Synthetic fertilizers	9	0.12	0.12	0.06	0.04	0.22
		Total	9	0.26	0.23	0.11	0.13	0.44
	FAOSTAT	Burning	9	0.02	0.02	0.01	0.01	0.04
		Crop residues	9	0.04	0.04	0.00	0.04	0.05
		Synthetic fertilizers	2	0.07	0.07	0.04	0.04	0.09
		Total	9	0.08	0.06	0.04	0.05	0.15
	IFPRI	Burning	9	0.01	0.01	0.00	0.01	0.02
		Crop residues	9	0.05	0.05	0.01	0.05	0.07
		Pesticide	9	0.02	0.02	0.01	0.00	0.03
		Synthetic fertilizers	9	0.12	0.10	0.07	0.03	0.26
		Total	9	0.20	0.17	0.07	0.12	0.34

Notes: Burning refers to burning of crop residues; lime the application of agricultural lime for soil pH balancing; manure the application of organic fertilizers. Only 4 data sources are available at a disaggregated level.

Table 6. Variation in emissions intensity, GHG emissions, and CSCC

Product	Country	Production (MMT)	SCC (USD/MT)	EI (min)	EI (max)	Emi (max-min, MMT)	CSCC (max-min, MM)
Maize	Brazil	97.91	26.85	0.06	0.30	23.40	628.35
	China	259.10	188.61	0.15	0.34	48.19	9089.46
	United States	371.10	111.71	0.05	0.24	72.36	8083.91
Wheat	Australia	31.82	8.57	0.08	0.29	6.75	57.78
	Canada	30.38	9.94	0.08	0.27	5.77	57.35
	China	134.20	188.61	0.07	0.46	52.61	9921.94
	France	38.68	14.25	0.06	0.22	6.23	88.76
	India	98.51	173.61	0.08	0.71	62.16	10791.84
	Russia	86.00	19.21	0.08	0.30	19.01	365.17
	United States	47.38	111.71	0.20	0.90	33.21	3710.28
Soybean	Argentina	54.97	6.69	0.063	0.206	7.86	52.60
	Brazil	114.70	26.85	0.075	0.496	48.29	1296.65
	United States	120.10	111.71	0.063	0.818	90.68	10129.45
Rice	Bangladesh	54.15	14.71	0.654	1.125	25.50	375.08
	China	212.70	188.61	0.746	1.311	120.18	22665.94
	Indonesia	55.25	34.57	1.207	2.74	84.70	2927.70
	India	169.10	173.61	0.843	1.481	107.89	18730.49
	Myanmar	26.55	2.09	0.965	2.969	53.20	111.29
	Philippines	19.28	11.03	1.201	3.747	49.08	541.28
	Thailand	32.90	10.61	1.35	2.428	35.47	376.14
	Viet Nam	42.76	8.23	0.87	1.641	32.97	271.22
Beef	Argentina	2.84	6.69	21.02	37.314	46.35	310.12
	Australia	2.07	8.57	16.519	42.952	54.68	468.33
	Brazil	9.55	26.85	24.952	53.161	269.40	7233.82
	China	5.71	188.61	10.951	29.754	107.39	20255.42
	United States	11.94	111.71	8.348	16.976	103.05	11511.64
Chicken	Brazil	13.61	26.85	0.226	1.196	13.20	354.42
	China	13.28	188.61	0.173	1.522	17.91	3378.59
	Indonesia	3.18	34.57	0.346	3.814	11.01	380.69
	India	3.77	173.61	0.375	0.503	0.48	83.71
	Mexico	3.21	19.44	0.247	0.473	0.73	14.11
	Russia	4.54	19.21	0.176	0.57	1.79	34.38
	United States	19.14	111.71	0.176	1.127	18.20	2033.44
Pork	China	54.52	188.61	1.042	3.297	122.94	23186.97
	Germany	5.51	14.11	1.451	2.823	7.55	106.57
	Spain	4.30	8.15	2.268	3.289	4.39	35.76
	United States	11.61	111.71	2.457	5.289	32.88	3673.31
Milk	Brazil	34.31	26.85	0.542	3.888	114.81	3082.78
	China	30.39	188.61	0.158	1.474	39.99	7542.06
	Germany	32.60	14.11	0.568	1.306	24.06	339.43
	India	83.63	173.61	0.526	2.545	168.86	29315.80
	United States	97.76	111.71	0.169	2.012	180.17	20127.47

Note: EI, emissions intensity (kg of CO2 eq per kg of product), EMI, total GHG emissions (MMT), SCC, the social cost of carbon (dollar per ton of CO2). The production quantity is based on the year 2017 sourced from the FAOSTAT.

Table 7. The standard deviation across products by economic status

Product	Developed (SD)	Developing (SD)
Maize	0.07	0.16
Wheat	0.12	0.26
Soybean	0.25	0.14
Rice	-	0.68
Beef	6.94	9.99
Chicken	0.36	0.83
Pork	0.93	0.95
Milk	0.36	0.87

Note: The classification of economic status (developing or developed) follows the UNSD.

Figure 1. Rice emissions intensities of top-producing countries across data sources

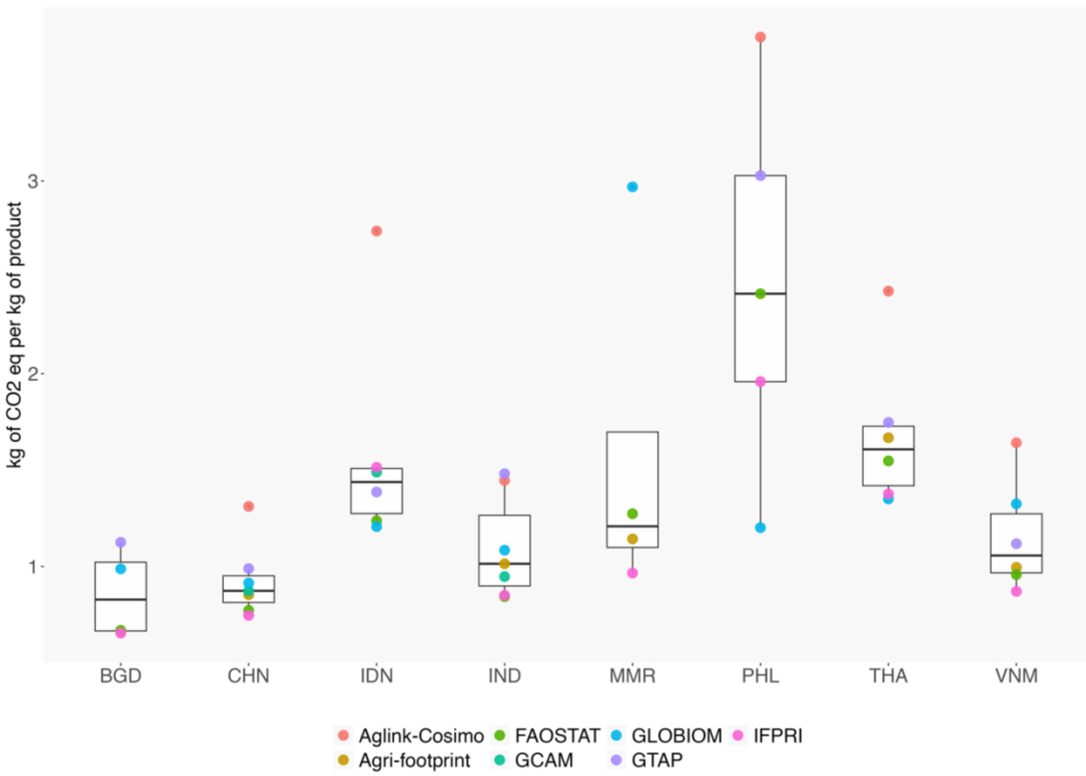


Figure 2. Beef emissions intensities for top-producing countries across data sources

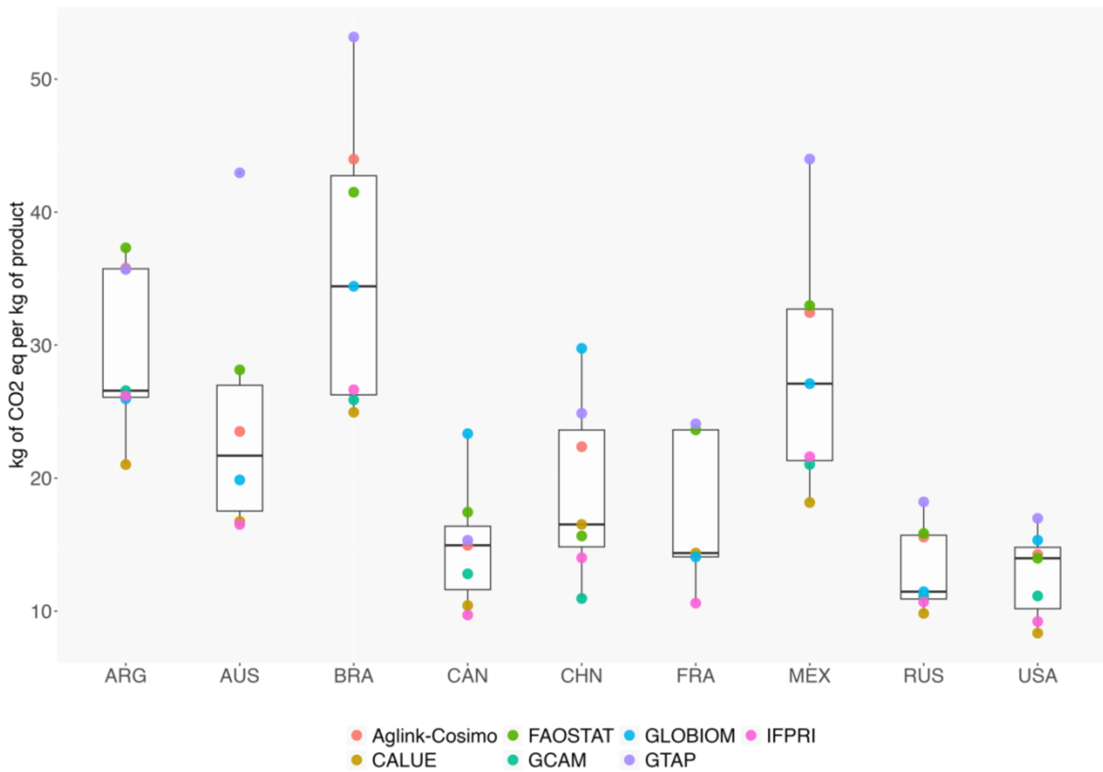
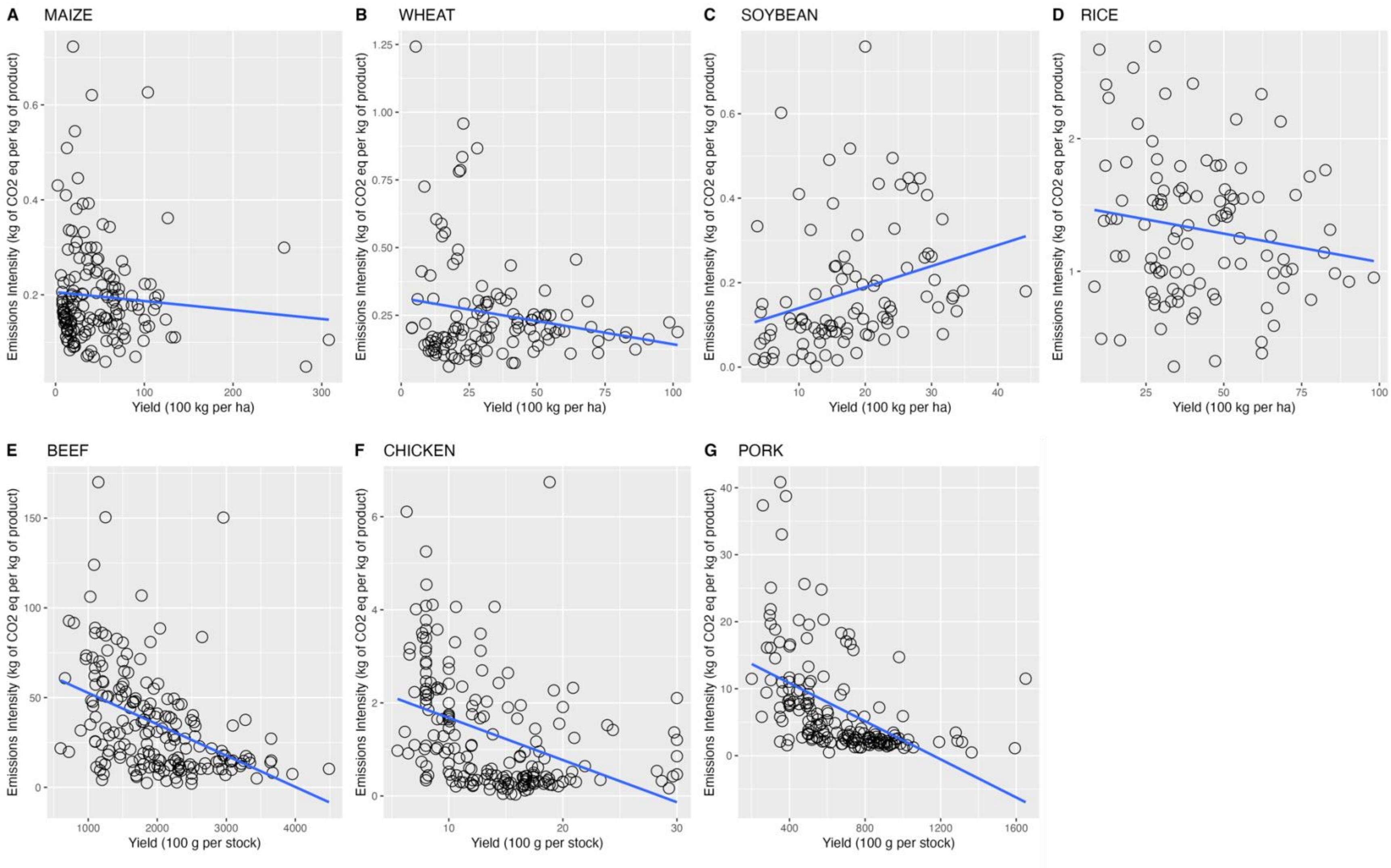


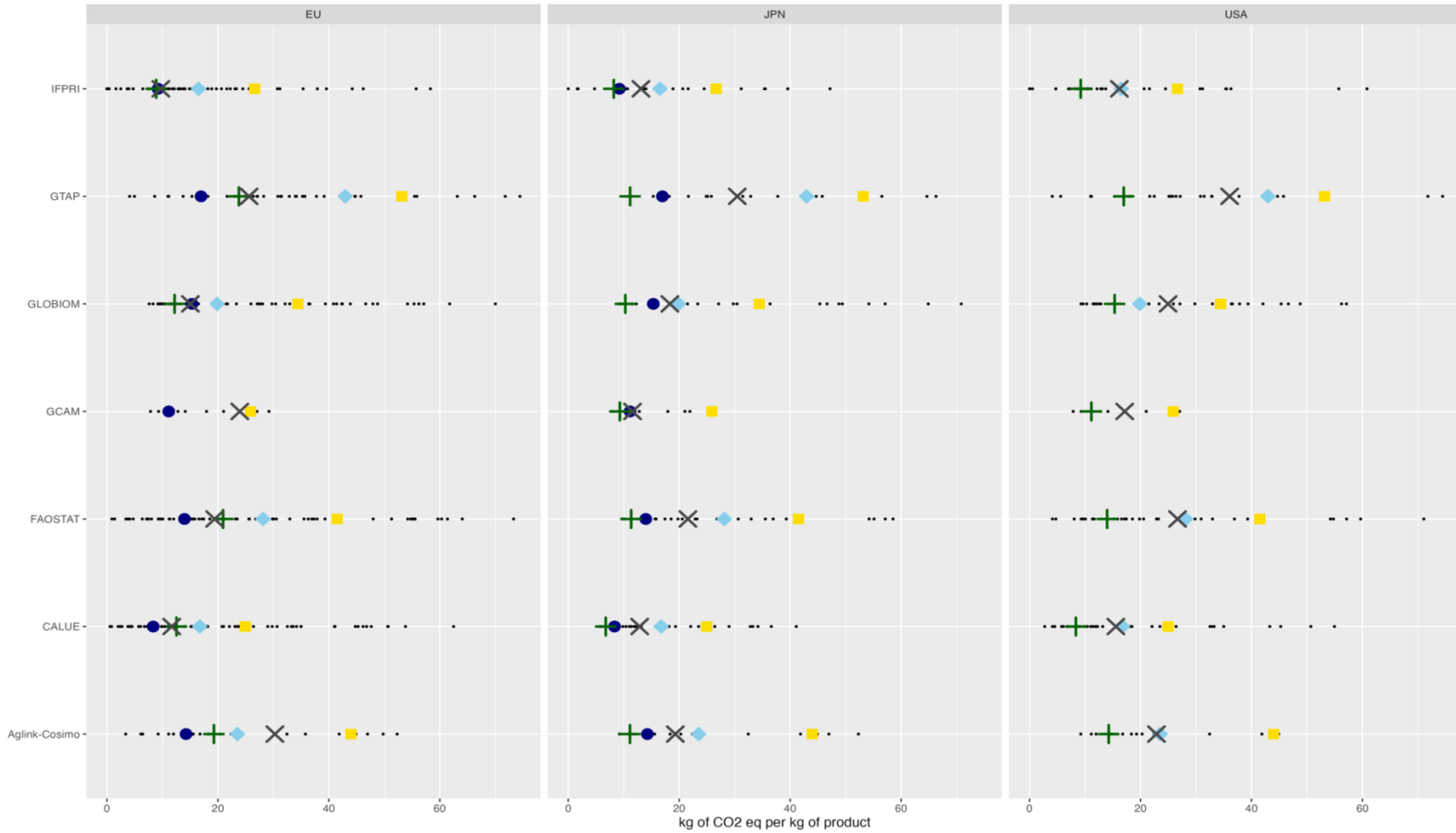
Figure 3. Emissions intensity and yield across commodities



Source: VT-USDA-ICF EI Database and FAOSTAT.

Note: Yield data is extracted from FAOSTAT and based on 2017 to match the reference year of the database. Some possible outlier values are excluded.

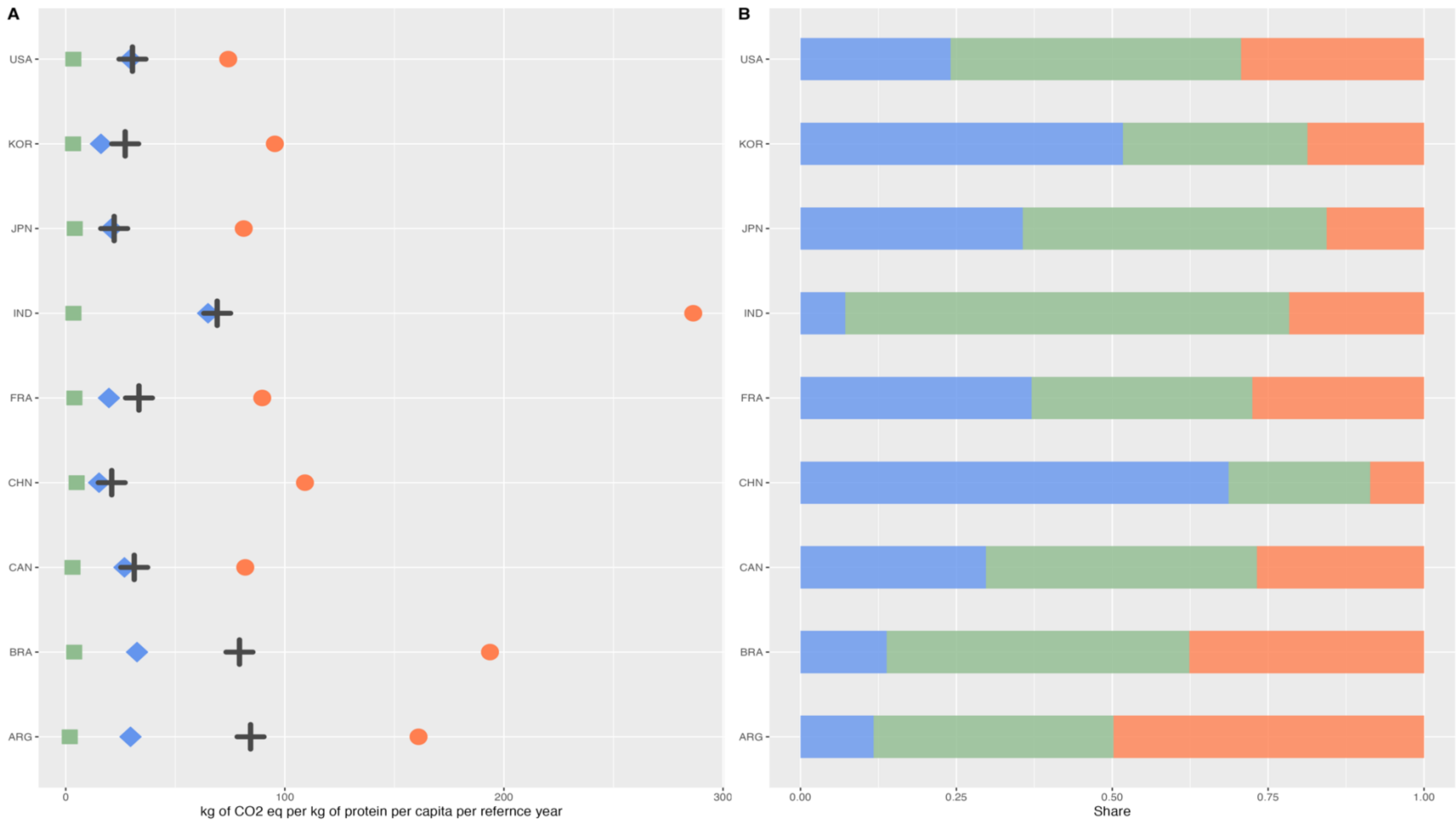
Figure 4. Emissions intensity embodied in beef consumption in major countries



Source: VT-USDA-ICF EI Database, FAOSTAT, and UN Comtrade.

Note: The green plus is the emissions intensity of an importing country, the gray cross is the emissions intensity embodied in consumption including domestic production and import, the navy circle is the US, the blue rhombus is Argentina, and the yellow square is Brazil. Other black small dots are other exporting countries to EU, Japan, and the US. The emission intensity embodied in beef consumption is the weighted average of the emission intensities of domestic production and exporting countries where the weights are the share of domestic supply (production – export) and exporting countries in total consumption.

Figure 5. Emissions intensity embodied in meat consumption per protein per capita



Source: VT-USDA-ICF EI Database, FAOSTAT, and UN Comtrade.
Note: The emissions intensity of chicken (green), pork (blue), beef (coral), and the emissions intensity embodied in three types of meat (plus) per 1 kg of protein per capita are plotted in (A). The consumption share of beef, chicken, and pork are presented in (B). The emissions intensity of beef, chicken, and pork is the average of emissions intensities for country-product pairs across data sources. Total consumption is the sum of domestic supply (production – export) and import. The protein content is based on the Food Composition Tables (FAO): 185 grams (beef), 123 grams (chicken), and 110 grams (pork). Production data is extracted from FAOSTAT using items (Maize (corn), Wheat, Rice, Soya beans, Meat of cattle, Meat of chickens, and Meat of pig) and population data also from FAOSTAT. Data from FAOSTAT is based on 2017 to match the reference year of the database.

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