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Abstract: Food is at the centre of efforts to combat climate change, reduce water stress, pollution, and conserve the world's wildlife. Assessing the environmental performance of food companies is essential to provide a comprehensive view of the production processes and gain insight into improvement options, but such a tool is currently non-existent in the literature. This study proposed a tool based on the life cycle assessment methodology focused on six stages of the food chain, raw materials acquisition, supplier, manufacturing, distribution, retail and wastes. The user can also evaluate the implementation of Internet of Things (IoT) technologies to reduce food waste applied in the real-world problems. The tool was validated through a case study of a food manufacturing company that prepares frozen meals via vending machines. The LCA results provided by the tool showed that food raw materials production is the main hotspot of nine impact categories. The IoT technologies' contribution increased the company's impact by around 0.4%. However, it is expected that employing these monitoring technologies would prevent food waste generation and the associated environmental impacts. Therefore, the results of this paper provide evidence that the proposed tool is suitable for determining environmental impacts and savings of food supply chain companies.

Keywords: environmental analysis; food supply chain; IoT technologies; life cycle assessment; excel-based tool; stand-alone model

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1. Introduction

Around 10% of food made available to EU consumers (at retail, food services and households) may be wasted [1]. These losses occurred at different stages of the food supply chain (FSC), i.e., in companies converting the raw agricultural materials into final products feasible for direct consumption [2]. Literature suggests that issues within FSC management leading to food waste are numerous, including inadequate processing and packaging, lack of transportation and distribution systems and inadequate storage facilities and techniques [3,4], and call for targeted action.

In particular, in the EU, nearly 57 million tonnes of food waste (127 kg/inhabitant) are generated annually, with an associated market value estimated at 130 billion euros [1]. By preventing food waste, companies can sell more food and create more revenue. However, the importance of reducing food waste has been recognised worldwide not only because food waste causes serious economic impacts but also due to environmental and social consequences [5]. Due to the amount of resources (water, nutrients, fertilisers, etc.) consumed during food production and distribution, food waste saved is much more than the face value of the waste itself for society [6]. Regarding environmental effects, the food sector accounts for over 30% of global greenhouse gas (GHG) emissions [2]. Significant carbon emissions result from the production of food that is wasted, and the wasted food will emit more GHG in landfill, causing significant environmental impacts. To reduce carbon emissions, various companies have been seeking ways to reduce their own emissions [7].

Recent research supports the importance of using smart technology such as the Internet of Things (IoT), machine learning and blockchain to advance and improve FSC management [5,8–12] and thus help reduce food waste. The IoT is a growing network of objects that communicate between themselves and other internet-enabled devices over the Internet and allows users to monitor and control the physical world remotely [13]. In the supply chain context, Abdel-Basset et al. [14] defined IoT as a set of digitally connected physical objects for sensing and monitoring supply chain interaction, agility, visibility and information sharing to facilitate the plan, control, and coordination of supply chain processes within an organisation. In addition, adopting IoT is a potential opportunity to upgrade and reshape the FSC [12], and help data-driven decision-making in supply chain management [15].

Several areas in the field of IoT implementation in the FSC were discussed in the literature, including implementation models and frameworks [16–18], managing risks and revenues [9,19], platform design [16], usefulness [20], supply chain sustainability [21], supply chain coordination and information sharing [19]. Even though IoT and FSC applications were discussed in the literature, there is a lack of studies on tools assessing the environmental performance of different food products, food supply chain stages and technologies used to reduce food waste in FSC [22].

Life cycle assessment (LCA) is a methodology that can analyse the environmental impacts of products or processes by inventorying all the inputs and outputs throughout the product's life cycle, from raw material production to end-of-life [23–25]. This methodology determines where the most significant impacts occur and where the most relevant improvements can be made while identifying potential trade-offs [26,27]. It allows companies to investigate areas where they might improve [28,29]. Although some LCA tools exist for other sectors [30–32], there is no generalised LCA tool for understanding the environmental impacts of different stages of the food supply chain or implementing IoT technologies to save food waste. Such a tool will be invaluable given the increasing trend in the food industry for using new technologies. This paper fills this gap and contributes to the literature.

Therefore, this study aims to develop a new adaptable open-source tool (REAMIT-LCA Tool) to conduct an extensive environmental evaluation of food supply chains. The tool is used to compute the contribution of each stage of the food supply chain to 12 different impact categories to support food producers, food supply chain companies (processing and logistics), local authorities, academics and digital technology providers in conducting LCA and exploring the problem of food waste and the solutions to achieve more sustainable food systems. It can also be used as an environmental decision support system to determine the trade-offs between IoT technologies implementation and food waste reduction. Additionally, developing a complete LCA can be difficult and time-consuming, particularly discouraging to non-experts. Therefore, it also aims to reduce the computational time and processing, which the other LCA tools have not yet resolved.

The paper is organised as follows. A literature review of LCA tools is shown in the next section. The REAMIT-LCA tool scope is discussed in Section 3, along with the modelling methods, data sources and validation in a UK food manufacturing company case study. Results are presented and discussed in Section 4. Additional sensitivity analyses are also performed in this section. Conclusions are shown in the Section 5.

2. Literature Review

In recent years, various computational tools were developed to assess the environmental impacts of different products and organisations from an LCA point of view. Table 1 presents some examples of tools proposed in the literature. It is not intended to be a comprehensive list of all available tools and/or methodologies proposed but only to present some of the most representative tools that can be used in practice.

Table 1. LCA tools available to assess the environmental impact of different products.

Authors	Year	Application	System Boundary	Geographical Coverage	LCI Database	Modelling Approach	Indicators	Analysis Tool
Hassan et al. [33]	2022	Residential building	Gate-to-gate (excludes transportation and other life cycle stages)	Egypt	Ecoinvent	ReCiPe and IPCC 2013	GW, DEQ, HH, RM	Excel
Kamari et al. [34]	2022	Building design	Cradle-to-grave (from materials production to building's end-of-life)	-	OKOBAUDAT platform	IMPACT 2002+	GW, OD, POF, AD, EU, AC	Plug-in icon in the Autodesk Revit software
Hollberg et al. [35]	2022	Building	Cradle-to-gate (from materials production to transportation)	Sweden	Boverket	IPCC 2013	GW	Grasshopper3D used as platform for the tool
Famiglietti et al. [36]	2022	Cities	Cradle-to-grave (from materials production to end-of-life stage)	-	-	EF 3.0	All categories of the EF method	Excel
Famiglietti et al. [37]	2019	Dairy products	Cradle-to-gate (from purchased feeds to dairy production)	-	Agribalyse, Ecoinvent, ELCD, USLCI, etc.	ILCD 2011 Midpoint +	All categories of the ILCD 2011 method	IT-tool
Tecchio et al. [38]	2019	Building structure	Gate-to-gate (material production stage only)	USA	Ecoinvent, USLCI, Athena, GaBi	-	GW, AC, EU, SF	Box plots
Hasik et al. [39]	2019	Office buildings	Cradle-to-gate (from materials production to building stage)	USA	Ecoinvent	-	GW, OD, SF, AC, EU, FD	Python
Hester et al. [40]	2018	Residential buildings	Cradle-to-grave (from materials production to building's end-of-life)	USA	Ecoinvent, GaBi, Athena, etc.	-	GW	Excel
Martins et al. [41]	2018	Electricity	Cradle-to-gate (from extraction of raw materials to final decommissioning)	Portugal	IPCC Emission Factors	CML	GW, OD, POF, EU, AC	Excel
Renouf et al. [42]	2018	Sugarcane	Cradle-to-gate (from farming inputs production to sugarcane harvesting)	Australia	AusLCI	CML, IPCC 2013, USEtox	GW, FD, EU, WS, EC	Excel
Goglio et al. [43]	2018	Soil emission	Cradle-to-gate (from agricultural phase to products transportation)	Canada	GHGenius	IPCC 2013, and CML	GW, CED, EU, AC	Open-source program R

Table 1. *Cont.*

Authors	Year	Application	System Boundary	Geographical Coverage	LCI Database	Modelling Approach	Indicators	Analysis Tool
Yang et al. [44]	2017	Airport pavement construction	Cradle-to-gate (from materials production to construction)	USA	Ecoinvent	-	GW, CED	Excel
Beccali et al. [45]	2016	Solar heating and cooling systems	Cradle-to-gate (from production of the main components to end-of-life)	23 European countries, Switzerland and Europe	-	Frischknecht and Rebitzer [46] and IPCC 2013	GW, CED	Excel
Al-Ansari et al. [47]	2015	Agri-food production	Gate-to-gate (food production)	Qatar	-	CML	GW, AC, HT, AD, AE, LF	-
Basbagill et al. [48]	2014	Residential complex	Cradle-to-gate (from materials production to building stage)	USA	Ecoinvent, Athena	-	GW, cost	ModelCenter software
El-Houjeiri et al. [49]	2013	Crude oil production	Well-to-refinery	All countries except Cameroon, Chile, South Africa, and Uzbekistan	Different databases	-	GW	Excel
Mata et al. [50]	2012	Pharmaceutical products	Gate-to-gate (from raw materials transportation to post-consumer)	-	-	CML	EI, PMI, PW, CF, FT	Excel
Reinhard et al. [51]	2011	Biofuels	Cradle-to-grave (from cultivation to usage)	-	Ecoinvent	IPCC 2006	GW	Web-based tool
Current study	2022	Food products	Cradle-to-grave (from materials production to waste end-of-life)	Ireland, Germany, France, Luxembourg, UK and the Netherlands	Ecoinvent [52,53]	ReCiPe	GW, FS, SOD, TA, TEc, LU, MEu, MEc, HT, FEu, FEc, WC	Excel

Acidification potential (AC), abiotic depletion (AD), aquatic ecotoxic (AE), cumulative energy demand (CED), carbon footprint (CF), damage to ecosystem quality (DEQ), ecotoxicity potential (EC), energy intensity (EI), eutrophication potential (EU), fossil fuel depletion (FD), freshwater ecotoxicity (FEc), freshwater eutrophication (FEu), freshwater aquatic toxicity (FT), fossil resource scarcity (FS), global warming (GW), human health (HH), human toxicity (HT), land footprint (LF), land use (LU), marine ecotoxicity (MEc), marine eutrophication (MEu), ozone depletion (OD), photochemical ozone formation (POF), process material intensity (PMI), process water (PW), resources metrics (RM), smog formation (SF), stratospheric ozone depletion (SOD), terrestrial acidification (TA), terrestrial ecotoxicity (TEc), water consumption (WC), water scarcity (WS).

It was observed that most of the tools are excel-based. Most of them only calculate the global warming potential. The focus on this category is understandable, as it is considered one of the most critical indicators, and most strategies and/or policies to mitigate the effects of climate are based on it, as the goals are expressed in terms of reduction in carbon emissions. Yet, other indicators are relevant, and some tools are being developed to address them, such as tools proposed by Famiglietti et al. [36] and Famiglietti et al. [37]. Some available tools are also starting to include other tools and methodologies, such as the LCA and economic evaluation proposed by Basbagill et al. [48]. Data sources vary and include emission factors recommended by international organisations such as the Ecoinvent database and the IPCC Emission Factors Database. Additionally, some tools use regional or country-specific data, limiting their applicability when used in other geographic areas.

Despite a protracted theoretical discussion on the simplification of LCA, few approaches and tools have been developed and proposed for the agri-food sector. Food products are not part of the scope of a significant part of the tools found in the literature, which are focused on the building [33–35,38] and energy [41,49,51] sectors. Only a few tools have been developed to conduct LCAs in agriculture [42,47]. Renouf et al. [42] developed a tool and framework to assess the impacts of sugarcane-growing practice alternatives. Briefly, this LCA tool focuses on 'cradle to farm gate' operations from farming inputs production to sugarcane harvesting and relevant impact categories, such as global warming, fossil depletion, eutrophication potential, water scarcity, etc. To validate the tool, the authors assessed a case study of actual practice changes in the Wet Tropics region of Australia. The results generated by this tool were consistent with those generated by past studies using LCA software. Al-Ansari et al. [47] created an integrated energy, water and food life cycle assessment tool to provide an environmental assessment of food production systems. However, the system boundary of this system is limited to the food production phase. As observed, these tools are either simple tools or have a limited scope.

Integrating agri-food processes within the incorporated databases of simplified LCA tools can be of fundamental importance for the agri-food products case studies. The REAMIT-LCA tool is publicly available online, has a user-friendly framework and can run in Microsoft Excel. Unlike previous tools developed for LCA, the REAMIT-LCA tool includes other impact categories besides global warming, such as fossil scarcity, land use, human toxicity and water consumption. Furthermore, it was developed in compliance with International Standard Organization's (ISO) 14040/14044 guidelines [52,53], applies characterisation factors from the ReCiPe method, focuses on different stages of the food supply chain and can be applied in different countries of North West Europe.

3. Methodology

3.1. The REAMIT-LCA Tool

This tool has been developed based on the work performed in the REAMIT project. This project was launched to support food companies in North-West Europe (NWE) to reduce food waste by applying existing innovative technologies, such as the Internet of Things (IoT) and Big Data [54]. IoT technologies have been identified as a potential breakthrough class of technologies to reduce food waste this decade [55–57]. Through testing and adaptation, these technologies enabled the continuous monitoring and recording of food quality and potential issues [8,58]. Through analytics, owners of 'food to be at risk of becoming waste' are provided with decision support options to minimise food waste, including redistribution to nearby customers [59,60]. The project focused on fruits, vegetables, meat and fish, which are wasted in large quantities. The supply chain included farms, packaging sites, food processors, distribution, logistics, wholesalers and retailers. The project was carried out in Ireland, Germany, France, Luxembourg, the UK and the Netherlands due to the interconnected food supply chains and massive food waste in these countries [54].

The REAMIT project observed that there was demand among its partners, food product manufacturers, for a tool providing insight into the environmental performance of their products. This demand arose from a desire to improve the environmental profile of products across the product chain. The food supply chain is a very diverse sector comprising manufacturers specialised in a wide range of complex food products [61,62]. In many cases, the results of existing generic LCAs tools cannot be translated into the food supply chain practice [22]. Therefore, it was essential for the tool to be adaptable, allowing the users to model and analyse their specific product system. The tool, which was named the REAMIT-LCA tool, was developed as a joint venture by researchers from a variety of organisations and food companies and is available to companies without fees.

It contains LCA information on the processes in each phase of the food production chain and provides a life cycle framework to help evaluate diverse categories of food products in a consistent manner. The user constructs a product's life cycle by selecting the relevant food materials and, subsequently, the appropriate production process(es) per life cycle phase. The tool focuses on 12 different impact categories to offer a comprehensive view of the potential environmental impacts of the organisation under analysis. With the tool, the company can gain insight into its products' life cycles and the contribution of company-specific production processes within the entire life cycle. It can also be used to develop strategies to reduce the environmental impacts associated with food waste production and for food companies to evaluate their processes and make necessary improvements at an early stage of development.

The REAMIT-LCA tool is a spreadsheet-based, stand-alone model operating in Microsoft Excel through which the user can navigate, and it is compatible with both PC and Mac versions of Excel. The tool is available in the Supplementary Material. Before starting, for security reasons, the "Trust Center" settings in Microsoft Excel must be set to allow needed Visual Basic for Applications (VBA) code to execute. Click the "Enable Content" button next to the security warning message to open the tool's main Menu dialogue box. The tool is organised in separate sheets where users can check and adjust the data to fit their own processes. It follows the four phases of the LCA methodology, according to ISO 14040/14044 [52,53]. The LCA tool's general structure, including the life cycle stages of the food supply chain, can be seen in Figure 1. The methodological framework and the Excel-based tool will be described in the sections below.

3.1.1. Goal and Scope

The tool is recommended for food producers, food supply chain companies (processing and logistics), local authorities, academics and digital technology providers to explore the problem of food waste and the solutions to achieve more sustainable food systems. In addition, it captures the entire food supply chain (from cradle-to-grave) and contains information on a wide range of materials, production processes of various food manufacturing phases, packaging materials, end-of-life treatments and transportation modes. The user can construct the entire life cycle by selecting the appropriate processes per life cycle stage. The life cycle stages considered by the tool are shown in Figure 2.

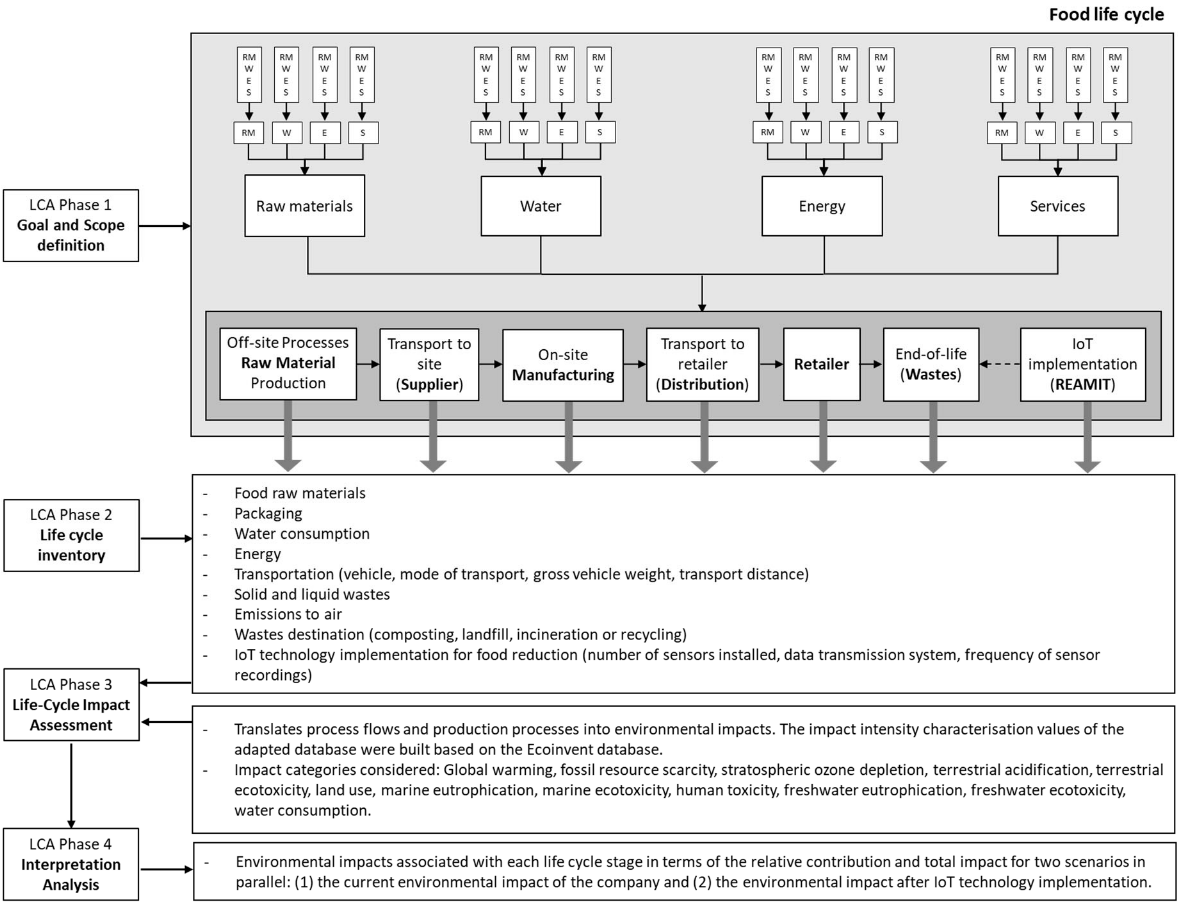

Figure 1. General structure of the LCA tool, including the life cycle stages of the food supply chain.

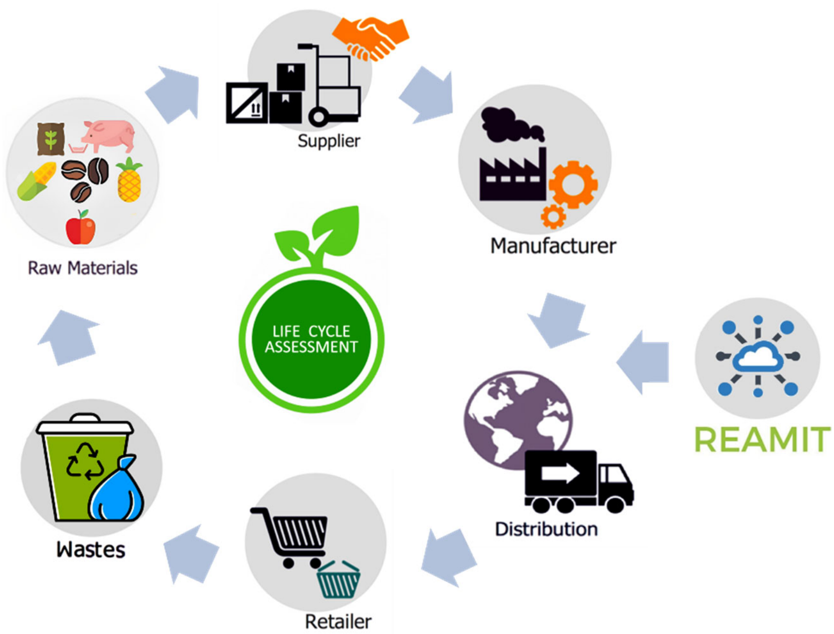

Figure 2. Life-cycle stages considered in the REAMIT-LCA tool.

The system boundary encompasses seven stages: raw materials, supplier, manufacturing, distribution, retail, wastes and REAMIT technology. The raw material's general scope includes acquiring an initial set of food products. More than 60 food products were included in the tool database and were organised into four categories: (i) cereals, leguminous crops and oil seeds, (ii) vegetables, roots and tubers, (iii) fruits, and (iv) animal products. The supplier stage includes raw materials transportation from the supplier to the food company under analysis. It allows the user to select between different types of vehicles, modes of transport and gross weight.

In the manufacturing stage, it is possible to include some inputs from the food manufacturing process, such as water consumption, energy (including electricity and fuels), and packaging materials. Some output emissions to air and water are also included in this stage. Solid waste generation, including packaging materials and food waste, were organised in a specific stage. The distribution consists of product transportation from the food company to retail. The inputs included in the retail consist of energy consumed during food storage.

The tool is general and should be adapted to each food company, i.e., each company can fill the stages present in their life cycle and disregard the unnecessary stages. The functional unit of the reporting results will refer to the amount and nature of food products provided by the food company over the reporting interval. In this case, the functional unit is the sum of all products included in the distribution stage and allocation between products is not available in this tool. The reporting interval is recommended to be one operation cycle of the food company, i.e., one year is the preferred option.

In the tool, the goal and scope worksheets include: (1) the menu with the links for all the stages of the food chain that can be analysed using this tool and (2) a more information worksheet that provides the author list, a brief user guide containing the purpose of the project and some specifications of the tool, the terms of use and a tutorial video.

3.1.2. Life Cycle Inventory

The food supply chain life cycle inventory worksheets include all essential inputs and outputs that need to be filled to run the tool and generate results. General and pathway-specific assumptions may be changed on this worksheet. Since the REAMIT-LCA tool is designed for food companies, users can either complete the product's entire life cycle (seven stages) or investigate one specific production phase (e.g., distribution).

Users start selecting the food raw material item of interest and the appropriate weight. By changing the values of consumption, the figures on the results worksheets will update automatically. The tool does not calculate any material quantities. The user should perform calculations before modelling the food materials in the tool. It should be noted that quality data is crucial in the life cycle assessment methodology. In this sense, the highest possible level of detail is required. In addition, the user should document any assumptions that go into the calculations.

If the user intends to evaluate the transportation performance in the distribution stage, additional information should be provided using the drop-down lists included in the tool. In this stage, the user must select the appropriate transportation specifications under three forms—train, ship, and road vehicle (lorry). In addition, the transportation distances (in km between origin and destination) associated with the food materials used by the company should be provided, as well as the mode of transport (freezing, cooling, or none) and, if applicable, gross lorry weight.

In the manufacturing stage, all inputs consumed for food production must be added, including consumption of water, energy and packaging materials. Some inputs have regionalised characterisation factors, such as electricity consumption; therefore, the user must select in which country the consumption is made. Data selected for inclusion in the tool reflect national averages and do not reflect regional variation in practice. A list of outputs that may occur during the manufacturing step is also provided, such as emissions to air and water. Solid waste was organised in a different worksheet, including all solid waste produced in the previous stages. In this stage, it is necessary to define the final destination of each solid waste using the drop-down menu, for example, composting, landfill, incineration or recycling. Some final destination options are limited to specific scenarios due to database limitations.

The REAMIT stage is treated as a sensitivity analysis case of the LCA methodology, where temperature and humidity sensors and a Big Data server are hypothetically implemented in the company to monitor food quality and prevent its degradation along the supply chain. In this stage, it is possible to simulate the incorporation of temperature sensors in the company's system, selecting the number of sensors planned, the data transmission system (GSM-based or LoRa) and the frequency of sensor recordings per hour, which will influence the amount of data stored in the Big Data cloud server and consequently the electricity allocation. Credit is given to the system for avoiding additional food production to cover the losses and all related upstream activities avoided, according to the amount and type of food avoided.

The sensors considered in the REAMIT-LCA tool are composed of a printed circuit board (PCB), flexible copper cables, a temperature/humidity probe, lithium batteries, stainless steel screws and a housing top and bottom made with plastic. Installation of the sensor is performed manually, and no environmental burden was assumed. The life span of the sensor considered in this study is 10 years [63]. The sensors transmit the temperature/humidity information to a Big Data Server, and the user can select the mode of transmission, i.e., via a GSM-based (4G) or LoRa network. In this study, sensors operating through a GSM-based mode are composed of four lithium batteries that provide energy to support temperature/humidity analysis and data transmission. Therefore, no other electricity or power is required during the use phase of this type of sensor. According to the supplier, the batteries last about 4 years, considering one recording every 20 min. However, the field testing showed that the lifetime is 87% lower. The complete inventory data of raw materials, manufacturing, use, and end-of-life were described in da Costa et al. [64].

On the other hand, sensors operating through a LoRa network have a lower power consumption and require only two batteries. According to the supplier, LoRa sensors batteries last around 4–6 years, considering one measurement every 20 min. In this case, additional digital technology is required to transmit the data to the Big Data Server, as many countries still do not have a countrywide LoRa network. Therefore, it is necessary to integrate a gateway connecting two networks with different transmission protocols. In this scenario, it was considered that the gateway operates 24 h per day and has a power consumption of 7W. The only exception is the sensor that operates in the Netherlands, as KPN deploys the LoRa IoT network across this country and sensors work without an additional gateway.

The data is transmitted to the server, and alerts are sent when the temperature exceeds an acceptable limit. This alert helps the company fix any malfunctioning of the fridge/freezer before the stored items go to waste due to temperature fluctuations. The Big Data Server comprises one unit of computer equipment, a redundant power supply, processors and storage drives with a total capacity of 3.7 TB. The estimated electricity consumption of the server is 1152 kWh per month. To allocate the electricity consumption, it was considered that each row of data generated per recording occupies around 87 bytes in the server.

The database worksheet contains a list of materials used in the food supply chain (e.g., food products, packaging, water, fuels, electricity, etc.) and associated characterisation factors used to perform the environmental impact estimation, as well as a list with acronyms. The inventory data of raw materials production, water, energy and emissions due to transportation were taken from the Ecoinvent database [65]. Environmental impact data are specified for the unit database items. Therefore, the user cannot edit or delete default database items in this worksheet since it may affect the reference and the code in the model's background. For each input and output, there is a specific cell with calculations in the worksheet life cycle impact assessment (LCIA); the methodology will be explained in the section below.

3.1.3. Life Cycle Impact Assessment Methodology Applied in the Tool

This section provides a summary of the LCIA methodology structure to give the user a quick overview of the model's main features used in the REAMIT-LCA tool. It follows the computational structure of the life cycle assessment proposed by Heijungs and Sangwon [66]. In short, the LCA principle can be presented with three matrix equations. Equation (1) is used to translate process data into a production system.

$$s = A^{-1} \cdot f \tag{1}$$

where s is the scaling vector which describes the necessary intensity of production processes, A is the database of process flows and production processes, and f is the final demand vector or the output desired from the system. The scaling vector calculated from the first equation is used to determine the intensity of emissions from unit processes (Equation (2)).

$$g = B \cdot s \tag{2}$$

where g is the emission inventory vector describing the emissions caused by the whole system, and B is the unit emission matrix (a database of process values).

Equation (3) translates emissions into environmental impacts (e.g., CO_2 emissions into climate warming potential).

$$h = Q \cdot g \tag{3}$$

where h is a vector representing the environmental impacts caused by the system and Q is a characterisation matrix (a database of impact intensity characterisation values).

The model follows the International Standard Organization's (ISO) 14040/14044 guidelines [52,53]. The characterisation factors and the impact categories used in this tool are those of the ReCiPe method at the midpoint level following a hierarchical perspective [67]. The following environmental impact categories were included in the tool: Global warming (GW), fossil resource scarcity (FS), stratospheric ozone depletion (SOD), terrestrial acidification (TA), terrestrial ecotoxicity (TEc), land use (LU), marine eutrophication (MEu), marine ecotoxicity (MEc), human toxicity (HT), freshwater eutrophication (FEu), freshwater ecotoxicity (FEc), water consumption (WC).

3.1.4. Interpretation

Having filled the inventory of relevant processes in the previous sections, the user can view the environmental results on the LCA results worksheet by clicking the "Next" button available in the top right corner of the tool. The charts built in this worksheet show the environmental impacts associated with each life cycle stage (raw materials, supplier, manufacturing, distribution, retail, wastes) for two scenarios in parallel: (1) the current environmental impact of the company and (2) the environmental impact after IoT technology implementation (REAMIT strategy). Results are shown for the 12 impact categories in terms of the relative contribution of each stage of the supply chain (Figure 3), while a table shows the absolute values of each impact category results per stage.

These graphs can support the user in visualise the life cycle stages that substantially influence the overall environmental impact of the organisation under consideration. To better comprehend the causes behind the environmental impacts, the user can explore the details of the numerous process contained in those life cycle stages, which can then be used to identify viable solutions to reduce those impacts. The user can find further explanations about how to interpret LCA findings in Zampori et al. [68]. To select and copy an existing graph in the results, click the "Copy" button and then click the "Paste" button in another document. Save the file and exit the tool.

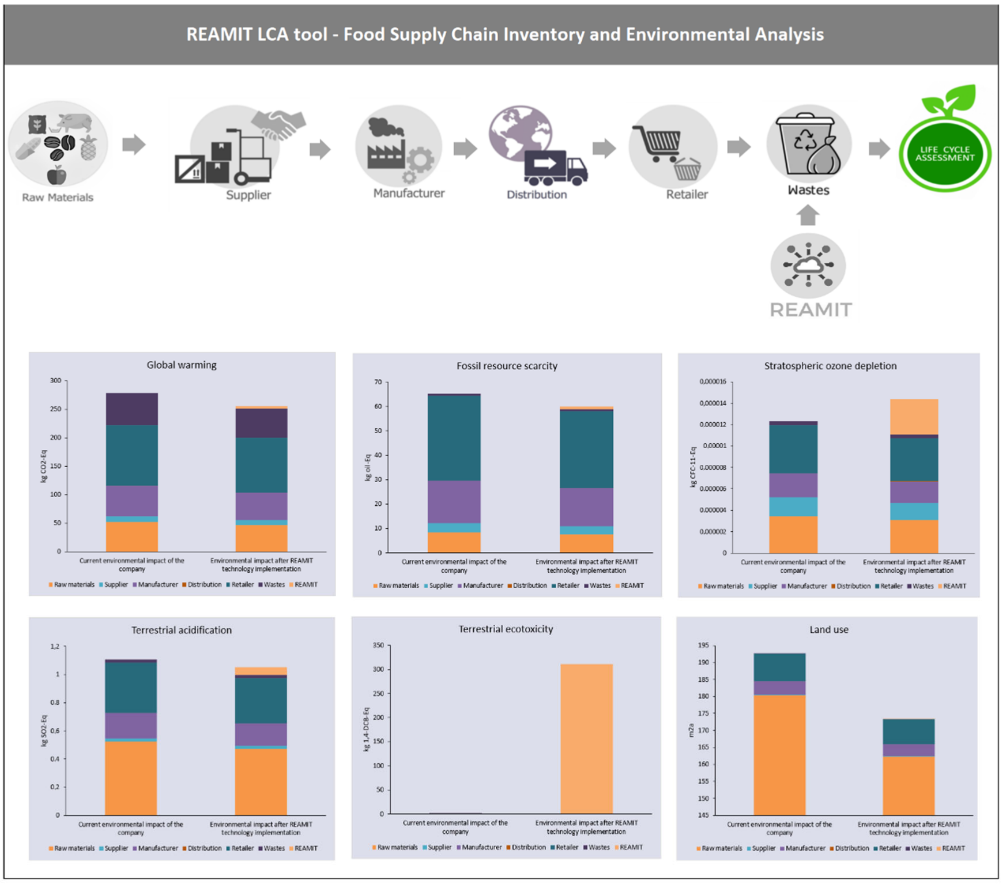

Figure 3. Example of results given by the REAMIT LCA tool.

3.1.5. Tool Assumptions and Limitations

The use of results is designed to provide insight into the life cycle of a company's food products, as well as the contribution of company-specific production stages within the entire life cycle. It can also be used for assessing the environmental impacts of improvement options. However, caution should be taken when interpreting the LCA results. To use the REAMIT-LCA tool, knowledge about the manufacturing phases of food products and LCA interpretation is recommended. The user is responsible for the selection of the appropriate inputs and outputs. The tool does not check data quality. The user is responsible for reviewing the completeness, consistency, and accuracy of the data related to all items (type of food products, quantity, etc) used in the analysis.

In addition, the tool is built assuming that each alternative's functional unit is the same. The definitions of the functional units or the alternatives should be equivalent if the study's objective is to compare alternatives. When comparing different options, it is the user's responsibility to choose the proper functional unit. In addition, the tool does not check for improper comparisons or does not provide warning message notices. The tool will still present the results for any analyses the user sets up, but the results may be unreliable or inaccurate. Therefore, it is the user's onus to make sure that the proper comparisons are made.

The tool supports only specific measurement units, mainly from the International System of Units. If the units the user needs to include are different from what the tool can handle, the user must convert them to the ones compatible with the tool before entering the data. For example, pounds (lbs) are not supported by the tool. The user would need to convert that to other units of mass compatible with the tool (e.g., kilogram) before adding the data.

Avoided impacts due to food waste reduction were modelled in the tool through the system expansion by substitution [69]. Credit was given for avoiding additional food production and all related upstream activities, such as collection, transport and energy required to store the food. However, time frame mismatch was not considered, so avoided emissions estimates must be interpreted cautiously. In addition, the consumption phase is not included in the system boundaries nor the impacts due to infrastructure establishment.

3.2. Validation: Case Study of Food Manufacturing in the UK

3.2.1. Definition of Goal and Scope

The goal of the assessment is to assess the potential environmental impacts of a food manufacturing company located in the UK that prepares frozen food meals for customers via vending machines in which microwave ovens are integrated for heating the food. This innovative hot-cooked food business creates meals that combine multi-cultural traditions, responsibly sourced ingredients free from added preservatives, colouring or flavourings, and packaged in environmentally friendly recyclable and biodegradable packaging. The study focuses on one facility where the entire operations occur.

The functional unit was defined as the total production of frozen food meals during one year of operation, i.e., 9900 kg of frozen food boxes, between January and December of 2021 (reference period). Two scenarios were built to determine the potential environmental savings due to the implementation of a monitoring system based on IoT technologies. Scenario A represents the baseline and includes the processes associated with the food company. Scenario B follows the same processes as scenario A but includes the IoT technologies used to monitor the food quality conditions in the cold storage process during manufacturing.

The system boundaries are illustrated in Figure 4 and follow a cradle-to-grave approach. The processes include raw materials acquisition from the supplier and transportation to the factory, manufacturing (vegetable, meat, poultry and dry ingredients preparation, cooking, finish goods and storage), distribution, retail and solid wastes treatment. Scenario B also comprises digital sensors for measuring the specific parameters, the Big Data server and the food waste avoided. Both scenarios exclude food raw materials production and consumption.

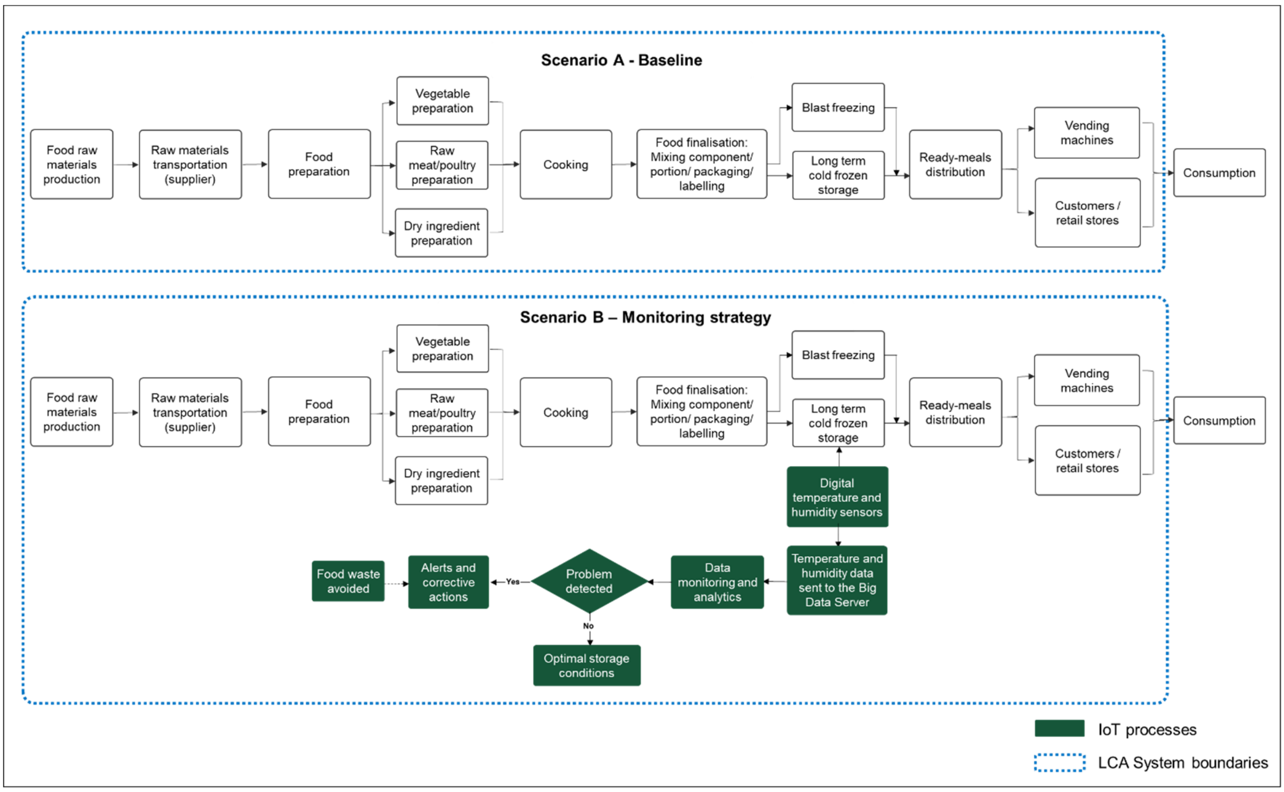

Figure 4. Schematic representation of the system boundaries. (**A**) refers to the baseline scenario, and (**B**) refers to the IoT monitoring strategy implementation.

3.2.2. Life Cycle Inventory

The direct activities data was collected through company interviews. The company uses locally sourced raw materials (vegetables and meat) to prepare their ready-meal products. Fresh vegetables (beans, pepper, etc.) are usually purchased from suppliers located within a radius of 100 km. The vegetables are manually washed, diced, and immediately frozen in blast freezers for 3 h. After the blast-freezing stage, the vegetables are stored in a chest freezer. Rice and other dry foods are stored in the dry room.

Meat (chicken and sheep) is purchased from local suppliers located 30–50 km from the factory. It was considered the average distance (mean: 40 km) for calculation purposes. The meat is transported fresh in temperature-controlled vehicles and stored in fridge storage as soon as it arrives at the production site. The meat is left marinating with oil and spices for two days in the fridge before cooking. Once the food is cooked, it is transferred into a blast freezer to refrigerate the meals for approximately 3 h. The food is weighed and manually packaged in paper boxes of 330 g each. After this process, the boxes are transferred to long-term storage in a cold room with temperatures from −18 to −24 °C. Although cooking is a straightforward method, it involves some waste, nearly 8–10%. For modelling purposes, it was assumed that the food waste would be sent to a municipal sanitary landfill for further management.

The food can be delivered directly to the consumer's home (online shopping) or sent to vending kiosks. The boxes are transported frozen over an average distance of 100 km in refrigerated lorries. Table 2 presents the transportation profile of the company under analysis.

Table 2. Food company transport profile.

Food Group	Inputs	Unit	Transport Distance	Vehicle	Mode of Transport	Gross Lorry Weight
Cereals, leguminous crops and oil seeds	Bean Rice	km km	100 100	Lorry Lorry	None None	3.5–7.5 t 3.5–7.5 t
Vegetables, roots and tubers	Pepper	km	100	Lorry	None	3.5–7.5 t
Animal production	Chicken Sheep	km km	40 40	Lorry Lorry	Freezing Freezing	3.5–7.5 t 3.5–7.5 t
Product	Food boxes	km	100	Lorry	Freezing	3.5–7.5 t

Currently, the company has 9 installed vending machines located at train stations, universities, and hospitals in London. Each vending machine can hold up to around 75 boxes of prepared food, and the stock is replenished when it goes below 25 packs (depending on the train station, it can take a few days). The retail kiosks are fitted with an integrated microwave, enabling the consumer to heat the food upon purchase. The product expiry date is 18 months from the production date when it is kept at a controlled temperature. However, the company is ensuring that no product spends more than 6 months in the freezer utilising the first in first out (FIFO) approach. The life cycle inventory of scenario A is shown in Table 3 and represents the total production of food boxes per year.

Table 3. Life cycle inventory per reporting flow.

Unit Process	Value	Unit
Inputs		
Vegetable preparation		
Beans	1200	kg
Pepper	4800	kg
Water	38.1	m^3
Plastic bag	8.4	kg
Electricity consumption blast-freezing	561.6	kWh
Electricity consumption short-term storage	232.8	kWh
Meat preparation		
Boneless chicken	6480	kg
Chicken wings	6480	kg
Sheep	3840	kg
Electricity consumption blast-freezing	561.6	kWh
Electricity consumption short-term storage	1555.2	kWh
Dry ingredient preparation		
Rice	18,000	kg
Food finalisation		
Paper box	1000	kg
Electricity consumption long-term storage	1509.1	kWh
Retail		
Electricity consumption vending machines	77,760	kWh
Outputs		
Products		
Food boxes	9900	kg
Solid Wastes		
Food losses	891	kg
Plastic bag	8.4	kg
Paper box	1000	kg
Liquid Wastes		
Wastewater	38.1	m^3

In scenario B, 10 sensors were installed to monitor the temperature and humidity to ensure that frozen food and raw materials for preparing the food are stored at the right temperature in the frozen food manufacturer's factory. The sensors considered in the REAMIT-LCA tool transmit data via a GSM-based communication network every 20 min.

3.3. Sensitivity Analyses

Two sensitivity analyses were performed to understand the influence of some parameters on the environmental impact assessment results. A sensitivity analysis was made to assess the effect of the food waste avoided on the environmental impacts. Therefore, a hypothetical scenario was considered in which the IoT technologies avoided wasting 2% of food products. In the tool, the environmental burdens avoided are modelled through the system expansion by substitution [69]. Credit is given to scenario B for avoiding additional food production to cover the losses in scenario A and all related upstream activities, such as transport and energy required to store and distribute the food.

The second analysis evaluated the influence of the number of vending machines on the environmental impacts. Currently, the company has 9 vending machines located at train stations, universities and hospitals in London. However, this number is expected to increase to 20 vending machines in the next 10 months. Therefore, this analysis evaluated the consequence of increasing electricity consumption due to the installation of new vending machines.

4. Results and Discussion

4.1. Environmental Impact Assessment and Hotspot Analysis

Figure 5 presents the relative contribution of each life cycle stage to the total impact obtained for the food company in the baseline scenario. Food raw materials production is the main hotspot of nine impact categories, global warming, terrestrial acidification, terrestrial ecotoxicity, land use, marine eutrophication, human toxicity, freshwater eutrophication, freshwater ecotoxicity and water consumption, contributing to 70–98.9% of the total impact in those categories.

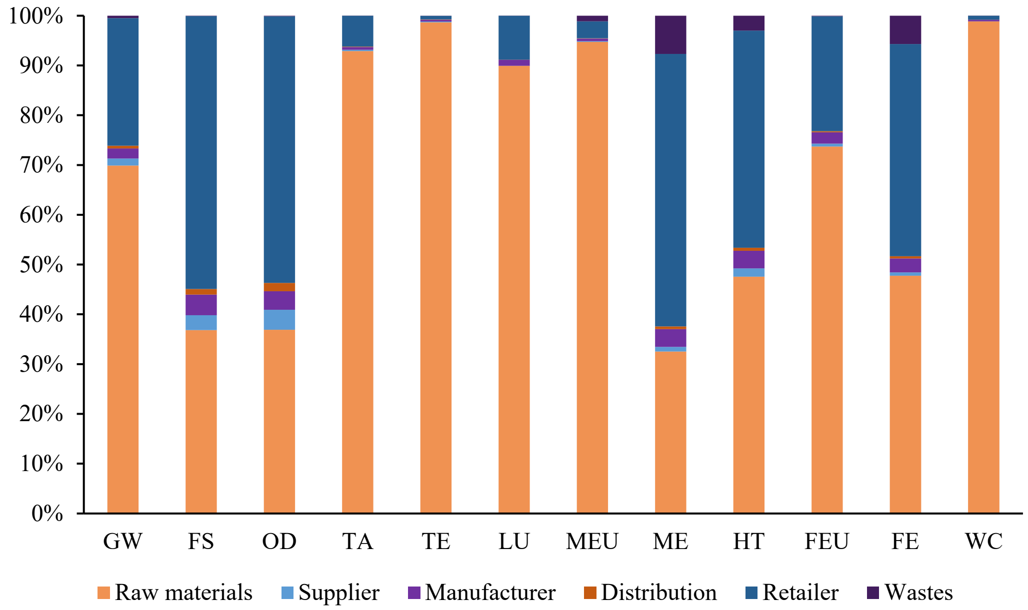

Figure 5. Relative contribution of each supply chain stage to the company's environmental impact.

Sustainable food production, therefore, must be prioritised to mitigate climate change, reduce water stress and pollution and restore lands to grasslands. The production of livestock (animals raised for meat, dairy and seafood products) contributes to emissions in several ways, for example, by producing methane through their digestive processes (enteric fermentation) [70–72]. Manure and pasture management, land use change, production of crops for animal feed, and fuel consumption also fall into this category [70,73]. Crops and vegetable production are mainly responsible for direct emissions, including elements such as the release of nitrous oxide from fertilisers and manure application, methane emissions from rice production, and carbon dioxide from agricultural machinery [74–76].

Water consumption and freshwater eutrophication are also valuable indicators of food production's environmental impact, as 70% of global freshwater withdrawals and 78% of global pollution of waterways are caused by agriculture [77]. The pollution of water bodies and ecosystems with excess nutrients is a major environmental problem [78,79]. Agriculture can represent the runoff of excess nutrients into the surrounding environment and waterways, which affect and pollute ecosystems with nutrient imbalances, especially from nitrogen and phosphate [80,81].

Contrary to many other areas of energy production where there are prospects for expanding the use of low-carbon energy, it is less obvious how agriculture may be decarbonised [82]. In agriculture, it is necessary to use inputs such as fertilisers to meet the rising demand for food, and it is impossible to stop animals from producing methane. Some solutions to decrease those impacts can include diet changes, food waste reduction, improvements in agricultural efficiency, and technologies that make low-carbon food alternatives scalable and affordable [83–85].

For the impact categories fossil resource scarcity, stratospheric ozone depletion and marine ecotoxicity, the retail stage was the main hotspot, representing 53.6–54.8% of the total impact. The retail stage consumed a high amount of electricity due to the vending machines used to store and sell the food boxes of the company. The electricity consumed during the retail stage was also relevant for human toxicity and freshwater ecotoxicity impact categories, contributing to around 42.6–43.6% of the total impact.

In this company, the effect of transportation (supplier and distribution stages) was not significant for any of the impact categories under analysis. Many could assume that eating locally is key to a low-carbon diet [86]. However, eating locally would only have a significant impact if transport was responsible for a large share of food's final environmental impact, but this is not the case for most foods. The greenhouse gas emissions from transportation make up a tiny amount of the emissions from food and what is consumed is far more important than where the food travelled from [87–91]. Overall, animal-based foods tend to have a higher footprint than plant-based; whether they are grown locally or shipped from the other side of the world matters very little for total emissions [92,93]. Therefore, eating less meat or switching to lower-impact meats such as chicken or eggs is the most effective way to reduce the environmental footprint [94–96].

Figure 6 presents the relative contribution of the REAMIT IoT technologies to the company's total impact disregarding the potential food avoided.

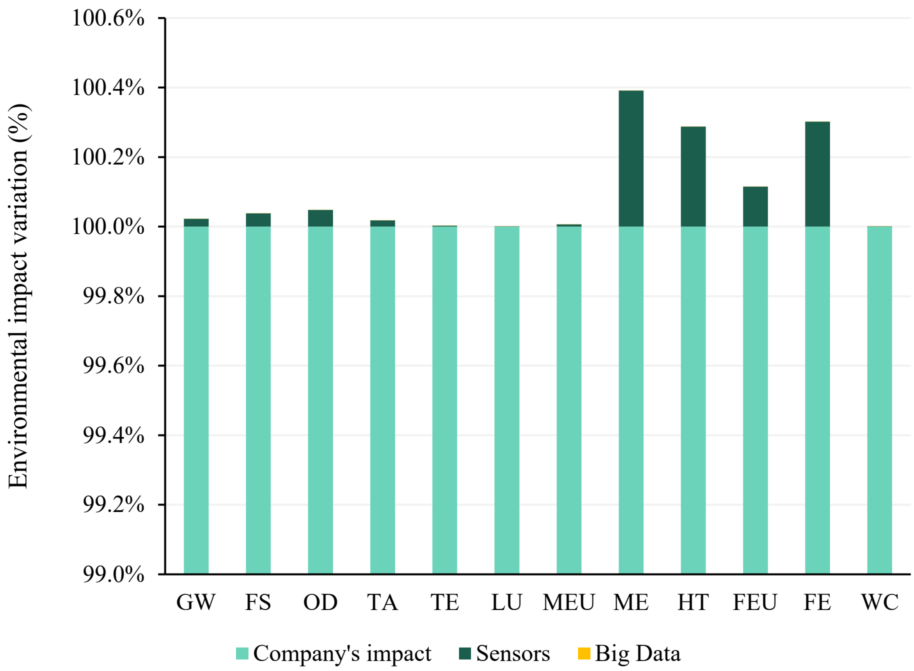

Figure 6. Relative contribution of the REAMIT IoT technologies implementation to the total impact of the food company (scenario B).

Although integrating IoT technologies to monitor temperature/humidity conditions can have many advantages, the environmental implications may also be analysed. In this study, it is possible to observe that this integration had little to no adverse effects on the company's overall impact. The contribution of the IoT technologies implemented in this study, including 10 sensors and a Big Data server to store and control the data, achieved a maximum impact contribution of 0.4% for the marine ecotoxicity category. Despite the impacts associated with implementing IoT technologies in this system, mainly due to components used to produce the sensors [97], there are still potential tangible benefits that should be considered. For example, a reduction in the environmental impact can be expected if part of the food waste is avoided due to implementing these technologies, which can equilibrate the additional impacts. The surplus food production to compensate for the waste may result in severe environmental and societal issues [98–100]. Therefore, to prevent food waste and the environmental impact related to this waste, it is advised to employ monitoring systems/technologies as the one suggested in this study. The potential avoided impacts resulting from the decreased amount of food waste due to implementing IoT technologies are shown in Section 3.2.

4.2. Sensitivity Analysis

Figure 7 presents the total impact obtained for the first sensitivity analysis, i.e., the influence of the monitoring IoT technologies on the environmental impacts considering a 2% reduction in food waste generation.

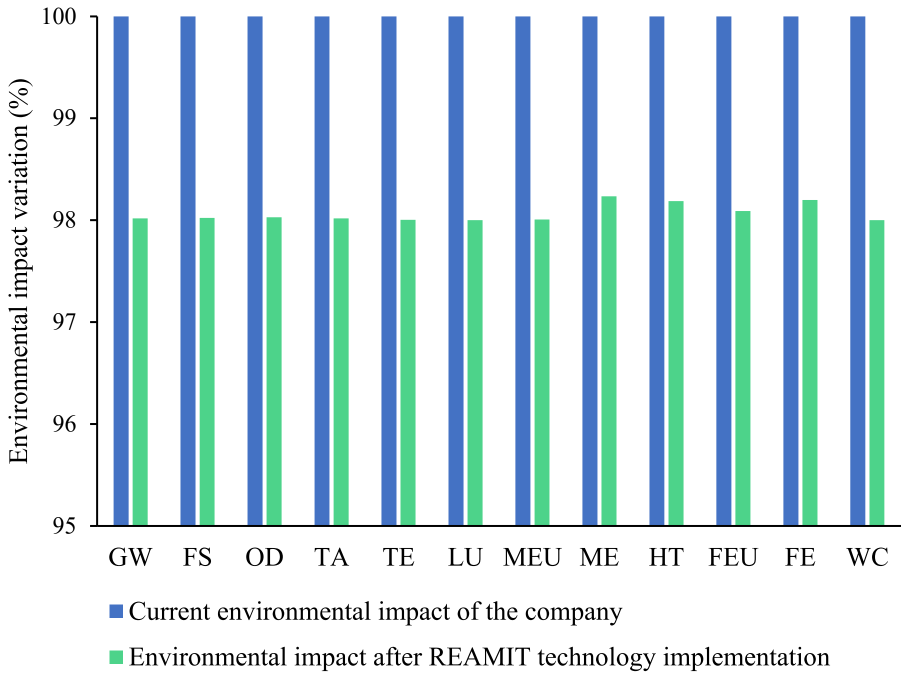

Figure 7. Results of the sensitivity analysis: effect of food waste reduction due to REAMIT technology implementation.

Food waste is linked to various adverse environmental effects [99,100]. When food is discarded, all the resources necessary to prepare, transport, process, and store it are also wasted. In addition, the environmental impact increases when food is discarded in the later stages of the supply chain because we also need to consider the energy and natural resources consumed in each stage [62]. Considering a food waste reduction of 2%, it is possible to decrease the environmental impacts from 1.7 to 2.1% (Figure 6). In the global warming category, this reduction represents the prevention of 2304 kg of CO_2eq per year. In addition to the environmental impacts avoided, reducing and preventing food waste can enhance food security, improve productivity and economic efficiency and promote resource and energy conservation [100,101]. In this scenario, additional food production would not be necessary to compensate for these losses. Therefore, contributing to the reduction of all downstream impacts observed during the food supply stages under analysis.

However, caution must be taken when affirming the positive effect of IoT technologies in reducing food systems' environmental impacts, as this can be a single case. Implementing IoT technologies in any system causes resource use, and if food waste reduction is not considered, the total impact of the organisation tends to increase. Furthermore, even considering the reduction, the overall balance of impacts depends on the amount of food avoided. The second sensitivity analysis in Figure 8 shows the influence of increasing the number of vending machines in the retail stage.

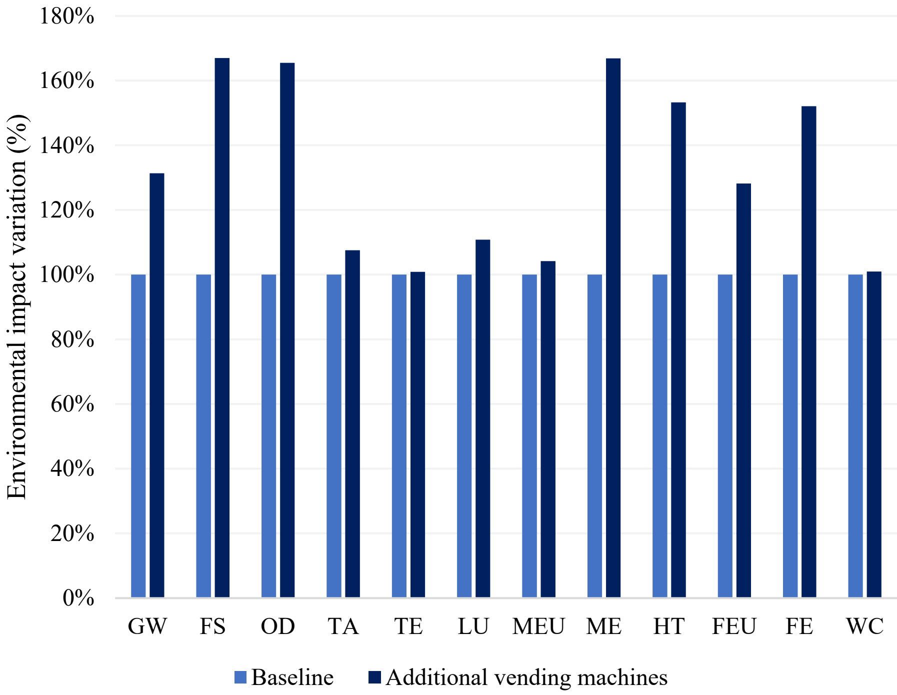

Figure 8. Results of the sensitivity analysis: effect of increasing the number of vending machines.

It was observed that the main categories negatively affected by this proposal were global warming, fossil resource scarcity, stratospheric ozone depletion, marine ecotoxicity, human toxicity and freshwater eutrophication and ecotoxicity. For fossil resource scarcity, stratospheric ozone depletion and marine ecotoxicity, the environmental impact increased by more than 60%, suggesting an environmental risk from using additional vending machines due to the high electricity consumption.

The environmental impacts related to electricity consumption are intrinsically linked to the electricity mix supplied in the country. In 2020, the electricity supplied in the UK came from 41% fossil-fuelled power (almost all from natural gas), 30.6% from renewable energy (including wind, solar and hydroelectricity), 16.1% from nuclear power and a small percentage from imports [102]. To the extent that more renewable energy sources like wind and solar are used to generate electricity, the total environmental impacts associated with using electricity could be reduced. However, it might take several decades for that to happen [103].

5. Conclusions

This paper describes an initial theoretical contribution to quantifying environmental effects related to food supply chains by integrating relevant insights from life cycle assessment science and sustainability theories. The result of this integration is a proposal for a prescriptive tool which explains how food waste can be addressed from an environmental point of view and applied to real-world problems. The excel-based tool is recommended for food producers, food supply chain companies (processing and logistics), local authorities, academics and digital technology providers. In addition, it has been populated with national average data (or closest equivalent) of six countries, i.e., Ireland, Germany, France, Luxembourg, the UK, and the Netherlands, due to the amount of interconnected food supply chains and huge food waste in these countries.

The tool is fully functional for different stages of the food life cycle, raw materials, suppliers, manufacturing, distribution, retail, and waste treatment. The REAMIT technology stage is treated as a sensitivity analysis where sensors and a Big Data server are used to reduce food waste. Credit was given to the system for avoiding additional food production to cover the losses and all related upstream activities avoided. The food consumption stage was not included, but the tool has been developed such that this stage can be added to the development of future modules. Using the developed LCA tool would assist food companies in understanding the benefits and drawbacks of moving toward sustainable food practices. Furthermore, using the tool can provide further insight into stages of the food supply chain that produce emissions that could be managed or minimised.

The tool was validated through a case study of a food manufacturing company in the UK that implemented IoT technologies to monitor environmental conditions, such as temperature and humidity, during the manufacturing stage. The tool proved to be suitable for determining environmental impacts and savings of the company under analysis and for understanding the environmental performance of their stages through a comprehensive framework. The LCA results provided by the tool showed that food raw materials production is the main hotspot of nine impact categories. For the impact categories fossil resource scarcity, stratospheric ozone depletion and marine ecotoxicity, the retail stage was the main hotspot.

The contribution of the IoT technologies to the company's total impact, including installing ten sensors and using a Big Data server, increased the company's impact by around 0.4%. However, it is expected that employing these monitoring technologies would prevent food waste generation and the associated environmental impacts observed during the food supply stages under analysis. Considering a food waste reduction of 2%, it is possible to decrease the environmental impacts by up to 2304 kg of CO2eq per year in the global warming category. However, the precise amount of food waste avoided due to IoT technologies implementation in this company is still under assessment, and further analysis is required. The sensitivity analysis regarding the performance of new vending machines showed that the impacts in the fossil resource scarcity, stratospheric ozone depletion and marine ecotoxicity categories increased more than 60%, suggesting an environmental risk due to the high electricity consumption.

Therefore, the results of this paper provide evidence of the benefits of using this tool to explore the problem of food waste and the solutions to achieve more sustainable food systems. The tool allowed the quantification of environmental effects such as climate change, resource use and other categories of impact. Through this holistic view, the user can identify which life cycle stage of the food company is the most resource, energy and impact intensive. This can help the user to identify the hotspots that need improvement in their operations or supply chains. Evaluating the supply chains can also help the user to determine which materials have the highest environmental impact. For foods with a blend combination of several ingredients, the REAMIT-LCA tool allows the comparison and testing out alternatives to make tactical sustainability decisions.

Further development of the tool in terms of functionality and adding food products and production processes is necessary. To make the REAMIT-LCA tool suitable for a larger group of companies, it is essential to extend beyond the current food product database to meet future users' specific needs. Additionally, the tool should be expanded with an option to select pre-defined inputs, from which the user can work. This will allow people in the food industry with little knowledge of LCA to use the REAMIT-LCA tool.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/su15010718/s1, Video S1: REAMIT-LCA TOOL USER MANUAL.

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Abbreviations

AC, acidification potential; AD, abiotic depletion; AE, aquatic ecotoxic; CED, cumulative energy demand; CF, carbon footprint; CO_2, carbon dioxide; DEQ, damage to ecosystem quality; EC, ecotoxicity potential; EI, energy intensity; EU, eutrophication potential; FD, fossil fuel depletion; FEc, freshwater ecotoxicity; FEu, freshwater eutrophication; FIFO, first in first out approach; FT, freshwater aquatic toxicity; FS, fossil resource scarcity; GW, Global warming; HH, human health, HT, human toxicity; ISO, International Standard Organization; IoT, Internet of Things; LCA, Life Cycle Assessment; LCIA, Life Cycle Impact Assessment; LF, land footprint; LU, land use; MEc, marine ecotoxicity; MEu, marine eutrophication; NEW, North West Europe; PCB, printed circuit board; PMI, process material intensity; PW, process water; RM, resources metrics; SF, smog formation; SOD, stratospheric ozone depletion; TA, terrestrial acidification; TEc, terrestrial ecotoxicity; VBA, Visual Basic Applications, WC, water consumption; WS, water scarcity.

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