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A Comparison of Environmental and Economic Sustainability across Seafood and Livestock Product Value Chains

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Abstract

This paper uses an environmentally extended input-output model of the Irish economy to estimate greenhouse gas (GHG) emissions and economic output multipliers in 2010 for two aquatic (aquaculture products and sea fisheries) and five land-based livestock products (beef and veal, sheep meat, pig meat, poultry meat, and dairy products). Moreover, the Global Value Chain (GVC) framework is adopted to qualitatively understand the structure of Irish food sectors and identify segments of the food value chains with the greatest emissions efficiency and economic potential. Aquaculture is found to have the highest output multiplier and a low to medium carbon footprint compared to pastoral livestock products (beef and veal, sheep meat, dairy). The direct and indirect economic benefits of the aquaculture sector along with the relatively low carbon footprint suggest that additional benefits from an expansion of Ireland's aquaculture sector can be gained. However, aquaculture is energy intensive, and therefore production requires the efficient use of energy and resources and the employment of low carbon technologies that strengthen aquaculture's sustainability.

Keywords: Aquaculture; Food value chains; GHG emissions; Environmentally-extended Input-Output model; Ireland.

1. **Introduction**

As the world's population grows, global food security is high on the development agenda. Based on the estimations of the United Nations, human population is expected to increase by more than 1 billion people over the 2017 to 2030 period, reaching approximately 8.6 billion in 2030 and 9.8 billion in 2050 (UN-DESA, 2017). Population growth, rising incomes, and urbanization are projected to lead to higher meat and milk consumption over the next 20 years (mainly in developing countries) (Herrero et al., 2016). However, agriculture, forestry, and associated land use changes are currently responsible for approximately 30% of global anthropogenic emissions (Tubiello et al., 2013). Consequently, substantial increases in food productivity which will be needed to meet the increasing demand for food will also require minimizing undesirable environmental outputs.

From local to global levels, seafood production plays a key role in food security and income generation (Cochrane et al., 2009). Global fish production (including crustaceans and molluscs) was about 171 million tonnes in 2016, with aquaculture accounting for 47% of total production. Aquaculture is the world's fastest-growing food sector providing 19.3 million jobs (FAO, 2018). Nevertheless, seafood consumption is 'obscured' by consumer concerns with overfishing and aquaculture production methods (e.g. use of captured fish as inputs in aquaculture feed manufacturing, disease transfer between farmed and wild animals) (Samuel-Fitwi et al., 2012).

Ireland has set ambitious economic growth targets for the agri-food sector up to 2025 and beyond, with sustainability being an important consideration in the national development strategies; Food Wise 2025 (DAFM, 2015a) and Harnessing our Ocean Wealth - An Integrated Marine Plan (Inter-Departmental Marine Coordination Group, 2012). Although Ireland has achieved a prominent position in global agri-food trade as one of the biggest net exporters of beef, sheep meat, and dairy products (O'Donoghue & Hennessy, 2015), seafood has the potential to contribute to exports and job creation by increasing aquaculture production by 78% until 2020 (DAFM, 2010). However, any expansion in the agri-food sectors must be carried out in accordance to environmental regulations and Ireland has made commitments to achieve a 30% reduction in emissions compared to 2005 levels by 2030 and carbon neutrality in the agriculture and land use sector by 2050 (EPA, 2019).

Addressing these challenges requires consideration of multiple economic and environmental effects and interactions between multiple components of the entire food value chain. Similar to other sectors, the production of agri-food products involves inputs use from various, often inter-linking, sub-sectors which may differ in terms of input-use intensity and overall emission footprints. Consequently, much of the environmental footprint of specific goods lies in the purchases and use of materials and services required for production within the complexity of the value chain that leads from producers through processors and marketers to the final consumers of the goods (O'Donoghue, Chyzheuskaya, et al., 2018). Thus, the quantification of emissions along the Irish food value chains is required to indicate possible environmental inefficiencies and optimise expansion in sectors with the greatest relative environmental and economic gains.

This study aims to assess the economic and environmental impact of aquatic (sea fisheries and aquaculture) and terrestrial livestock (beef and veal, sheep, pig, poultry, dairy) food value chains in Ireland. An environmentally-extended economic input-output model has been developed to analyse the structure of the economic activity and the associated carbon footprints.[1] The BIO model (Grealis & O'Donoghue, 2015) is a disaggregated agri-food input-output model and has been previously used by Grealis et al. (2017) to evaluate the economic impact of aquaculture on other sectors and on the Irish economy at a national level. However, Grealis et al. (2017) did not consider the potential environmental externalities of aquaculture and agriculture to other sectors and the wider economy. This work aims to fill this gap by incorporating environmental impacts into the BIO model that allows the estimation of sub-sectoral carbon footprints along and across emissions-intensive food value chains. Given the predominance of extensive pasture-based livestock production and the economic importance of livestock and seafood production in Ireland's agri-food sector, the analysis is focused only on animal sources of protein.

2. A Profile of Ireland's Agri-Food Industries

The agri-food and drink sector continues to play an important role in Ireland's economy. The agri-food and drink sector in 2016 accounted for 7% of Ireland's economy-wide gross value added (GVA) and for 9.8% of exports, whilst provided 8.5% of national employment (Teagasc, 2019). There are approximately 137,500 farms and 700 food and drinks companies exporting food and seafood to more than 160 countries, with the UK being Ireland's largest export destination (38% of total exports) (Teagasc, 2019). Beef, dairy products, and beverages were the top three export categories in 2017, valued more than €8 billion of total worldwide exports. More specifically, the value of beef and dairy exports was €2.5 and €4.6 billion respectively. Irish seafood exports reached €666 million in 2017 (DAFM, 2018).

Irish agriculture is characterized by extensive grass-based livestock systems. Beef and dairy sectors represent the most important components of Ireland's agriculture with over 80,000 farms engaged in specialist cattle production and about 18,000 farms specialized in dairy production (O'Donoghue & Hennessy, 2015). Despite the importance of beef farming in terms of export earnings and rural employment, the beef sector is characterized by low profitability, high dependence on the European Union's direct support payments and asymmetries of power within the beef supply chain (Hooks et al., 2018). On the other hand, dairy farming is the most competitive and profitable farming activity in Ireland with an average farm income of €51,809 and the vast majority of dairy processing undertaken by farmer-owned co-operatives (Hooks et al., 2018; Hyland et al., 2018). Growth in the national dairy herd, due to the recent removal of EU milk quota, resulted in increased milk production, a higher number of dairy calves and an 8% increase in emissions from 2012 to 2016 (Lanigan et al., 2018).

Ireland's seafood industry is a significant source of marine employment occupying 9,048 employees (in fisheries, aquaculture, and seafood processing) in 2018 and directly contributing €434 million to Ireland's gross domestic product (GDP) (BIM, 2019). The Irish seafood industry is complex and fragmented, involving the commercial wild catching sector, the aquaculture sector, seafood processing, seafood retail, and the food services sectors. In 2018, there were an estimated 2,127 registered fishing vessels, 288 aquaculture production units, and 158 seafood processing companies (BIM, 2019) (see also Fig. 1). The value of exports in 2018 was €653 million whilst imports were valued at €330. The catching sector (sea fisheries) consists of shellfish (lobster,

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[1] Here, the term value chain refers to the entire range of activities that firms undertake to bring a product or service from its conception to final consumers.

Dublin Bay prawns, mussels, scallops, razor clams) pelagic (herring, mackerel, horse mackerel and blue whiting) and demersal fish (cod, hake, haddock and flatfish), while aquaculture largely concerns finfish (Atlantic salmon and sea trout) and shellfish (rope mussels, clams, bottom mussels, and gigas oysters) (Tsakiridis et al., 2019). The main export seafood products included organic salmon, seaweed, scrimp, and whiting with France being the most important export market (BIM, 2018).

Aquaculture takes place mainly in coastal areas but can also occur inland using freshwater (DAFM, 2015b). The majority of aquaculture sites are located in bays along the west coast of Ireland, with about 70 sites operating in inland freshwater areas (Grealis et al., 2017). Aquaculture production was valued (turnover) at €163 million in 2016 (Independent Aquaculture Licencing Review Group, 2017) and €176 million in 2018 (Tsakiridis et al., 2019). While government policy on aquaculture proposes that production could increase to 81,700 tonnes by 2023, concerns have been raised by industry stakeholders regarding the complexity and effectiveness of the licensing process in relation to EU's Natura 2000 requirements (Independent Aquaculture Licencing Review Group, 2017; Renwick, 2018). Based on recommendations of the Independent Review of Aquaculture Licencing, the Irish Minister of the Department of Agriculture, Food and the Marine (DAFM) made 109 licence determinations in 2017. This increased to 305 in 2018. Moreover, concerns amongst the public on the environmental impacts of farmed salmon have been growing (Tsakiridis et al., 2019).

Sheep enterprises have demonstrated low market profitability (on average) over recent years, and increasing dependence on government direct support payments (Bohan et al., 2016; Kilcline, 2018). Contrary to the beef and sheep sectors, the pig meat sector is more concentrated, with approximately 320 commercial pig producers producing approximately 3.5 million pigs annually. Elsewhere, over 800 farms are involved in commercial poultry meat and egg production, breeding, and hatching, with the broader poultry industry supporting approximately 6,000 jobs, mainly in north-east rural areas (DAFM, 2016, 2018).

According to the 10-year national development strategy for the agri-food sector, Food Wise 2025 (DAFM, 2015a), an 85% increase in Irish exports valued at €19 billion, a 65% increase in the value of primary production valued at €10 million, and creation of 23,000 new jobs along the value chain from primary level to high end value-added segments, are projected in the period to 2025 (DAFM, 2017). At the same time, climate change poses challenges to agriculture which require actions and effective policies throughout the agri-food value chains. According to the EU's Effort Sharing Regulation, Ireland aims to reduce emissions by 30% compared to 2005 levels by 2030, and achieve full carbon neutrality in agriculture by 2050. Under the full carbon-neutral scenario, Ireland's GHG emissions from agriculture are fully offset by the carbon sequestration of grassland soils, forestry and other land use (Schulte et al., 2013). Agriculture's (including emissions from on-farm fuel combustion and fishing) estimated GHG emissions were 19.25 Mt CO_2e (CO_2 equivalents) with methane (CH_4) comprising 64% of emissions and nitrous oxide (N_2O) from fertilizer, manure and animal excreta, and emissions from liming and urea application constituting the remaining emissions. Approximately, 80% of CH_4 emissions are related to bovine and ovine enteric fermentation and 20% to manure management (Lanigan et al., 2018).

3. Sustainability Assessment Tools in Food Value Chains

The concept of sustainability is multidimensional. Sustainability refers to environmental sustainability when the focus is on the environmental impact of human activities, but it can also be used to mean economic or social sustainability when the focus is on assessing economic or social impacts of human activities respectively. Many environmental sustainability indicators (e.g. carbon footprint, water footprint) and tools have emerged to evaluate sustainability at a firm or higher level, with the most widely-used environmental impact assessment methods covering various impact categories, such as global warming, acidification, eutrophication, abiotic and biotic resource depletion. A number of impact assessment tools and frameworks have been developed to facilitate the incorporation of the environmental aspects of production processes into decision making. These include the process-based life cycle assessment (P-LCA), the economic input-output life cycle assessment (EIO-LCA) based on environmentally extended input-output models (Chen et al., 2018; O'Donoghue, Chyzheuskaya, et al., 2018; Wilting, 2012), the hybrid life-cycle assessment, the ecological footprint analysis, the methodology of the Intergovernmental Panel on Climate Change (IPCC, 1997, 2000, 2003, 2006) and others (Finnveden & Moberg, 2005).

In the past two decades, a popular method to analyse the potential environmental impact of various products (including seafood and livestock products) is the life cycle assessment (LCA) method. LCA is an ISO (International Organization for Standardization)-standardized holistic tool that conducts a systematic and detailed account of all resources and inputs used, and associated emissions, from raw material extraction and production to end-of-life disposal and waste management (Avadí & Fréon, 2015)[2]. The method of P-LCA involves the quantification of input and output flows of every production stage through the phase of life cycle inventory analysis. Consequently, it is often difficult to carry out a P-LCA due to insufficient information and complex interdependencies in inputs that have to be modelled. Thus, the boundaries of the production system should be cautiously selected to avoid truncation errors due to the exclusion of underlying production processes.

Downstream and horizontal truncation errors can be minimized by combining process data with economic input-output data. The EIO-LCA approach is a cost- and time-saving technique to attribute pollution and resource use to final demand in a consistent framework. EIO-LCA models use publicly available input-output data to describe economic interactions between sectors, allocate environmental loads across industries, and capture trade in services and secondary processed products (e.g. animal feedstuffs) (Kitzes, 2013). In the EIO-LCA approach, the whole economy is considered as the boundary of the system with economy-wide interdependencies being modelled as a set of simultaneous linear equations (Joshi, 1999).

Nevertheless, the EIO-LCA approach also has its drawbacks. EIO-LCA models apply the carbon emission intensity coefficients to the final demand with the aid of the Leontief inverse matrix under the assumption that each sector in the economy produces a single homogenous sectoral product. It is rare though for a commodity sector to produce a single homogenous good in terms of quality characteristics and environmental impact. Consequently, EIO-LCA is appropriate for the comparison of aggregate products but not for comparing heterogeneous products within a commodity sector (Joshi, 1999). Aggregation errors inherent to input-output modelling can be

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[2] As society is increasingly interested in the inclusion of economic and social aspects in the sustainability assessment of human activities; economic and social counterparts of LCA, namely, the life cycle costing and the social life cycle assessment respectively, also have been developed (cf. e.g. Jørgensen et al., 2007; Moreau & Weidema, 2015).

minimized by using system process methods supported by an emission intensity database derived from systems input-output models (Chen et al., 2017; Wu et al., 2019). Within the framework of system process analysis, emission intensities are applicable to the sectoral output products regardless of the use of products (either for intermediate production or final consumption).

Input-output analyses of closed economies (single-country or single-region models) are based on the assumption that imported inputs and final products and services have been produced with the same technology as the domestic technology in the same sector. In reality, production efficiency, technology and consequently emission intensities differ across countries, whilst embodied energy use and pollution emissions may be transferred along the international supply chain in the same way that production factors continue far upstream in the domestic supply chain (Wiedmann, 2009; Wu & Chen, 2017). Multi-region input-output (MRIO) models and variants of MRIO models (e.g. systems input-output models) have been developed to internalize trade flows within intermediate demand (e.g. Chen et al., 2019; Chen & Wu, 2017; Guillen et al., 2019). However, such models require detailed international trade data that is often difficult to obtain (Wiedmann et al., 2007).

To comply with GHG emissions reporting requirements of the United Nations Framework Convention on Climate Change (UNFCCC), the Intergovernmental Panel on Climate Change (IPCC) suggested guidelines for GHG emissions accounting (Crosson et al., 2011). The approach of IPCC is often used to calculate emissions under policy change scenarios. However, the IPCC emissions accounting only estimates total emissions generated within national boundaries as it does not account for emissions embodied in international trade and transportation. Therefore, it is inconclusive with regard to the process of carbon leakage.[3] In what follows, the EIO-LCA framework is adopted to analyse the economic and environmental sustainability of the seafood and livestock value chains in Ireland.

4. Theoretical Framework

Theory of Global Value Chains

Sequential production characterises modern manufacturing processes since the first decades of the 20th century. Advances in production methods, information technology and market liberalization have diminished production boundaries with some firms only retaining a subset of their production stages in their domestic economies (Alfaro et al., 2015). Higher volumes of intermediate products and services are being produced by various actors in different countries and then exported abroad for further transformation processes or provision of final goods and services. The entire range of production processes and services that firms and workers perform to bring a product from its conception to final consumption describes a value chain (Gereffi & Fernandez-Stark, 2016). When more than one country is involved in the value chain e.g. through international trade, one refers to a global value chain (GVC) (Heery et al., 2016; Banga, 2013).

Introduced in the early 2000s, the concept of GVC has been useful for capturing several features of the world economy, such as the internationalization and geographical fragmentation of supply

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[3] As not all regions (or countries) in the world would abate their national anthropogenic GHG emissions to the same degree, the carbon leakage rate in a non-abating region is defined as the change in its emissions as a fraction of the reduced emissions by the abating regions in the globe. Then, the sum of the regional leakage rates makes up the global leakage rate (Babiker, 2005).

chains, the creation of value within supply chains, the role of actors and inter-firm networks, and the specialization of countries in tasks and business functions rather than in specific goods (de Backer & Miroudot, 2014). According to Gereffi and Fernandez-Stark (2016) there are three global dimensions that the GVC framework explores; (1) the input-output structure of a GVC, which includes all supply segments (inputs, components, final products, distribution/sales) and value-adding activities (research, design, support services); (2) the geography of the industry and GVC activities; and (3) the governance structure which explains how firms control and coordinate the value chain. This analysis focuses on the first global dimension of the GVC framework. The input-output structure of a GVC is useful to qualitatively understand the structure of the Irish food sector, and identify the segments of the value chain which can add value and achieve the greatest emissions efficiency from cradle-to-farm gate and through to final demand of food products. Following a similar approach, Heery et al. (2016), O'Donoghue, Clavin, Ryan, Leavy, & Heery (2018) and Kilcline (2018) mapped and analysed the Irish dairy and beef, organic beef, and sheep value chains respectively.

Environmentally-extended Input-Output modelling

Input-output models are linear inter-sectoral models describing the relative relationship between the flow of inputs and resultant distribution and destination of an industry's product throughout the economy (Grealis et al., 2017). Under the assumption of linear technology, total output (goods and services), ***x***, is produced either for final consumption (including inventories but excluding exports), ***y*** or for use in further production segments, ***Ax***, along the supply chain. That is,

$$\begin{aligned} x_1 &= a_{11}x_1 + a_{12}x_2 + \ldots + a_{1n}x_n + y_1 \\ x_2 &= a_{21}x_1 + a_{22}x_2 + \ldots + a_{2n}x_n + y_2 \\ \ldots & \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \\ x_n &= a_{n1}x_1 + a_{n2}x_2 + \ldots + a_{nn}x_n + y_n \end{aligned} \tag{1}$$

The input-output system (eq. 1) can be written in stacked form

$$x = Ax + y \Leftrightarrow x = (I - A)^{-1}y \tag{2}$$

which can be expanded to infinite series of inter-sectoral transactions

$$x = (I + A + A^2 + A^3 + \ldots)\, y \tag{3}$$

$$x = y + \textstyle\sum_{i=1}^{\infty} A^i y \tag{4}$$

In equation 2, ***x*** is a column vector representing output from each sector of the economy, matrix ***I*** is the identity matrix of *N* dimension, corresponding to *N* sectors in the economy; column vector ***y*** is the part of output sold to final demand (exogenous final demand), while ***A*** is the matrix of input-output coefficients (also known as technical or unit-output coefficients matrix) indicating how many units of inputs from sectors *i-j* are required to produce one more unit of output for sectors *i-j* (economy's direct requirements matrix). Input-output coefficients are defined as

$$\alpha_{ij} = \frac{z_{ij}}{x_j} \tag{5}$$

where z_{ij} represents intermediate demand for inputs between sector i and the supply sector j, and x_j is the total output of sector j. The matrix $\boldsymbol{(I\text{-}A)^{-1}}$ is called the matrix of multipliers or Leontief inverse matrix. Equation 4 shows that a sector's output can be broken down in output required to meet final demand and output used by other sectors (intermediate demand). The Leontief inverse matrix allows the estimation of individual sectoral output multipliers capturing the direct and indirect economic effects of exogenous shifts in final demand.

The input-output model can be extended to account for environmental emissions associated with production activities by multiplying the economic output of a sector at each stage (vector $\boldsymbol{x}$ in eq. 2) by the diagonal matrix of sectorial environmental burden coefficients (e.g. GHG emissions per monetary or physical unit of output) $\boldsymbol{B}$

$$e_k = B_k(I - A)^{-1}y \tag{6}$$

In equation 6, $\boldsymbol{e}$ is the total (direct and indirect) environmental impacts vector per unit of final demand. The subscript k denotes the type of environmental impact, while matrix $\boldsymbol{B_k}$ has diagonal elements representing the environmental impacts of interest per unit of output for each process (Hendrickson et al., 1998). The elements of matrix $\boldsymbol{B_k(I\text{-}A)^{-1}}$ are the emission multipliers that measure the amount of type i emissions caused by exogenous and unitary inflows to the final demand for goods and services in sector j (Cristóbal, 2010). A variety of environmental burdens related to inputs (e.g. fertilizers, fuel, electricity) and outputs (e.g. GHG emissions, ozone-depleting substances) can be quantified and analysed.

5. Empirical Model

Economic and environmental input-output (desirable and undesirables) data for the entire food value chain are often used to conduct a value chain analysis and evaluate the environmental performance (carbon footprint) of different food value chains. Due to the national scale of the study and available data, an environmentally extended disaggregated input-output modelling approach (EIO-LCA) is considered the most appropriate. In this analysis, carbon footprint accounts for domestic carbon emissions, emissions embedded in imports, and emissions related to international transportation of products by national carriers.

The BIO model is an input-output model, described in detail by Grealis & O'Donoghue (2015) which aims to analyse the relative multitude of linkages between seafood and land-based food sectors and the wider Irish economy. It is based on national Supply, Use and Input-Output Tables and enables the assessment of impact of national sectoral strategies on the entire value chain in terms of turnover (gross output), GVA and employment (Kilcline, 2018). The BIO model builds upon earlier input-output models, developed by O'Toole & Matthews (2002a, 2002b) and Morrissey & O'Donoghue (2013), and disaggregates the national 58-sector 2010 Irish Input-Output table into 138 sectors, including the primary seafood (sea fisheries and aquaculture) and seafood processing sectors.

The BIO model is systematised to allow the value chains to be expanded for further use in LCAs with added information on GHG emissions. Although there are several environmental impact categories, the carbon footprint (global warming potential) has been adopted in this study as a metric to quantify the effect of the major GHG emissions on climate (air pollution) to render the emission sources in different food value chains more comparable. The 138 x 138 sector by sector requirement coefficients matrix of the Irish economy for the year 2010 is augmented with estimates of the various environmental burdens of each sector. The system boundary which determines which unit processes will be included in the analysis is the entire Irish economy, accounting for GHG emissions generated by imports. Due to the lack of detailed international trade data, it is assumed that imported production inputs and final goods are produced with technologies identical to domestic technologies implying that the same emissions intensities are embedded in import sectors as in Irish industries. Thus, the domestic emissions vector is also applied to the imports data (O'Donoghue, Chyzheuskaya, et al., 2018).

The major processes contributing to GHG emissions in meat production include emissions from animal feed production, production of various agricultural inputs (e.g. fertilizers, pesticides), enteric fermentation by ruminants, manure management, and energy use. This study accounts for emissions from livestock, production of animal feed crops, energy use, transportation, and imports. Livestock emissions are calculated based on the methodology outlined in the Irish National Inventory Report (Duffy et al., 2017) and described in the IPCC guidelines for national greenhouse gas inventories (IPCC, 2006). Emission factors and livestock numbers, as reported in Duffy et al. (2017) and Ireland's Central Statistics Office (CSO) livestock survey, are applied to the outputs from the input-output tables to calculate aggregate sectoral livestock emissions per million euro (€m) of output.

Enteric fermentation and manure management are the main sources of CH_4 emissions in cattle production systems. Total and per unit of livestock CH_4 emission factors are derived according to the 2006 IPCC guidelines (Tier 1 and Tier 2 approaches based on types of livestock) by combining the emission factors for enteric fermentation and manure management. Subsequently, the derived livestock emission factors are expressed in kilo tonnes per €m of output (kt CH_4 / €m) according to sectoral output from the input-output table and livestock population statistics from the Common Reporting Format (CRF) tables of the Irish National Inventory Report (NIR).[4] As with CH_4 emissions, the direct and indirect N_2O emissions from manure management and fertilizer application in cattle, sheep, pigs and poultry sectors, are calculated (Hendrickson et al., 2006). Once the CH_4 and N_2O emissions output from each livestock sector are calculated, emissions are allocated to each segment of the value chain (product stage) according to where they occur.

A feed crop production sub-model was also developed to calculate emissions associated with growing a wide range of animal feed crops, such as concentrates (wheat, barley and oats), winter forages, silage, hay, grazing grass, and root crops. The availability of nationally representative farm-level input costs, sales, and production data (Teagasc National Farm Survey), enables the calculation of GHG emissions per produced crop. Direct and indirect emissions associated with each feed crop are summed and average total emissions factors per unit value of crop are calculated.

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[4] See BIO Annex in O'Donoghue, Chyzheuskaya, et al. (2018) for further details of the emission calculation methodology and data requirements.

In the case of aquaculture, land-based emissions from feed crop production are calculated according to the share of plant ingredients in aquafeeds. Salmon is an important seafood product in terms of volume and value for the Irish seafood economy and is therefore selected as the reference input to disaggregate land-related emissions for the aquaculture sector. Information on shares of marine- and plant-origin inputs used in salmon feeds are taken from Ellingsen & Aanondsen (2006). The figures used are similar to those from Marine Harvest Ireland as reported in Wang et al. (2018).

As regards emissions associated with the direct and indirect fuel energy content of products, energy balance and cost data from the Sustainable Energy Authority of Ireland (SEAI) (SEAI, 2016) are used to map energy flows across the aquatic and terrestrial food value chains. Following Beutel (1983), energy sectors (mining, quarrying and extraction, electricity and gas supply) producing primary energy (e.g. coal, lignite, crude oil) or transforming primary energy into secondary energy (e.g. petroleum products, electricity) are disaggregated and subsequently the calorific content of fuel energy flows is calculated on a terra joule basis. The carbon emissions throughout the entire value chain are then calculated by interacting the calculated calorific content of fuel energy flows with energy emission factors for the range of energy sources as published by SEAI.

The distance-based method is adopted to estimate emissions from transportation[5]. According to the distance-based method, distance is multiplied by the mass or volume of goods transported and the associated modal GHG emission factors (GHG Protocol, 2013).

$$CO_2e = \sum_m^M (D \times M \times EF_m) \tag{7}$$

where D is the distance travelled by m's mode of transport, M is the weight (mass) of goods, and EF is m's mode-specific emissions factor obtained from (O'Donoghue, Chyzheuskaya, et al., 2018). The estimated value of total emissions (CO_2e) from equation 7 is divided by the total value of imported goods (€m) to derive a weighted-average emissions factor per import value, which is further used to calculate transport emissions from imported inputs.

In the present study, the environmental impact coefficients e_k (eq. 6) are calculated in CO_2e per €m of output. In order to enable the comparison of estimated emissions of different food products on a non-monetary basis, emissions are also calculated on a per protein and per food energy basis: t CO_2e per tonne of protein and t CO_2e per kilocalorie (kcal) of food energy. Initially, volumes of traded beef and veal, sheep meat, and pig meat, expressed in carcass weight equivalent (CSO, 2011) were converted to edible meat yield adjusted for 'bone loss' according to FAO's meat processing technology guidelines (Heinz & Hautzinger, 2007) and Orr et al. (1984).[6] The protein content values of beef and veal, pig meat and poultry meat are taken from De Vries and De Boer (2010) and applied to edible meat quantities. Energy content values of edible boneless carcass of beef and veal, sheep meat and pig meat from FAO's meat procession technology guidelines (Heinz

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[5] Emissions from mobile sources could also be calculated by applying the fuel-based method or the spend-based method. The fuel-based method is more accurate method than the distance-based and the spend-based method but it requires data on fuel use from transport providers which are not easily accessible. However, the distance-based method was chosen to estimate emissions from transportation due to unavailable fuel use data from transport providers.

[6] While the nutritional value of meat cuts derived from carcass may vary, a single weighted meat nutritional value is assigned to represent all types of beef and veal and avoid complexity in the analysis. The same procedure is also applied for sheep meat, pig meat and poultry meat.

& Hautzinger, 2007) are used to express emissions on a per kcal energy basis. The energy value of poultry meat is based on macronutrient values reported for '*raw meat and skin from whole chicken*' using McCance and Widdowson's Composition of Foods Integrated Dataset (cf. Roe et al., 2015).

A similar methodology is employed to express emissions for aquaculture and sea fisheries products on a per protein and food energy basis. The protein and food energy content values of capture and aquaculture fish products are derived by using the macronutrient values of individual fish species from McCance and Widdowson's Composition of Foods Integrated Dataset (Roe et al., 2015) and applied further to the edible fraction of landed fish (including shellfish) and domestic aquaculture production.[7] To account for variation in macronutrient values across species, a single weighted 'representative fish product' was derived and used to ultimately calculate weight protein (grams of protein per 100 gram of edible fish species) and energy (kcal per 100 gram of edible fish species) conversion factors for various species such as mackerel, whiting, hake, lobster and other species.

Dairy products include cheese, butter, cream, milk powder, drinking milk and buttermilk. The classification of dairy products in this study is based on that applied by the Irish Central Statistics Office (CSO, 2010) and is used to derive macronutrient values for dairy products. Fixed protein percentages per tonne of dairy products are applied as previously have been used in the CAPRI model (Heckelei & Britz, 2001). Again, the food energy content values for dairy products from McCance and Widdowson's Composition of Foods Integrated Dataset (Roe et al., 2015) were combined to create a weighted 'dairy' product in terms of energy and protein values.

Sensitivity and Uncertainty Analyses

The EIO-LCA is a robust method for life cycle analysis. However, there are various sources that contribute to uncertainty in EIO-LCAs. The sources of uncertainty are often related to inconsistencies in raw data collection, and errors due to the aggregation of industry sectors and environmental vectors. These sources introduce uncertainties into the components of the EIO-LCA model, namely the input-output coefficients of matrix $\boldsymbol{A}$, the vector of final consumption $\boldsymbol{y}$, environmental burden coefficients $\boldsymbol{e}$, and consequently the estimated carbon footprints (Wilting, 2012). Although, uncertainty analysis is not yet extensively incorporated in input-output based analyses, the inclusion of uncertainty and sensitivity analyses provides insights into the uncertain aspects of the model, assesses the sensitivity of the results obtained, quantifies the confidence in the predicted carbon footprints, and help users, such as, policy makers to make more robust decisions.

Uncertainty analysis can be performed on input-output based models by making changes (introducing errors) to elements of the direct requirement matrix $\boldsymbol{A}$. These changes are propagated in the Leontief inverse matrix, $\boldsymbol{(I\text{-}A)^{-1}}$ and eventually affect the carbon footprint and other impact values. Thereafter, stochastic simulation techniques (e.g. Monte Carlo simulations) can be used to

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[7] Data on fish landings by species for Irish vessels for 2010 is provided by the Sea Fisheries Protection Authority, whilst BIM (Bord Iascaigh Mara) provided data regarding value and volumes (in tonnes) of domestic aquaculture production broken down by species for 2010. It is assumed that the composition of internationally traded and domestically consumed sea fisheries and aquaculture products is the same as the species composition of domestic sea fisheries and aquaculture products.

investigate the effect of sensitivity and uncertainties in the elements of matrix ***A*** on model outcomes (Bullard & Sebald, 1988; Kumar et al., 2016; Wilting, 2012). In LCA studies, uncertainty in the data can be investigated using stochastic simulation, analytical modelling, fuzzy analysis, range and resampling methods (Chen et al., 2018).

A sensitivity analysis was carried out to assess the contribution of individual model components to estimated carbon footprints by changing single components. As per Rotz et al. (2015, 2020), a sensitivity index was constructed as the ratio of the percent change in the assessed output (carbon footprint) over a 10% increase in one tested component (emission factor) at a time. It is assumed that components do not interact, therefore sensitivity indices are not correlated. A sensitivity index near zero suggests that there is little change in the predicted output with changes in the tested factor. Index values near or greater to unity indicate a high sensitivity of output with respect to the tested component, where a 10% change in the tested component leads to a 10% or greater change in the predicted difference in the output. The tested components were selected on the basis of their importance to the carbon footprints of livestock and seafood production. Empirical studies have shown that enteric methane and methane emitted from manure management practices are major components of the carbon footprint of livestock production, whilst fuel energy use is a key driver for the carbon footprints of aquaculture and sea fisheries value chains (Nijdam et al., 2012). Thus, the sensitivity analysis is focused on enteric CH_4 emissions from livestock enteric fermentation and manure handling, and CO_2 emissions related to liquid fuel (gasoil and diesel) use in seafood and livestock value chains.

In general terms, emissions are estimated by applying an emission factor to related activity data (Ramírez et al., 2008). Assuming that the largest component of uncertainty in carbon footprint estimates of this study lies in three key emission sources in livestock and seafood production (i.e. enteric CH_4, CH_4 emitted from manure management, and CO_2 emissions related to gasoil and diesel use), uncertainty in carbon footprints of food value chains was represented by using the uncertainty ranges of emission factors as reported in the most recent National Inventory Report (NIR) (Duffy, 2019). The uncertainties assigned for estimated carbon footprints of beef and veal and dairy value chains were ±15% for enteric CH_4 and manure management CH_4, whereas a range of ±30% uncertainty was assigned for the footprints of sheep and pig meat value chains. For the carbon footprint of poultry value chain, ±30% uncertainty range was used for manure management CH_4. The uncertainties of carbon footprints associated with emissions from fuel (gasoil and diesel) combustion were assigned a value of ±5% for all food value chains. The impacts of enteric CH_4 in the uncertainty analysis of the estimated carbon footprints of poultry meat, aquaculture and sea fisheries value chains were not considered due to zero enteric CH_4 emissions in these value chains. In the same vein, the impact of uncertainty in CH_4 emissions from manure management on the carbon footprint of aquaculture and sea fisheries was not examined.

For statistical inference, stochastic simulations were undertaken for each carbon footprint to generate hypothetical samples of carbon footprints, and assess independently the contribution of the uncertainty in emissions of each factor (enteric CH_4, CH_4 emitted from manure management, and CO_2 emissions related to gasoil and diesel use) to the variability of simulated carbon footprints. The intervals within which simulations would randomly choose a value for each carbon footprint were defined by the uncertainty ranges of emission factors. Given that the estimated carbon footprints from the EIO-LCA model used in this study, are point estimates referring to 2010, a small sample of 50 observations was assumed to represent the hypothetical original sample in each sector case. A uniform distribution is assumed for expected values of carbon footprints due to the absence of specific information on the probability distribution and uncertainties in technical coefficients of matrix ***A*** (Shan et al., 2016; Wilting, 2012). The uncertainty estimates are the standard deviations of predicted mean carbon footprints (Romano et al., 2004).

6. Results

The Structure of the Food Value Chain

The activities and processes of each sector, as contained in the BIO model, are grouped and mapped in seven supply segments (see Figures 3 and 4): (1) Primary 1: Refers to primary inputs from the same value chain; (2) Primary 2: Primary inputs from other value chains; (3) Secondary 1: Secondary inputs from the same value chain; (4) Secondary 2: Secondary inputs from other value chains; (5) Industry: All other industrial inputs into the value chain; (6) Services: All other services into the value chain; and (7) Energy: Energy inputs into the value chain.

For instance, an input from the Primary 1 segment of the aquaculture value chain could be juveniles primarily sourced from within the industry itself and destined for processing in the Secondary 1 segment of the aquaculture value chain. Products from aquaculture's Primary 1 segment can also be used as inputs by other industries. For example, fish by-products, such as viscera, frames, and heads are used as ingredients by the Primary 2 segment to compound fish meal for poultry, pig and carnivorous finfish (Stevens et al., 2018).

The input-output structure of a product value chain can also be mapped as an array of value chain 'boxes' showing the flow of inputs and outputs (including services) across the supply chain as shown in Fig. 1. In the case of aquaculture, the 'Inputs' segment refers to inputs used at fish farm level (e.g. fertilizer, seed fish, fish feed), whereas outputs from fish farms are grouped in the 'Production' (primary) segment of the value chain. Downstream segments of the value chain include 'Processing and Packaging', 'Branding, Marketing and Distribution', and 'Sales and Retail' segments.[8]

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[8] 'Processing and Packaging' encompasses Secondary 1 and Secondary 2 segments in Figures 3 and 4.

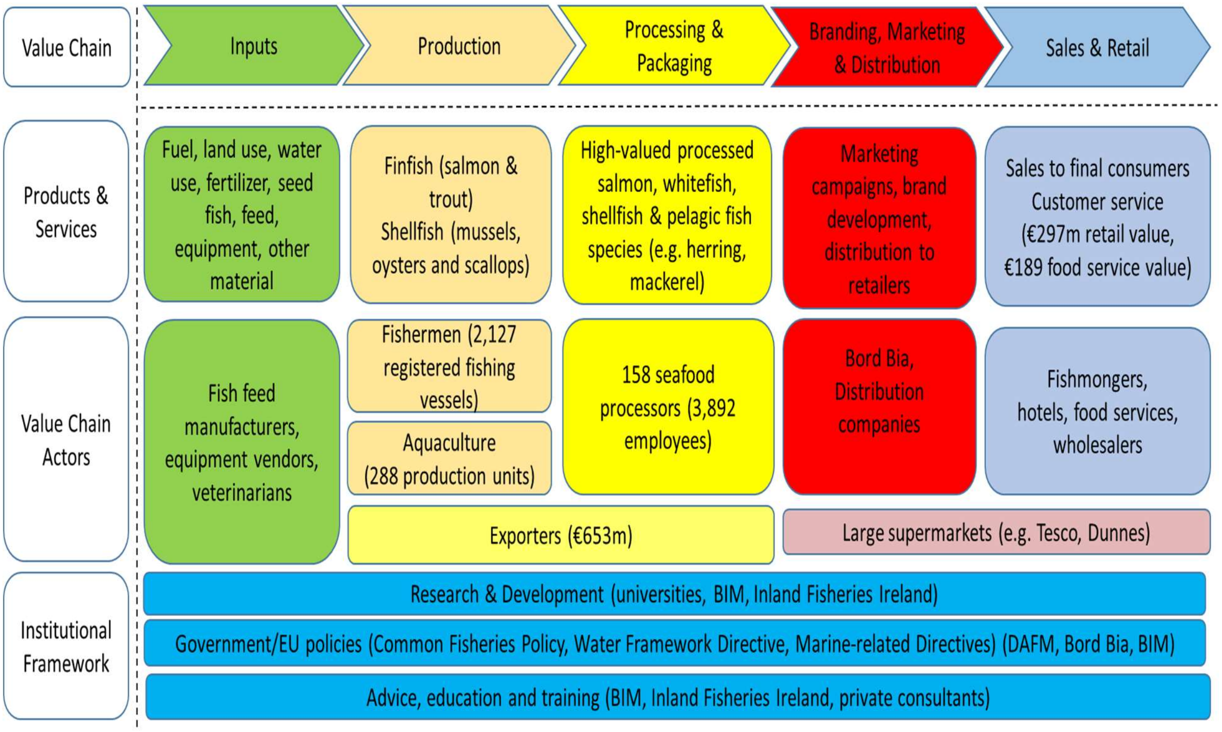

Fig. 1. Irish Aquaculture (Marine and Freshwater) Value Chain (values refer to 2018)

Economic Impact of Seafood and Livestock Production

As mentioned in Section 4, the Leontief inverse matrix enables the estimation of individual sectoral (output) multipliers capturing the direct and indirect effects of exogenous changes on new outputs of sectors, employment and household income generated by producing new outputs, and value-added generated by production. An output multiplier for sector *i* is the total value of production in all sectors of the economy that is necessary in order to satisfy €1 worth of final demand for sector *i*'s output (Miller & Blair, 2009). Hence, the total effect of a change in final demand on output across the national economy can be estimated from the interaction of output multipliers with the changes in the volume of demanded output. The disaggregated output multipliers for aquaculture, sea fisheries, beef and veal, sheep meat, pig meat, poultry meat, and dairy products are presented in Fig.2.

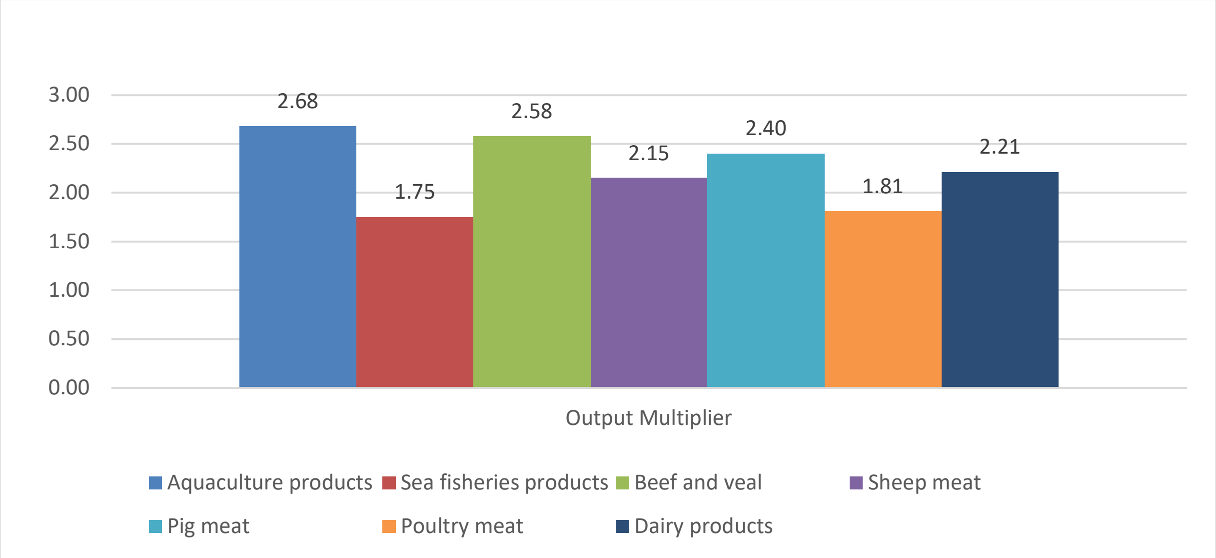

Fig. 2: Disaggregated Output Multipliers of Food Value Chains

Aquaculture products have the highest output multiplier (2.68), implying that aquaculture requires more intermediate inputs from other sectors and therefore has a greater carryover effect on production than other food products. Specifically, for each €1 output produced by the aquaculture sector, €1.68 of indirect and indirect output is generated in other sectors of the economy. Output multipliers are also high in the beef and veal (2.58) and pig meat value chains (2.40), whereas sea fisheries and poultry meat value chains have the lowest output multipliers.

Fig. 3 shows the percentage share of the output multiplier from each segment of the food value chains. The Primary 1 segment of the aquaculture value chain supplies juveniles to aquaculture sector and creates 22.3% of the value of output which has to be produced in order to satisfy €1 worth of final demand for aquaculture products. Inputs from the Secondary 1 segment account for 37.4% of aquaculture's output value, whilst the Secondary 2 segment, which is predominantly processed animal feed, accounts for 16.8% of the value. Sea fisheries have the highest share of energy inputs at 53.6%, combined with 34.5% of processing (Secondary 1 and 2) inputs. The grass-based meat value chains (beef and veal and sheep meat) also have high value shares of inputs from the Primary 1 segments reflecting the extensive nature of pastoral value chains. Inputs from the Primary 2 beef and veal segment (e.g. beef cattle transferred to the dairy herd) make up 8.5% of the beef and veal output multiplier. The Secondary 1 segment accounts for a substantial proportion of the value of output in land-based livestock product value chains. The share of fuel energy input into the multipliers are low in all food value chains except for the fuel-intensive sea fisheries value chain, whilst the shares of industry inputs (including fertilizers and pesticides) and services exhibit limited variation across the food value chains.

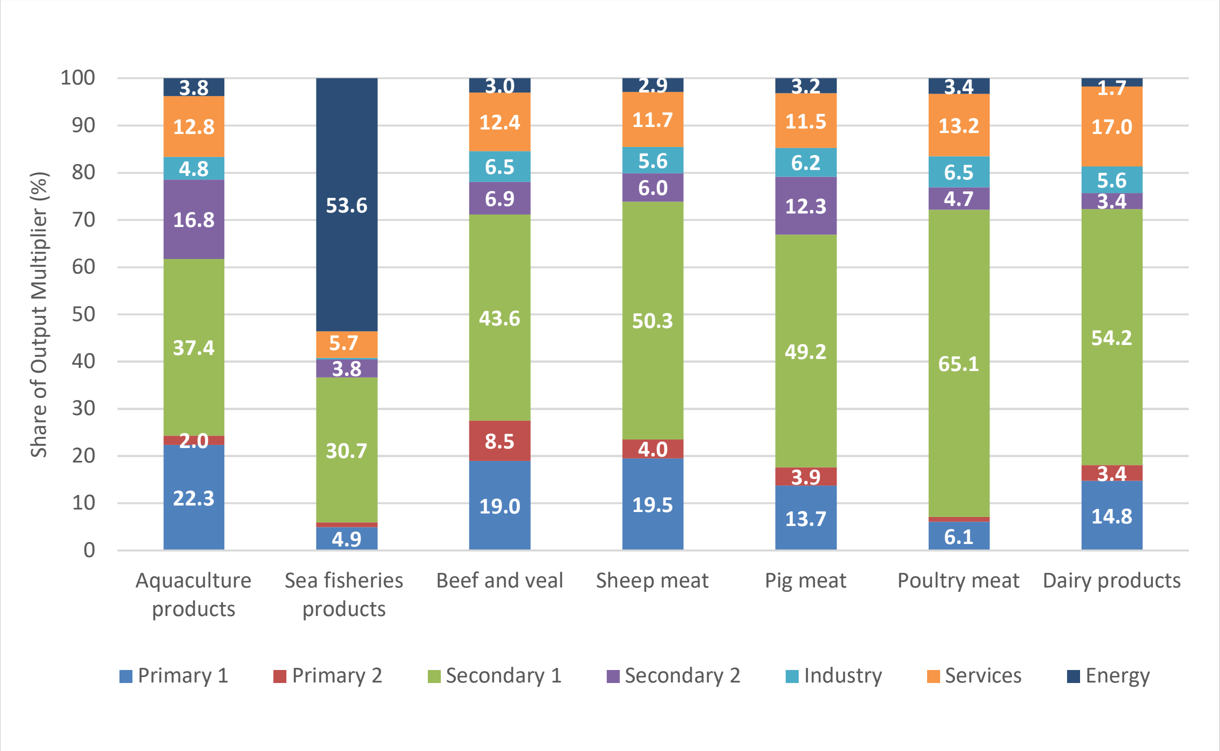

Fig. 3. Percentage Share of the Output Multiplier from each Segment of Food Value Chains

Emissions Associated with Final Demand

Fig. 4 illustrates the emission flows in terms of their proportional contribution to the disaggregated sectors. In line with findings from previous studies highlighting the strong correlation between energy use and GHG emissions in sea fisheries (Parker et al., 2018; Parker & Tyedmers, 2015), the environmental impact of fuel energy use dominates in the sea fisheries value chain representing more than 74% of total emissions. GHG emissions from commercial sea fishing vessels and fleets are primarily a waste product of fossil fuel combustion and secondarily associated with the use of refrigerants, the provision of fuels, ice and gear, and the construction and maintenance of vessels (Driscoll & Tyedmers, 2010).

The share of fuel energy emissions is also high in aquaculture and poultry meat production. Energy costs are high in Ireland whilst intensive production systems of carnivorous species (e.g. salmon and shrimp) require high energy inputs due to requirements for compound feed made of raw material of marine (e.g. wild caught fish is a major component of salmon feed) or terrestrial origin (e.g. crop-derived ingredients), medication for fish and use of sophisticated cages (Warrer-Hansen, 2015). Moreover, land-based recirculating aquaculture systems can be energy-intensive due to the energy use for water aeration and pumping in fish farm ponds (Troell et al., 2004). In the case of intensive poultry meat production (as well as in pig meat production), energy emissions can be high (50.1%) due to energy use for house lighting, heating, ventilation and air circulation equipment, although energy may account for a small percentage of product sales value.

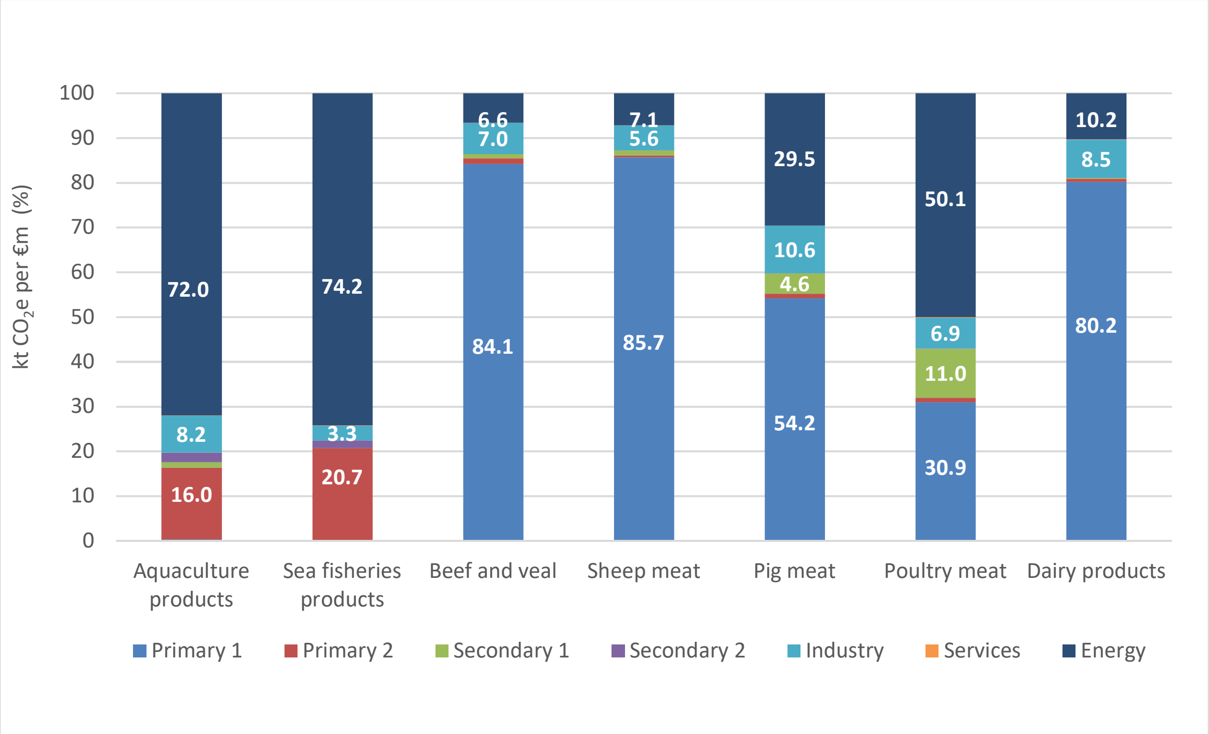

Fig. 4. Percentage Distribution of Total Life-Cycle Emissions across Food Value Chains

Emissions from the Primary 1 segment are negligible in aquatic food value chains due to zero CH_4 emissions from enteric fermentation and manure management, whereas Primary 2 segment emissions account for 20.7% and 16% of total emissions in sea fisheries and aquaculture respectively. Emissions from the Primary 2 segment are related to imported fish used as ingredients in fishmeal manufacturing aimed for poultry and pig diets. Fishmeal manufacturers source ingredients from a global pool of resources (e.g. marine ingredients from South America) leading to higher transport (fuel) emissions.

In contrast to the seafood value chains, the proportion of emissions from the Primary 1 segment is substantially higher in terrestrial value chains. The Primary 1 segment of beef and veal, sheep meat, and dairy value chains is the main contributor to the total environmental burden accounting for more than 80% of emissions. High farm-level emissions in ruminant value chains are associated with high levels of enteric CH_4 emitted from ruminants, and CH_4 and N_2O emitted from manure management. The estimated proportion of emissions from the Primary 1 dairy segment is congruent to that reported by Finnegan et al. (2017), while O'Brien et al. (2016) also conclude that on-farm GHG emissions account for 80-87% of GHG emissions in Irish sheep farms. On-farm emissions are lower in the value chains of monogastric livestock products (pig meat and poultry meat) due to the higher efficiency of swine and chickens to convert animal feed to meat as compared to cattle and sheep.

While results in Fig. 4 provide insights to the percentage distribution of GHG emissions across the segments of food value chains, they are not conclusive as regards to the magnitude of the environmental burdens of food products. Consequently, the carbon footprints of seafood and livestock product value chains are also estimated in terms of CO_2e per €m of output and macronutrient content of the respective food products (CO_2e per tonne of protein and kt CO_2e per kcal of energy) (Fig. 5).

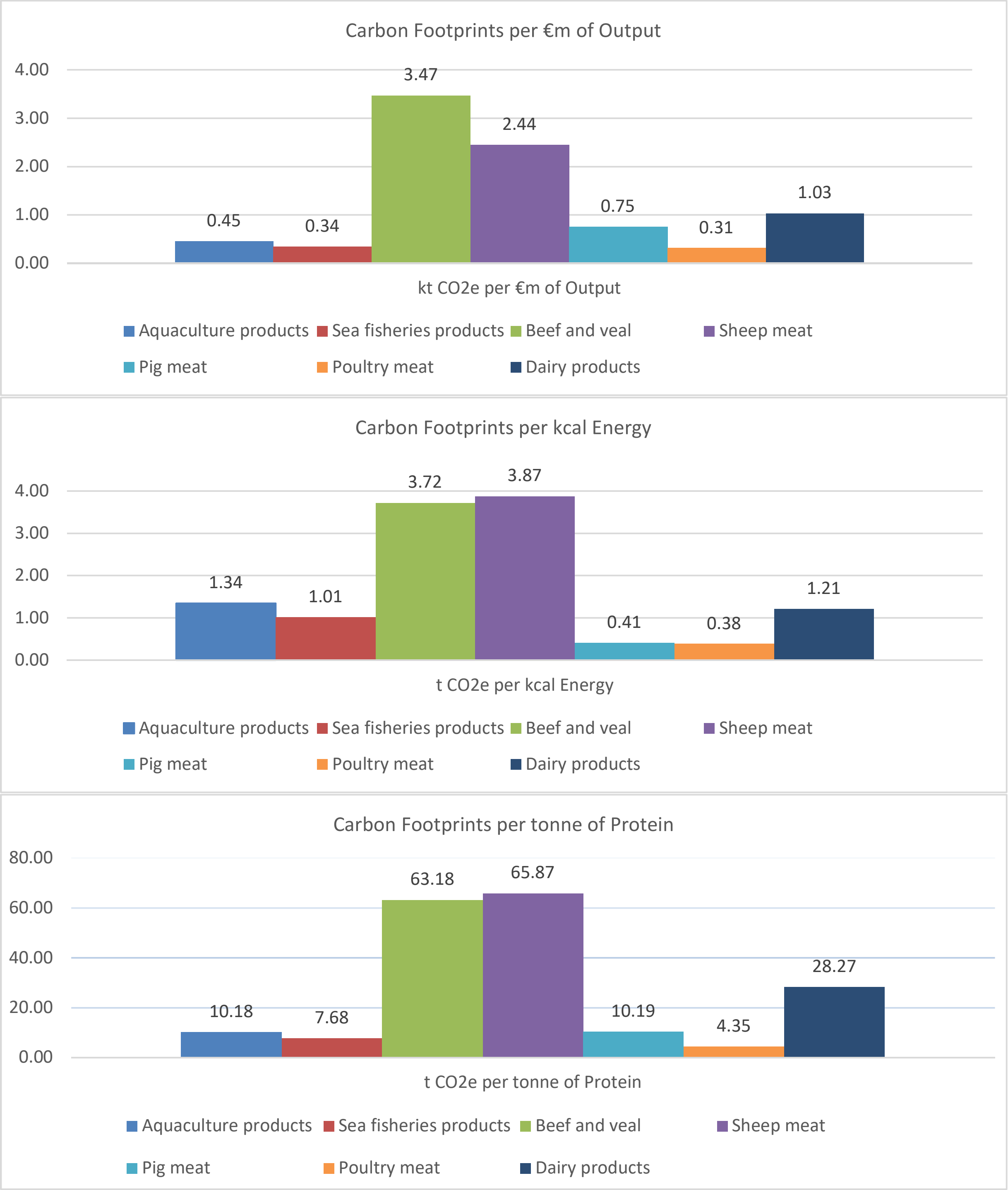

Fig. 5. Carbon Footprints of Food Products

When carbon footprint is expressed in terms of kt CO_2e per unit output, the production of poultry meat has the lowest environmental impact followed by sea fisheries, whereas beef and veal and sheep meat have the highest impact. Aquaculture products also have low carbon footprint followed by pig meat and dairy products. Several LCA studies have indicated that ruminant production systems dominate emissions from agriculture, primarily due to enteric CH_4 emissions (Herrero et al., 2016; Wanapat et al., 2015).

Measuring the carbon footprint on an energy content basis, the situation does not change dramatically as beef and veal, and sheep meat are still the most emissions intense products. Seafood and dairy products have medium impact, whereas poultry and pig meats have the lowest impacts. Emissions per tonne of protein are low for poultry meat and sea fisheries products, followed by aquaculture and pig meat. Again sheep meat and beef and veal are the largest sources of emissions, whereas dairy production has a medium impact.

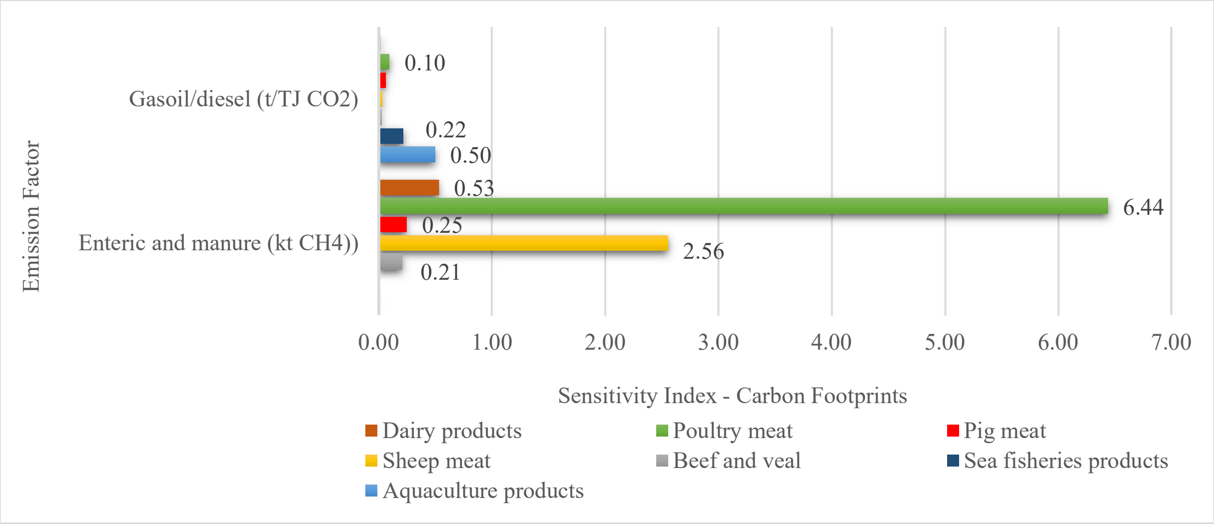

Fig. 6. Sensitivity of Estimated Carbon Footprints

Impacts of Variability of Emission Factor Intensities on Food Carbon Footprints

In this study, the effect of a 10% change in emission factor intensity on estimated carbon footprints of food value chains was examined. Results of sensitivity analysis suggests, that irrespective of the selected functional unit, the carbon footprint of poultry meat value chain is highly sensitive to changes in the emission factor for CH_4 from manure management. The carbon footprint of sheep meat production is also sensitive to changes in the emission factor for enteric CH_4 and CH_4 from manure management. The GHG emission intensities of dairy products, pig meat and beef and veal are also responsive to changes in CH_4 emission sources but to a lesser degree. As fuel energy use is primarily associated with sea fisheries and aquaculture production, it is not surprising that sea fisheries and aquaculture value chains are relatively the most sensitive value chains to changes in gasoil and diesel fuel emissions.

Based on the uncertainty ranges of enteric CH_4, CH_4 methane from manure management and CO_2 emissions associated with liquid fuel combustion, uncertainty analysis was conducted with predicted means, standard deviations, 95% confidence intervals, and minimum/maximum values of predicted footprints summarized in Appendix. Across all emission sources, the source category whose change contributed least to uncertainty in predicted carbon footprints is fuel combustion as the estimated standard deviations of carbon footprints of all food value chains are near zero. The impact of variability in enteric CH_4 differs across food products, whereas the impact of uncertainty in CH_4 emissions related to manure management varies across functional units. Uncertainty driven by enteric CH_4 emissions variability is higher in sheep meat and beef and veal carbon footprints, while uncertainty in CH_4 emissions from manure management affect uncertainty in carbon footprints of all food products, especially those of sheep and pig meats, when footprints are expressed on a protein basis.

7. Discussion and Conclusions

The findings of this study show that aquaculture has the highest output multiplier amongst the examined food products, whereas sea fisheries have the lowest multiplier. Aquaculture and sea fisheries products have low to medium carbon footprints compared to pastoral livestock products (beef and veal, sheep meat, dairy). The direct and indirect economic benefits of the aquaculture sector along with the relatively low carbon footprint of aquaculture products suggest that additional benefits from an expansion of Ireland's aquaculture sector can be gained. However, aquaculture is energy intensive, and therefore production requires the efficient use of energy and resources and the employment of low carbon technologies that strengthen aquaculture's sustainability.

Comparing aquaculture and sea fisheries emissions, the carbon footprint of sea fisheries is found to be lower than the carbon footprint of aquaculture when carbon footprint is calculated on monetary, protein and energy use basis. When GHG emissions are expressed per €m of output or per tonne of protein, aquaculture and sea fisheries have relatively low carbon footprint outperformed only by poultry meat. In sea fisheries production, variation in the magnitude of energy demand and environmental impacts is mainly driven by differences in fuel consumption by fishing vessels. Seafood life cycle analyses indicate that fuel use at the fishing stage (up to the point of landing) account for 75-95% of total GHG emissions of the product (Ziegler, Hornborg, Green, et al., 2016). In this study, energy use accounts for 74.2% of total emissions in the sea fisheries value chain. Variation in fuel consumption by fishing vessels depends on differences in fishing technology (engine power, vessel length, fishing gear, fuel type), target species, density of stocks and the distance to fishing grounds (Greer et al., 2019; Parker et al., 2017).

Iribarren et al. (2010, 2011) quantified the carbon footprint of species from coastal fishing, offshore fishing, deep-sea fishing, extensive and intensive aquaculture and found that species from extensive aquaculture, coastal fishing, and deep-sea fishing entailed lower carbon footprints than offshore species. The higher carbon footprint of offshore fishing species, when compared to deep-sea species, was due to differences in the fishing gear used, whereas energy-intensive aquaculture practices increased the carbon footprint of aquaculture products. Clark & Tilman (2017) found that GHG emissions per unit of food were on average similar, in non-circulating aquaculture, non-trawling fisheries, pork, poultry and dairy products. Parker et al. (2018) found that over half of fishery-derived products for human consumption had lower GHG emissions than pork, beef and lamb.

Similar to other studies, ruminant meats (beef and veal and sheep meat) were found to have the largest impact in terms of GHG emissions, irrespective of the choice of functional unit (kt CO_2e

per €m of output, t CO_2e per tonne of protein, t CO_2e per kcal energy). The value chains of ruminants are dominated in terms of carbon footprint by emissions from the primary segments. However, the beef and veal sector has high output multiplier with more than 20% of the value of beef (and veal) being generated by the primary segment of the value chain. Consequently, significant reductions should be achieved at farm-level by identifying management practices that allow for GHG emissions to be reduced at low cost, and optimise trade-offs between beef production and environmental protection. Poultry meat was found to have the lowest carbon footprint amongst all food products, whilst seafood (sea fisheries and aquaculture) products have relatively low to medium carbon footprints.

Clark and Tilman's (2017) meta-analysis of more than 700 LCA food studies shows that the environmental impact of ruminant meats is 3-10 times greater than the impact of other animal-based food products. Nijdam et al. (2012) and Clune et al. (2017) also conclude that ruminant meats have the largest GHG emissions. The substitution from beef to dairy that has been visible since the abolishment of milk quotas in 2015 is expected to lead to an overall reduction in the emissions per € of output. It should be noted though that there is significant variation in estimated the environmental impacts of food products, mainly caused by differences in; farming systems (e.g. Cao et al., 2011; Samuel-Fitwi et al., 2013; Yacout et al., 2016; Zehetmeier et al., 2014), production practices adopted in various countries and regions (e.g. Dangal et al., 2017; Pelletier et al., 2009; Ziegler, Hornborg, Valentinsson, et al., 2016), types of product or species (e.g. seabass versus seabream) within the food sector (Abdou et al., 2017; Ziegler et al., 2013), fuel consumption by fishing vessels, and the choice of functional unit or environmental sustainability indicator (Henriksson et al., 2012).

The results presented in this paper also show the importance of the choice of functional unit in quantifying the environmental performance of food products. While the carbon footprint of sheep meat on a monetary basis is lower than the footprint of beef and veal, it is slightly higher when emissions are calculated on a protein or energy basis. The reason for the relative change between functional units is on account of the significant price differential between the beef and veal and sheep meat, and the premium associated with sheep meat. When emissions are compared on a standardised macronutrient basis, the estimated emissions are broadly in line. Although, somebody could plausibly argue that results expressed on an energy use basis seem to be more reliable as the use of arable land for the production of feed products utilized in terrestrial and aquaculture systems cannot be directly compared with a sea bottom area covered by trawling (Ellingsen & Aanondsen, 2006), the ranking of food products with respect to their carbon footprints is quite consistent regardless the choice of the functional unit. The carbon footprint per kcal energy of pig meat is found to be lower than the footprints of seafood products due to the relatively higher fat content and energy value of pig meat. Furthermore, results from the uncertainty analysis suggest that the reliability of estimated carbon footprints of sheep meat is largely dependent on the variability of CH_4 emission sources (enteric CH_4 and CH_4 from manure management).

The analysis presented in this paper is subject to limitations. As mentioned in Section 3, aggregation errors are inherent to input-output models. This renders the estimates uncertain regarding production units and consequently specific fish species. However, due to the diverse nature of the data and since this analysis is not based on emission intensity data collected originally for this study, it was not practically possible to define the uncertainty of all components of the GHG emissions (see also Vergé et al., 2008; Webb et al., 2013). Thus, uncertainty analysis of carbon footprints of seafood and livestock value chains was based on uncertainties related to only a few, but major, emission factors.

Moreover, the utilized data and chosen environmental impact category (carbon footprint) do not incorporate some sea fisheries and aquaculture-related environmental impacts, such as biotic resource use, impacts on biodiversity, escapes of farmed fish, marine ecotoxicity and coastal use changes. Furthermore, farmed salmon was selected as the representative aquaculture species to allocate land-related emissions for Ireland's aquaculture. This choice may lead to overestimated emissions from aquaculture as salmon farms depend strongly on manufactured aquafeeds. Alternatively, shellfish, which is another important component of Ireland's aquaculture industry, could be used as representative species to allocate land-related emissions for aquaculture. In this case though, emissions from aquaculture could be underestimated as shellfish farms are independent of manufactured feeds. Nevertheless, farmed salmon was selected as the most representative aquaculture product in 2010 because salmon culture was the highest value sector of Ireland's aquaculture industry in 2011, accounting for 58% of the value (BIM, 2011).

In light of results and of the limitations in this study, future research should incorporate more disaggregated food sectors and possibly use methods, such as system process methods, that lessen the uncertainty of the results. Hence, policy makers could use these models to understand changes in the economic and environmental impact of food value chains through time and potential sustainability effects of policies related to the level of produced output and employment in food value chains.

References

Abdou, K., Aubin, J., Romdhane, M. S., Le Loc'h, F., & Lasram, F. B. R. (2017). Environmental assessment of seabass (Dicentrarchus labrax) and seabream (Sparus aurata) farming from a life cycle perspective: A case study of a Tunisian aquaculture farm. Aquaculture, 471, 204–212.

Alfaro, L., Antràs, P., Chor, D., & Conconi, P. (2015). Internalizing global value chains: A firm-level analysis. National Bureau of Economic Research, Working Paper No. 21582.

Avadí, A., & Fréon, P. (2015). A set of sustainability performance indicators for seafood: Direct human consumption products from Peruvian anchoveta fisheries and freshwater aquaculture. Ecological Indicators, 48, 518–532.

Babiker, M. H. (2005). Climate change policy, market structure, and carbon leakage. Journal of International Economics, 65(2), 421–445.

Banga, R. (2013). Measuring value in global value chains. UNCTAD, Background Paper No. RVC-8.

Beutel, J. (1983). Interregional analysis of energy flows. Papers of the Regional Science Association, 53(1), 83–104.

BIM (2011). Annual Aquaculture Survey. Bord Iascaigh Mhara.

BIM (2018). The Business of Seafood 2017. Bord Iascaigh Mhara.

BIM (2019). The Business of Seafood 2018. Bord Iascaigh Mhara.

Bohan, A., Shalloo, L., Malcolm, B., Ho, C. K. M., Creighton, P., Boland, T. M., & McHugh, N. (2016). Description and validation of the Teagasc Lamb Production Model. Agricultural Systems, 148, 124–134.

Bullard, C. W., & Sebald, A. V. (1988). Monte Carlo Sensitivity Analysis of Input-Output Models. The Review of Economics and Statistics, 70(4), 708–712.

Cao, L., Diana, J. S., Keoleian, G. A., & Lai, Q. (2011). Life cycle assessment of Chinese shrimp farming systems targeted for export and domestic sales. Environmental Science and Technology, 45(15), 6531–6538.

Chen, G. Q., Wu, X. D., Guo, J., Meng, J., & Li, C. (2019). Global overview for energy use of the world economy: Household-consumption-based accounting based on the world input-output database (WIOD). Energy Economics, 81, 835–847.

Chen, G. Q., & Wu, X. F. (2017). Energy overview for globalized world economy: Source, supply chain and sink. Renewable and Sustainable Energy Reviews, 69, 735–749.

Chen, X., Griffin, W. M., & Matthews, H. S. (2018). Representing and visualizing data uncertainty in input-output life cycle assessment models. Resources, Conservation and Recycling, 137, 316–325.

Clark, M. & Tilman, D. (2017). Comparative analysis of environmental impacts of agricultural production systems, agricultural input efficiency, and food choice. Environmental Research Letters, 12, 064016.

Clune, S., Crossin, E., & Verghese, K. (2017). Systematic review of greenhouse gas emissions for different fresh food categories. Journal of Cleaner Production, 140, 766–783.

Cochrane, K., De Young, C., Soto, D., & Bahri, T. (2009). (eds), Climate change implications for fisheries and aquaculture: overview of current scientific knowledge. FAO Fisheries and Aquaculture Technical Paper. No. 530. Rome.

Cristóbal, J. R. S. (2010). An environmental/input–output linear programming model to reach the targets for greenhouse gas emissions set by the Kyoto Protocol. Economic Systems Research, 22(3), 223–236.

Crosson, P., Shalloo, L., O'Brien, D., Lanigan, G. J., Foley, P. A., Boland, T. M., & Kenny, D. A. (2011). A review of whole farm systems models of greenhouse gas emissions from beef and dairy cattle production systems. Animal Feed Science and Technology, 166–167, 29–45.

CSO (2010). Milk & Milk Products Supply Balance 2010. CSO Statistical Release. Cork.

CSO (2011). Meat Supply Balance 2010. CSO Statistical Release. Cork.

DAFM (2010). Food Harvest: a vision of Irish Agri-food and Fisheries 2020. Department of Agriculture, Food and the Marine. Dublin.

DAFM (2015a). Food Wise 2025. Department of Agriculture, Food and the Marine. Dublin. Retrieved from https://www.agriculture.gov.ie/media/migration/foodindustrydevelopmenttrademarkets/agri-foodandtheeconomy/foodwise2025/report/FoodWise2025.pdf

DAFM (2015b). National Strategic Plan for Sustainable Aquaculture Development. Department of Agriculture, Food and the Marine. Dublin.

DAFM (2016). Report of the Pig Industry Stakeholder Group. Department of Agriculture, Food and the Marine. Dublin.

DAFM (2017). Food Wise 2025-Steps to Success 2017. Department of Agriculture, Food and the Marine. Dublin. Retrieved from https://www.agriculture.gov.ie/foodwise2025/foodwise2025-stepstosuccess2017/

DAFM (2018). Annual Report 2017. Department of Agriculture, Food and the Marine. Dublin.

Dangal, S. R. S., Tian, H., Zhang, B., Pan, S., Lu, C., & Yang, J. (2017). Methane emission from global livestock sector during 1890–2014: Magnitude, trends and spatiotemporal patterns. Global Change Biology, 23(10), 4147–4161.

de Backer, K. & Miroudot, S. (2014). Mapping global value chains. In: Hernández, R.E, Martínez-Piva, J.M., Mulder, N. (Eds.), ‘Global Value Chains and World Trade: Prospects and challenges for Latin America’. ECLAC Books, No. 127 (LC/G.2617- P), Santiago, Chile, Economic Commission for Latin America and the Caribbean (ECLAC).

de Vries, M., & de Boer, I. J. M. (2010). Comparing environmental impacts for livestock products: A review of life cycle assessments. Livestock Science, 128(1–3), 1–11.

Driscoll, J., & Tyedmers, P. (2010). Fuel use and greenhouse gas emission implications of fisheries management: the case of the new england atlantic herring fishery. Marine Policy, 34(3), 353–359.

Duffy, P., Black, K., Hyde, B., & Ponzi, J. (2019). Ireland’s National Inventory Report 2019. GHG emissions 1990–2017. Reported to the United Nations Framework Convention on Climate Change. Environmental Protection Agency. Johnstown Castle.

Duffy, P., Black, K., O’Brien, P., Hyde, B., Ponzi, J., & Alam, S. (2017). Ireland’s National Inventory Report 2017. GHG emissions 1990–2015. Reported to the United Nations Framework Convention on Climate Change. Environmental Protection Agency, Johnstown Castle.

Ellingsen, H., & Aanondsen, S. A. (2006). Environmental Impacts of Wild Caught Cod and Farmed Salmon - A Comparison with Chicken (7 pp). The International Journal of Life Cycle Assessment, 11(1), 60–65.

EPA (2019). Ireland's Greenhouse Gas Emissions Projections (2018-2040). Environmental Protection Agency. Johnstown Castle.

FAO (2018). The State of World Fisheries and Aquaculture 2018-Meeting the sustainable development goals. Food and Agriculture Organization of the United Nations. Rome.

Finnegan, W., Goggins, J., Clifford, E., & Zhan, X. (2017). Global warming potential associated with dairy products in the Republic of Ireland. Journal of Cleaner Production, 163, 262–273.

Finnveden, G., & Moberg, Å. (2005). Environmental systems analysis tools – an overview. Journal of Cleaner Production, 13(12), 1165–1173.

Gereffi, G. & Fernandez-Stark, K. (2016). Global Value Chain Analysis: A Primer, 2nd edition. Center on Globalization, Governance and Competitiveness, Duke University, North Carolina.

GHG Protocol (2013). Technical Guidance for Calculating Scope 3 emissions (version 1.0): Supplement to the Corporate Value Chain (Scope 3). Accounting & Reporting Standard. Greenhouse Gas Protocol. World Resources Institute and World Business Council for Sustainable Developme. Retrieved from www.ghgprotocol.org/standards/scope-3-standard.

Grealis, E., Hynes, S., O'Donoghue, C., Vega, A., Van Osch, S., & Twomey, C. (2017). The economic impact of aquaculture expansion: An input-output approach. Marine Policy, 81, 29–36.

Grealis, E., & O'Donoghue, C. (2015). The Economic Impact of the Irish Bio-Economy. Joint Report issued by the Teagasc Rural Economy Programme and the Socio-Economic Marine Research Unit, National University of Ireland, Galway.

Greer, K., Zeller, D., Woroniak, J., Coulter, A., Winchester, M., Palomares, M. L. D., & Pauly, D. (2019). Global trends in carbon dioxide (CO2) emissions from fuel combustion in marine fisheries from 1950 to 2016. Marine Policy, 107, 1–9.

Guillen, J., Natale, F., Carvalho, N., Casey, J., Hofherr, J., Druon, J. N., Fiore, G., Gibin, M., Zanzi, A., & Martinsohn, J. T. (2019). Global seafood consumption footprint. Ambio, 48(2), 111–122.

Heckelei, T., & Britz, W. (2001). Concept and explorative application of an EU-wide regional agricultural sector model (CAPRI-Project). Agricultural Sector Modelling and Policy Information Systems. Hrsg.: T. Heckelei, HP Witzke, W. Henrichsmeyer. Kiel.

Heery, D., O'Donoghue, C., & Fathartaigh, M.Ó. (2016). Pursuing added value in the Irish agri-food sector: an application of the global value chain methodology. Proceedings in System Dynamics and Innovation in Food Networks, pp.161-179.

Heinz, G. & Hautzinger, P. (2007). Meat Processing Technology for Small- to Medium-scale Producers. Food and Agriculture Organization of the United Nations-Regional Office for Asia and the Pacific, Bangkok.

Hendrickson, C., Horvath, A., Joshi, S., & Lave, L. (1998). Peer Reviewed: Economic Input–Output Models for Environmental Life-Cycle Assessment. Environmental Science & Technology, 32(7), 184A-191A.

Hendrickson, C.T., Lave, L.B., & Matthews, H.S. (2006). Environmental life cycle assessment of goods and services: an input-output approach. Resources for the Future.

Henriksson, P. J. G., Guinée, J. B., Kleijn, R., & de Snoo, G. R. (2012). Life cycle assessment of aquaculture systems---a review of methodologies. The International Journal of Life Cycle Assessment, 17(3), 304–313.

Herrero, M., Henderson, B., Havlík, P., Thornton, P. K., Conant, R. T., Smith, P., Wirsenius, S., Hristov, A.N., Gerber, P., Gill, M., Butterbach-Bahl, K., Valin, H., Garnett, T., & Stehfest, E. (2016). Greenhouse gas mitigation potentials in the livestock sector. Nature Climate Change, 6(5), 452–461.

Hooks, T., Macken Walsh, Á., McCarthy, O., Power, C., & Henchion, M. (2018). Co-operation among Irish beef farmers: Current perspectives and future prospects in the context of new producer organisation (PO) legislation. Sustainability, 10(11).

Hyland, J. J., Heanue, K., McKillop, J., & Micha, E. (2018). Factors influencing dairy farmers' adoption of best management grazing practices. Land Use Policy, 78, 562–571.

Independent Aquaculture Licencing Review Group (2017). Review of the Aquaculture Licensing Process-Public Consultation 2017. Review commissioned by the Irish Department of Agriculture, Food and the Marine.

Inter-Departmental Marine Coordination Group (2012). "Harnessing Our Ocean Wealth: An Integrated Marine Plan for Ireland", Inter-Departmental Marine Coordination Group.

IPCC (1997). Revised 1996 Guidelines for National Greenhouse Gas Inventories Workbook, vol. 2, Cambridge University Press. Cambridge.

IPCC (2000). In: Houghton, J.T., Meira Filho, L.G., Lim, B., Treanton, K., Mamaty, I., Bonduki, Y., Griggs, D.J., Callanders, B.A. (Eds.), Good Practice Guidance and Uncertainty Management in National Greenhouse Gas Inventories Accepted IPCC Plenary in Montreal, 1–8 M. Paris.

IPCC (2003). In: Penman, J., et al. (Eds.), Good Practice Guidance for Land Use, Land-Use Change and Forestry (GPG-LULUCF). IPCC-IGES. Kanagawa.

IPCC (2006). IPCC guidelines for national greenhouse gas inventories. In: Eggleston, H., Buendia, L., Miwa, K., Ngara, T., Tanabe, K. (Eds.), The National Greenhouse Gas Inventories Programme, Intergovernmental Panel on Climate Change. Kanagawa.

Iribarren, D., Vázquez-Rowe, I., Hospido, A., Moreira, M. T., & Feijoo, G. (2010). Estimation of the carbon footprint of the Galician fishing activity (NW Spain). Science of The Total Environment, 408(22), 5284–5294.

Iribarren, D., Vázquez-Rowe, I., Hospido, A., Moreira, M. T., & Feijoo, G. (2011). Updating the carbon footprint of the Galician fishing activity (NW Spain). Science of The Total Environment, 409(8), 1609–1611.

Jørgensen, A., Le Bocq, A., Nazarkina, L., & Hauschild, M. (2007). Methodologies for social life cycle assessment. The International Journal of Life Cycle Assessment, 13(2), 96.

Joshi, S. (1999). Product environmental life-cycle assessment using input-output techniques. Journal of Industrial Ecology, 3(2–3), 95–120.

Kilcline, K. (2018). Integrated Assessment of Sheep Production Systems and the Agricultural Value Chain. PhD Dissertation. National University of Ireland, Galway.

Kitzes, J. (2013). An introduction to environmentally-extended input-output analysis. Resources, 2(4), 489–503.

Kumar, I., Tyner, W. E., & Sinha, K. C. (2016). Input–output life cycle environmental assessment of greenhouse gas emissions from utility scale wind energy in the United States. Energy Policy, 89, 294–301.

Lanigan, K.R. G., Donnellan, T., Hanrahan, K., Paul, C., Shalloo, L., Krol, D., Forrestal, P., Farrelly, N., O'Brien, D., Ryan, M., Murphy, P., Caslin, B., Spink, J., Finnan, J., Boland, A., Upton, J., & Richards, K. (2018). An Analysis of Abatement Potential of Greenhouse Gas Emissions in Irish Agriculture 2021-2030. Prepared by the Teagasc Greenhouse Gas Working Group. Teagasc, Carlow.

Miller, R. E., & Blair, P. D. (2009). Input–Output Analysis. Cambridge University Press.

Moreau, V., & Weidema, B. P. (2015). The computational structure of environmental life cycle costing. The International Journal of Life Cycle Assessment, 20(10), 1359–1363.

Morrissey, K., & O'Donoghue, C. (2013). The role of the marine sector in the Irish national economy: An input–output analysis. Marine Policy, 37, 230–238.

Nijdam, D., Rood, T., & Westhoek, H. (2012). The price of protein: Review of land use and carbon footprints from life cycle assessments of animal food products and their substitutes. Food Policy, 37(6), 760–770.

O'Brien, D., Bohan, A., McHugh, N., & Shalloo, L. (2016). A life cycle assessment of the effect of intensification on the environmental impacts and resource use of grass-based sheep farming. Agricultural Systems, 148, 95–104.

O'Donoghue, C., Chyzheuskaya, A., Grealis, E., Finnegan, W., Goggin, J., Hynes, S., Kilcline, K., & Ryan, M. (2018). Measuring GHG Emissions Across the Agri-Food Sector Value Chain: The Development of BIO - a Bio-economy Input-Output Model. Proceedings in Food System Dynamics, 38–69.

O'Donoghue, C., Clavin, D., Ryan, M., Leavy, E., & Heery, D. (2018). Policy incentives and the organic value chain in Ireland. International Journal on Food System Dynamics, 9(1), 21–37.

O'Donoghue, C., & Hennessy, T. (2015). Policy and economic change in the agri-food sector in ireland. Economic and Social Review, 46(2), 315–337.

O'Toole, R., & Matthews, A. (2002a). The IMAGE CGE model: Constructing the Base 1993 database: Department of Economics, Trinity College Dublin.

O'Toole, R., & Matthews, A. (2002b). The IMAGE CGE Model: Understanding the model structure, code and solution methods: Department of Economics, Trinity College Dublin.

Orr, H. L., Hunt, E. C., & Randall, C. J. (1984). Yield of carcass, parts, meat, skin, and bone of eight strains of broilers. Poultry Science, 63(11), 2197–2200.

Parker, R. W. R., Blanchard, J. L., Gardner, C., Green, B. S., Hartmann, K., Tyedmers, P. H., & Watson, R. A. (2018). Fuel use and greenhouse gas emissions of world fisheries. Nature Climate Change, 8(4), 333–337.

Parker, R. W. R., Gardner, C., Green, B. S., Hartmann, K., & Watson, R. A. (2017). Drivers of fuel use in rock lobster fisheries. ICES Journal of Marine Science, 74(6), 1681–1689.

Parker, R. W. R., & Tyedmers, P. H. (2015). Fuel consumption of global fishing fleets: Current understanding and knowledge gaps. Fish and Fisheries, 16(4), 684–696.

Pelletier, N., Tyedmers, P., Sonesson, U., Scholz, A., Ziegler, F., Flysjo, A., Kruse, S., Cancino, B., & Silverman, H. (2009). Not all salmon are created equal: Life cycle assessment (LCA) of global salmon farming systems. Environmental Science and Technology, 43(23), 8730–8736.

Ramírez, A., de Keizer, C., Van der Sluijs, J. P., Olivier, J., & Brandes, L. (2008). Monte Carlo analysis of uncertainties in the Netherlands greenhouse gas emission inventory for 1990–2004. Atmospheric Environment, 42(35), 8263–8272.

Renwick, A. (2018). Regulatory challenges to economic growth in aquaculture: The case of licensing in the Irish oyster industry. Marine Policy, 88, 151–157.

Roe, M., Pinchen, H., Church, S., & Finglas, P. (2015). McCance and Widdowson's Composition of Foods Seventh Summary Edition and updated Composition of Foods Integrated Dataset. Nutrition Bulletin, 40(1), 36–39.

Romano, D., Bernetti, A., & De Lauretis, R. (2004). Different methodologies to quantify uncertainties of air emissions. Environment International, 30(8), 1099–1107.

Rotz, C.A., Asem-Hiablie, S., Dillon, J., & Bonifacio, H. (2015). Cradle-to-farm gate environmental footprints of beef cattle production in Kansas, Oklahoma, and Texas. Journal of Animal Science, 93(5), 2509–2519.

Rotz, C., Alan, Stout, R. C., Holly, M. A., & Kleinman, P. J. A. (2020). Regional environmental assessment of dairy farms. Journal of Dairy Science, 103(4), 3275–3288.

Samuel-Fitwi, B., Nagel, F., Meyer, S., Schroeder, J. P., & Schulz, C. (2013). Comparative life cycle assessment (LCA) of raising rainbow trout (Oncorhynchus mykiss) in different production systems. Aquacultural Engineering, 54, 85–92.

Samuel-Fitwi, Biniam, Wuertz, S., Schroeder, J. P., & Schulz, C. (2012). Sustainability assessment tools to support aquaculture development. Journal of Cleaner Production, 32, 183–192.

Schulte, R. P. O., Donnellan, T., Black, K. G., Crosson, P., Farrelly, N. et al. (2013). Carbon Neutrality as a horizon point for Irish Agriculture: a qualitative appraisal of potential pathways to 2050. Teagasc, Carlow.

SEAI (2016). Energy-Related Emissions in Ireland: CO2 Emissions from Fuel Combustion. 2016 Report. Sustainable Energy Authority of Ireland. Dublin.

Shan, Y., Liu, Z., & Guan, D. (2016). CO2 emissions from China's lime industry. Applied Energy, 166, 245–252.

Stevens, J. R., Newton, R. W., Tlusty, M., & Little, D. C. (2018). The rise of aquaculture by-products: Increasing food production, value, and sustainability through strategic utilisation. Marine Policy, 90, 115–124.

Teagasc (2019). Agriculture in Ireland. Teagasc, Carlow.

Troell, M., Tyedmers, P., Kautsky, N., & Rönnbäck, P. (2004). Aquaculture and energy use. Encyclopedia of Energy, 1, 97–108.

Tsakiridis, A., Aymelek, M., Norton, D., Burger, R., O'Leary, J., Corless, R., & Hynes, S. (2019). Ireland's Ocean Economy, SEMRU Report Series, ISSN 2009-6933 (online) Ireland's Ocean Economy Report 2019.

Tubiello, F. N., Salvatore, M., Rossi, S., Ferrara, A., Fitton, N., & Smith, P. (2013). The FAOSTAT database of greenhouse gas emissions from agriculture. Environmental Research Letters, 8(1).

UN-DESA (2017). Word Population Prospects: the 2017 Revision, Key Findings and Advance Tables, ESA/P/WP/248. United Nations, Department of Economic and Social Affairs, Population Division. New York.

Vergé, X. P. C., Dyer, J. A., Desjardins, R. L., & Worth, D. (2008). Greenhouse gas emissions from the Canadian beef industry. Agricultural Systems, 98(2), 126–134.

Wanapat, M., Cherdthong, A., Phesatcha, K., & Kang, S. (2015). Dietary sources and their effects on animal production and environmental sustainability. Animal Nutrition, 1(3), 96–103.

Wang, Y. V., Wan, A. H. L., Lock, E.-J., Andersen, N., Winter-Schuh, C., & Larsen, T. (2018). Know your fish: A novel compound-specific isotope approach for tracing wild and farmed salmon. Food Chemistry, 256, 380–389.

Warrer-Hansen, I. (2015). Potential for Land Based Salmon Grow- out in Recirculating Aquaculture Systems (RAS) in Ireland. IFA Aquaculture. Dublin.

Webb, J., Williams, A. G., Hope, E., Evans, D., & Moorhouse, E. (2013). Do foods imported into the UK have a greater environmental impact than the same foods produced within the UK? International Journal of Life Cycle Assessment, 18(7), 1325–1343.

Wiedmann, T. (2009). A review of recent multi-region input-output models used for consumption-based emission and resource accounting. Ecological Economics, 69(2), 211–222.

Wiedmann, T., Lenzen, M., Turner, K., & Barrett, J. (2007). Examining the global environmental impact of regional consumption activities - Part 2: Review of input-output models for the assessment of environmental impacts embodied in trade. Ecological Economics, 61(1), 15–26.

Wilting, H. C. (2012). Sensitivity and uncertainty analysis in mrio modelling; some empirical results with regard to the Dutch carbon footprint. Economic Systems Research, 24(2), 141–171.

Wu, X. F., & Chen, G. Q. (2017). Energy use by Chinese economy: A systems cross-scale input-output analysis. Energy Policy, 108, 81–90.

Wu, X. D., Ji, X., Li, C., Xia, X. H., & Chen, G. Q. (2019). Water footprint of thermal power in China: Implications from the high amount of industrial water use by plant infrastructure of coal-fired generation system. Energy Policy, 132, 452–461.

Yacout, D. M. M., Soliman, N. F., & Yacout, M. M. (2016). Comparative life cycle assessment (LCA) of Tilapia in two production systems: semi-intensive and intensive. International Journal of Life Cycle Assessment, 21(6), 806–819.

Zehetmeier, M., Gandorfer, M., Hoffmann, H., Müller, U. K., de Boer, I. J. M., & Heißenhuber, A. (2014). The impact of uncertainties on predicted greenhouse gas emissions of dairy cow production systems. Journal of Cleaner Production, 73, 116–124.

Ziegler, F., Hornborg, S., Green, B. S., Eigaard, O. R., Farmery, A. K., Hammar, L., Hartmann, K., Molander, S., Parker, R.W., Skontorp Hognes, E., & Smith, A. D. M. (2016). Expanding the concept of sustainable seafood using Life Cycle Assessment. Fish and Fisheries, 17(4), 1073–1093.

Ziegler, F., Hornborg, S., Valentinsson, D., Hognes, E. S., Søvik, G., & Eigaard, O. R. (2016). Same stock, different management: quantifying the sustainability of three shrimp fisheries in the Skagerrak from a product perspective. ICES Journal of Marine Science, 73, 1806–1814.

Ziegler, F., Winther, U., Hognes, E. S., Emanuelsson, A., Sund, V., & Ellingsen, H. (2013). The Carbon Footprint of Norwegian Seafood Products on the Global Seafood Market. Journal of Industrial Ecology, 17(1), 103–116.

Appendix

Table A.1. Uncertainty Estimates of Food Value Chains

<table>
<tr><td colspan="7">Carbon footprints per €m of output related to uncertainty in enteric CH_4 emissions</td></tr>
<tr><td></td><td>Predicted mean</td><td>Standard deviation</td><td>Min.</td><td>Max.</td><td>95% CI (lower bound)</td><td>95% CI (upper bound)</td></tr>
<tr><td>Beef and veal</td><td>3.44</td><td>0.17</td><td>3.19</td><td>3.73</td><td>3.40</td><td>3.49</td></tr>
<tr><td>Sheep meat</td><td>2.41</td><td>0.26</td><td>1.98</td><td>2.89</td><td>2.34</td><td>2.49</td></tr>
<tr><td>Pig meat</td><td>0.75</td><td>0.00</td><td>0.74</td><td>0.76</td><td>0.75</td><td>0.75</td></tr>
<tr><td>Dairy products</td><td>1.01</td><td>0.05</td><td>0.93</td><td>1.12</td><td>1.00</td><td>1.03</td></tr>
<tr><td colspan="7">Carbon footprints per kcal energy related to uncertainty in enteric CH_4 emissions</td></tr>
<tr><td></td><td>Predicted mean</td><td>Standard deviation</td><td>Min.</td><td>Max.</td><td>95% CI (lower bound)</td><td>95% CI (upper bound)</td></tr>
<tr><td>Beef and veal</td><td>3.73</td><td>0.16</td><td>3.44</td><td>4.00</td><td>3.68</td><td>3.78</td></tr>
<tr><td>Sheep meat</td><td>3.88</td><td>0.43</td><td>3.12</td><td>4.59</td><td>3.76</td><td>4.00</td></tr>
<tr><td>Pig meat</td><td>0.41</td><td>0.00</td><td>0.40</td><td>0.41</td><td>0.40</td><td>0.41</td></tr>
<tr><td>Dairy products</td><td>1.21</td><td>0.07</td><td>1.09</td><td>1.31</td><td>1.19</td><td>1.23</td></tr>
<tr><td colspan="7">Carbon footprints per tonne of protein related to uncertainty in enteric CH_4 emissions</td></tr>
<tr><td></td><td>Predicted mean</td><td>Standard deviation</td><td>Min.</td><td>Max.</td><td>95% CI (lower bound)</td><td>95% CI (upper bound)</td></tr>
<tr><td>Beef and veal</td><td>62.95</td><td>2.81</td><td>58.33</td><td>67.93</td><td>62.14</td><td>63.75</td></tr>
<tr><td>Sheep meat</td><td>66.17</td><td>7.44</td><td>53.14</td><td>78.38</td><td>64.05</td><td>68.29</td></tr>
<tr><td>Pig meat</td><td>10.19</td><td>0.10</td><td>9.99</td><td>10.37</td><td>10.15</td><td>10.22</td></tr>
<tr><td>Dairy products</td><td>28.61</td><td>1.52</td><td>25.75</td><td>30.83</td><td>28.18</td><td>29.05</td></tr>
</table>

Carbon footprints per €m of output related to uncertainty in CH_4 emissions from manure management

	Predicted mean	Standard deviation	Min.	Max.	95% CI (lower bound)	95% CI (upper bound)
Beef and veal	3.47	0.01	3.44	3.49	3.46	3.47
Sheep meat	2.44	0.02	2.41	2.47	2.44	2.45
Pig meat	0.74	0.03	0.69	0.80	0.73	0.75
Poultry meat	0.31	0.00	0.30	0.32	0.31	0.31
Dairy products	1.02	0.00	1.02	1.03	1.02	1.03

Carbon footprints per kcal energy related to uncertainty in CH_4 emissions from manure management

	Predicted mean	Standard deviation	Min.	Max.	95% CI (lower bound)	95% CI (upper bound)
Beef and veal	3.72	0.01	3.69	3.74	3.71	3.72
Sheep meat	3.87	0.03	3.82	3.92	3.86	3.88
Pig meat	0.41	0.01	0.38	0.43	0.40	0.41
Poultry meat	0.38	0.00	0.37	0.39	0.38	0.38
Dairy products	1.21	0.00	1.20	1.21	1.20	1.21

Carbon footprints per tonne of protein related to uncertainty in CH_4 emissions from manure management

	Predicted mean	Standard deviation	Min.	Max.	95% CI (lower bound)	95% CI (upper bound)
Beef and veal	63.24	0.24	62.73	63.64	63.17	63.32
Sheep meat	65.80	0.58	65.00	66.73	65.63	65.96
Pig meat	10.24	0.39	9.45	10.94	10.12	10.35

Poultry meat	4.37	0.11	4.17	4.54	4.33	4.40
Dairy products	28.27	0.13	28.05	28.50	28.23	28.30
Carbon footprints per €m of output related to uncertainty in CO_2 emissions from gasoil and diesel use						
	Predicted mean	Standard deviation	Min.	Max.	95% CI (lower bound)	95% CI (upper bound)
Aquaculture products	0.44	0.00	0.44	0.45	0.44	0.45
Sea fisheries products	0.34	0.00	0.33	0.34	0.33	0.34
Beef and veal	3.46	0.00	3.46	3.47	3.46	3.46
Sheep meat	2.45	0.00	2.44	2.47	2.45	2.46
Pig meat	0.75	0.00	0.74	0.75	0.75	0.75
Poultry meat	0.31	0.00	0.31	0.31	0.31	0.31
Dairy products	1.03	0.00	1.03	1.03	1.03	1.03
Carbon footprints per kcal energy related to uncertainty in CO_2 emissions from gasoil and diesel use						
	Predicted mean	Standard deviation	Min.	Max.	95% CI (lower bound)	95% CI (upper bound)
Aquaculture products	1.34	0.01	1.32	1.36	1.33	1.34
Sea fisheries products	1.01	0.00	1.00	1.02	1.01	1.01
Beef and veal	3.71	0.00	3.71	3.72	3.71	3.72
Sheep meat	3.87	0.00	3.86	3.87	3.87	3.87
Pig meat	0.40	0.00	0.40	0.41	0.40	0.40
Poultry meat	0.38	0.00	0.38	0.38	0.38	0.38

Dairy products	1.20	0.00	1.20	1.20	1.20	1.20
Carbon footprints per tonne of protein related to uncertainty in CO_2 emissions from gasoil and diesel use						
	Predicted mean	Standard deviation	Min.	Max.	95% CI (lower bound)	95% CI (upper bound)
Aquaculture products	10.17	0.11	10.01	10.35	10.14	10.20
Sea fisheries products	7.68	0.03	7.62	7.74	7.67	7.69
Beef and veal	63.19	0.03	63.12	63.24	63.18	63.20
Sheep meat	65.85	0.04	65.78	65.94	65.84	65.87
Pig meat	10.18	0.01	10.16	10.21	10.18	10.19
Poultry meat	4.35	0.00	4.33	4.36	4.35	4.35
Dairy products	28.27	0.01	28.25	28.28	28.26	28.27

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