Gowreesunker and Tassou *Energy, Sustainability and Society* (2015) 5:7
DOI 10.1186/s13705-015-0035-y

Energy, Sustainability and Society
a SpringerOpen Journal

ORIGINAL ARTICLE Open Access

Approaches for modelling the energy flow in food chains

Baboo Lesh Gowreesunker* and Savvas A Tassou*

Abstract

Background: The heavy reliance of the global food chain on the use of fossil fuels and anticipated rise in global population threatens future global food security. Due to the complexity of the food and energy systems, the impact of adequate food, climate or energy policies should be carefully examined in a modelling framework which considers the interaction of the food and energy systems. However, due to the different modelling approaches available, it can be very difficult to identify which method best suits the required purpose.

Method: This paper presents the three main modelling approaches as 'top-down', 'bottom-up' and hybrids. It reviews different models under each category in terms of the practicality, benefits and limitations with reference to different past studies.

Results: Bottom-up approaches generally tend to provide high levels of details, but their specificity to particular products/processes detracts their application to holistic models. On the other hand, top-down approaches consider the holistic aspects of the food chain, but the limited level of disaggregation prevents the identification of energy and environmental hot-spots. As a result, hybrid models seek to reduce the limitations of the individual approaches.

Conclusions: This paper shows that the choice of one modelling approach over another depends on a variety of criteria including data requirements, uncertainty, available tools, time and labour intensity. Furthermore, future models and studies have to increasingly consider the inter-dependence of implementing social, demographic, economic and climate considerations in a holistic context to predict both short- and long-term impacts of the food chain.

Keywords: Food and energy chain; Modelling approaches; Top-down models; Bottom-up models; Hybrid models

Background

Overall perspective

The Food and Agriculture Organisation of the United Nations (FAO) has expressed concern over the high dependence of the global food sector on fossil fuels and the projected 70% increase in current food consumption by 2050 due to the rise in global population (FAO [1]). The food sector accounts for 30% of the global energy consumption and 20% of global greenhouse gas (GHG) emissions, with a major contribution from fossil fuels (FAO, [1,2]). Developed economies such as the UK used approximately 18% of the total energy consumption for the food sector, which produced approximately 32% of the country's GHG emissions in 2011 [3]. The disparity in energy consumption is, however, significant between developed and developing countries, whereby the former use the majority of energy in processing and distribution, whilst the latter use energy mainly for retail, preparation and cooking (FAO [1]).

Due to increased use of depleting fossil fuel resources, the energy-food-climate nexus (FAO, [1]) has been found to be a crucial and complicated challenge for the planet. Energy, food and climate change are intricately linked such that actions taken or policies imposed in one area are very likely to have consequences in the other areas. The nexus can be summarised as follows: high usage of fossil fuels impacts the climate due to GHG emissions - the food sector is heavily dependent on fossil fuels and becoming even more so due to rise in global population - but fossil fuel reserves are depleting and climate change is expected to lower average agricultural yields (Lobell *et al.* [4]; Roberts *et al.* [5]). The scenario is therefore complex, and the Food and Agriculture

* Correspondence: lesh_g@yahoo.com; Savvas.Tassou@brunel.ac.uk
RCUK National Centre for Sustainable Energy Use in Food Chains, Brunel University, UB8 3PH, Uxbridge, Middlesex, UK

Organization (FAO [1]), the United Nations Environment Programme (UNEP [6]), the Clinton Global Initiative (CGI [7]), Grace Communications Foundation [8] and Mistry and Misselbrook [9] suggest that a reduced dependency on fossil fuels and an increased use of renewable energy technologies are imperative in an attempt to tackle this nexus.

Current barriers to adopting renewable energy technologies are mainly the high capital costs [10] and relatively low-energy efficiencies of some common systems (e.g. ≈3 to 20% for photovoltaic systems [11]). Although various governmental incentives are available, subsidies for renewable energy technologies worldwide are low, hindering their rapid adoption relative to fossil fuels [12]. Nonetheless, renewable energy systems are proving to be cost effective in countries where there is a heavy reliance on diesel electricity-generators and which have high fuel costs (WFP [13]). A study by Maggio and Cacciola [14] conveyed that although there is considerable uncertainty in the lifetime of fossil fuel reserves, the global production of oil will start declining by 2015, whilst gas and coal production will peak in 2035 and 2052, respectively. Historically, the prices of oil and food commodities have been interlinked (FAO [1,15]; Heinberg and Bomford [16]), but some studies also suggest that in the long run, the price of agricultural commodities have a higher impact on food prices than oil commodities ([17]; Lambert and Miljkovic [18]). This ambiguity in projections can be associated with the assumptions made and modelling approach used in the respective studies [19]. It is generally agreed, however, that due to the current intensive use of fossil fuels in the food sector, the uncertainties in fossil fuel energy availability and prices may threaten food security and affect political stability in the future (FAO [1,2]). It is therefore imperative that the impact of increased use of renewable energy technologies and the adoption of new more efficient technologies and energy supply systems on food security and supply chain sustainability be investigated further (FAO [1,20,21]).

Scope of this review

This review mainly targets readers interested in furthering their understanding with respect to developing models which study parameters influencing the energy and GHG emissions flows in product-specific, national and international levels of the food chain. It aims at providing an appreciation of existing models and hence informs the reader of the potential benefits and drawbacks of employing different modelling methodology. This review focuses on the food and energy/GHG chain, where the growing field of sustainable consumption suggested that food, home energy and transportation together form a large share of most consumers' personal impacts [22]. Food represents a unique opportunity for consumers to lower their personal footprints due to the high impact of food, high degree of personal choice and a lack of long-term 'lock-in' effects which limit consumers' day-to-day choices [23]. In this regard, Garnett [24] summarised three perspectives on tackling the food security and sustainability issues as: efficiency oriented; demand restraint and food system transformation, of which efficiency oriented measures have been advocated by governments and food industry decision makers [23,24]. As such, it is imperative to understand the flow of energy in the food chain in order to identify optimum energy efficient and sustainable pathways.

The food chain refers to the successive collection of the farming, food processing, distribution, packaging, retail, catering, household operations, waste and disposal industries, for different types of food products. The emphasis of this review is on the direct and indirect energy consumption and the associated GHG emissions of the overall food chain (or specific food product chains), where the definition of food products abides by the EU foodstuff law (Regulation (EC) No. 178/2002) which refers to foodstuff as 'any substance or product whether processed, partially processed or unprocessed, intended to be, or reasonably expected to be ingested by humans'.

As alluded in the 'Overall perspective' section, the linkages between the food and energy sectors are complex and depend on a variety of factors. The energy systems are currently at a crossroad whereby policies need to determine a balance between sustainable development, competitiveness and supply security [20]. As a result, the interactions involved in the food and energy system should be addressed in a quantitative manner and a modelling framework, so as to aid effective policy design [25]. These models can be employed to evaluate energy effective pathways and the implementation of renewable energy technologies to deliver the energy/GHG emissions reduction targets, at present and in the future. However, in order to allow the proper selection of a modelling method, it is important for the user to understand the particularities of the model. The rationale for this paper therefore relates to the need for examining the benefits and drawbacks of current modelling approaches employed in relation to the food chain and its products and to understand the degree to which such approaches capture the complex and nonlinear interactive behaviour of the food-energy components [25,26]. The modelling approaches considered in this review are 'bottom-up', 'top-down' and hybrid, and their appreciation will aid in identifying and consolidating new developments in food-energy/GHG models and in elaborating on the performances and discrepancies of current models. In this regard, the paper is divided into the different modelling methods in the 'Methods' section -

which describes the models, as well as various studies that employed these models; the 'Results and discussion' section then compares the models and presents and analyses the benefits and limitations of each approach and the 'Conclusion' section then concludes on the general progression of adopted modelling approaches in the literature and suggests future modelling pathways.

Methods

Bottom-up approach

Bottom-up approaches adopt a view of assembling the local disaggregated influences in order to determine the global impacts associated with a particular product, process, service or industry. It is a detailed approach and therefore requires compiling inventories of energy, environmental, economic and material inputs for the various processes. The following sections do not attempt at describing the technicalities of the modelling methods, but rather to depict the applicability, practicality and benefits/limitations of these methods.

Life cycle assessment (LCA) LCA refers to a product- or process-based analysis of the GHG emissions and energy consumption, usually employing a 'cradle-to-grave' approach. In the food chain, it considers all stages from the farming/agricultural process through to consumption and waste disposal [27]. This method has been deemed important to examine the intricacies attached to food products or systems, where a current dearth of data exists and where future research is crucial [24,28,29]. As LCA and life cycle inventory (LCI) studies are extensive and apply to particular regions, this section will explore studies related to the food chain in the UK. AEA group and partners report on the comparative LCA of seven food commodities procured for UK consumption through different supply chains (DEFRA report no. FO 0103 [30]). The analysis was performed with reference to primary energy use and global warming potential, with assumptions relating to agricultural yields, transportation, and uncertainties due to imports increasing the overall uncertainty of the study. Fisher *et al.* [31] adopted a cradle-to-retail approach to study the GHG and secondary energy impacts of UK groceries, with special emphasis on high sales-volume products. The food products include alcoholic drinks, ambient products (breakfast cereals, canned food etc.), bakery, dairy, fruit and vegetables, meat, fish, poultry, eggs, non-alcoholic drinks and chilled and frozen products. Data were obtained from various sources including journals, industries, government reports and eco-labels. The study therefore assumes that the different sourced data can be combined together to form a whole chain analysis, but acknowledges the implications of this assumption in the final results of their study. Similar to the previous study, caution is suggested by the authors before using the quantitative results from this study due to the high level of uncertainty. Lillywhite *et al.* [32] studied the embedded energy associated with producing, processing and distributing a range of food products, with a view to addressing the food chain security issue in the UK. Data were also obtained from academic and grey literatures, where the lack of LCA data for multi-ingredient products such as pasta sauce, soup and pizza were derived by the authors' own LCA. This study further explored the price volatility and elasticity of food products with regard to food security and showed that the UK's food supply is almost completely dependent on fossil energy, raising concerns for future food security. The common trait of LCA studies to assume different sourced data can be combined, increases uncertainty in the analysis, where the authors generally caution the reader of the implications in the final results of their study.

In the UK, publicly available specification (PAS) 2050 was developed in 2008 to provide a consistent method for quantifying carbon footprints. The PAS 2050 standard was adopted from the ISO 14044 standard and has been refined with consultation of various research and user communities (PAS 2050 [33,34]). The stepwise procedures are as follows: (i) defining the 'system boundary' of the product life cycles, (ii) data collection, (iii) compilation and validation of emissions flows and (iv) identification of hot-spots and emissions reduction opportunities. The resource and energy use data are therefore crucial for this method, and primary data generally improve the accuracy (PAS 2050 [34]). This method requires that assumptions - generally relating to primary energy conversion factors, transportation energies, refrigerant leakages, waste disposal and agricultural emissions - are made clear and conservatively. The PAS 2050 method is valid if the assumptions are $< 5\%$ of the total footprint and the sample size is adequate (PAS 2050 [34]).

Holmes *et al.* [35] conducted a PAS 2050 life-cycle study for five food products in the UK, starting with agricultural production, up to the delivery of food to the catering site, employing past studies' data to evaluate the GHG emissions resulting from raw materials, energy use in manufacture, distribution, retail and wastes. The main assumptions related to GHG emission factors from fertilisers and pesticides, and transportation distances. The study provided emission reduction practices and showed that the level of assumptions, time and resources required pose potential barriers to LCA methods. Tassou *et al.* [36] employed the PAS 2050 method to explore the GHG impacts of food retailing. The report focused on emissions from energy consumption, refrigerant leakage and waste for products ranging from fresh meat to bread. The authors demonstrated that PAS 2050 can be used to quantify GHG emissions from food retail operations if stores are submetered to a sufficient level. They showed that appropriate functional units and boundaries must be selected when studying services with PAS 2050. Campden and Chorleywood Food Research Associates and Partners (DEFRA FO0409 [37]) employed PAS 2050 to study the GHG emissions from the preparation and consumption of complex meals such as cottage pies, bread and apple juice. The authors made assumptions relating to the energy use in cooking processes, storage temperatures and amount of water used. This study similarly conveyed that product-based studies should be preferred for PAS 2050, to minimise the uncertainties associated with technology models in process-based studies.

Although LCA methodologies can be applied to products, processes or even industry, it is observed that LCA approaches in the food chain relate mainly to the supply chain of specific food products. Its use tends to focus on GHG emissions rather than energy consumption, which is also an integral part of the assessment. The high level of details possible from LCA can indicate resource efficiency hot-spots and allow targeted actions for improvements [29]. However, the literature suggests that although there are vast LCI of various products, because research is done on a random basis, the compilation of data and hence the comparison of different food supply chains becomes complex (The Ecoinvent database is an example of consistency in LCIs (Ecoinvent [38])). Thus, the system boundaries, assumptions made and uncertainties of the different studies should be clearly specified to increase the potential and practicality of this approach.

MARKAL model

The MARKAL model is a multi-period linear programming and optimisation tool which allows the simultaneous assessment of several technologies for specific industries or the whole economy (Rath-Nagel and Stocks [20,39]). The competition between technologies is affected by energy/GHG emission policies, associated costs and technical constraints. MARKAL models can determine the trade-offs between various objective functions such as costs, environmental indicators, oil security, renewable primary energy etc. (Rath-Nagel and Stocks [39]).

MARKAL models are demand-driven models (Rath-Nagel and Stocks [39]), with exogenous energy demands specified by the modeller for a specific network of processes linked through their inputs and outputs, technical, economic and policy based parameters [20]; see Figure 1. As such, the model operates from energy technology databases which detail the current energy system as well as the technical and cost parameters of potential energy systems (Rath-Nagel and Stocks [39]). The model aims to find a partial equilibrium on the energy market which satisfies the maximisation of the net surplus of consumers and suppliers, via linear programming [40]. It should be noted that since the development of MARKAL models by the International Energy Agency in 1976, the MARKAL family has grown to include various improvements. The specifics of the extrapolated models can be found in Loulou *et al.* [40,41].

The TIMES model is an extension of the original MARKAL model and includes variable time periods, time-data decoupling, higher flexibility energy processes, age-dependent parameters and climate equations (Lolou *et al.* [41]). Seck *et al.* [20] employed the TIMES model to analyse the impact of heat pumps on the French food and drink (F&D) industry. The authors used this bottom-up approach as they argue that the French F&D industry ('a non-energy intensive' industry) requires a fine and disaggregated understanding of the existing and emergent technologies. The benefits of adopting such an approach was found to be as follows: (i) the detailed and explicit formulation of the technologies and processes, (ii) the ease of modelling the effect of different policies and (iii) the explicit modelling of the evolution of demand and energy prices. However, the authors state that the TIMES model does not incorporate feedback from other economic sectors and the large quantity of data required for the analysis make the application of the model difficult and perhaps uncertain. Concerning the former point, Loulou *et al.* [40] argue that the change in energy demand is itself the main economic feedback. Seck *et al.* [20] assumed an expected evolution of demand for different F&D products, future energy price scenarios and the technical performance of heat pump systems, and showed that the use of heat pumps is a promising technology, possible of 21% reduction in CO_2 emissions and 13.6% reduction in energy consumption in 2020, compared to a scenario without heat pumps.

Gerlagh and Gielen [43] developed a supplementary module 'MATTER 2.0' for the agriculture and food sector of Western European countries. The impetus for this module relates to the increasing importance of competing interest of land use for food, energy and material production, GHG emission reductions and food consumption lifestyle changes. The model assumes a constant mass flow of resources and various proportions of product/energy wastage for different processes, noting that most emissions are converted from the calorific energy content of food. The development of this module shows the versatility of MARKAL for providing a platform for further research and model development.

It should be noted that the MARKAL is now superseded by TIMES, which is supported by the International Energy Agency, and as mentioned before, TIMES has a similar underlying basis as MARKAL, but with several improvements in the techno-economic aspects of the model. MARKAL/TIMES is seen to depict a more aggregated bottom-up approach compared to LCA, therefore allowing a broader overview of the supply chain

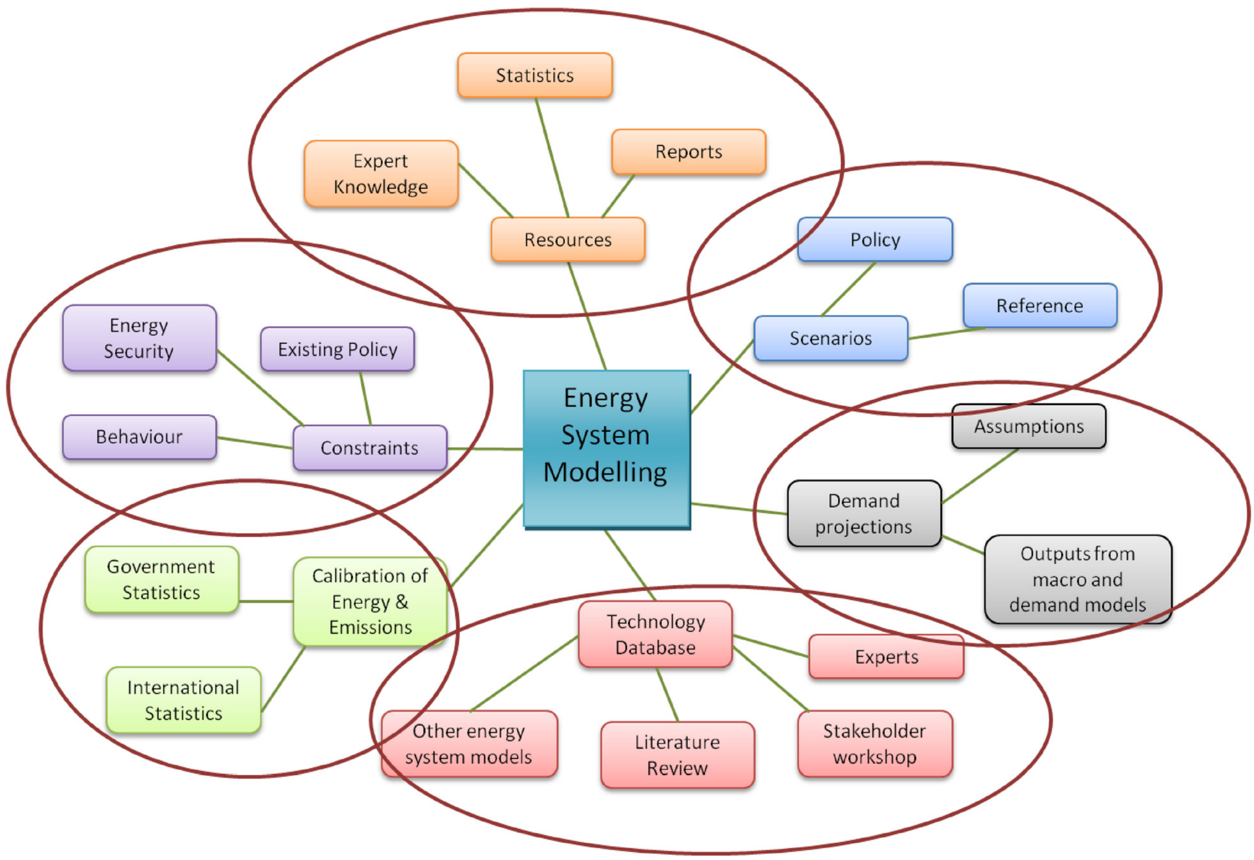

Figure 1 **Parameters/database considered in the development of a MARKAL model [42].**

of various food products or the food chain. The use of MARKAL/TIMES for the food chain is limited in the literatures; however, its use can be promoted especially as it provides a valid and IEA-supported linear optimisation platform for various user-defined scenarios [44]. A more in-depth evaluation is given in the 'Results and discussion' section.

Regression models

Regression models aim at understanding the causal relationship between two or more variables - where simply adopting correlations may not actually represent this causality - and to quantify how close and well determined the relationship is. It is therefore important in regression models to determine the influential dependent and independent variables, through statistical methods or empirical observations [45].

Spyrou *et al.* [46] studied the electricity and gas demand drivers for a UK food-retail organisation's buildings using a linear regression method. The authors identified a list of variables that affect the electricity and gas demands based on theoretical concepts and preliminary correlation tests, and observed that the level of detail is limited based on the availability of information. The dependent variables were electricity and gas intensity consumption, whilst the independent variables were divided into physical, operational and regional parameters. The main assumptions relate to the operation and efficiency of the electrical and gas systems, obtained from academic and grey literatures. The authors were able to develop three regression models for the electricity consumption ($R^2 = 0.75$, $p < 0.001$), gas consumption without CHP ($R^2 = 0.62$, $p < 0.001$), and gas consumption with CHP ($R^2 = 0.77$, $p < 0.001$). Employing such a simple model allows the food organisation to quickly identify retail buildings that are under-performing, but does not direct the modeller towards the factors causing the inefficiency.

Boyd [47] developed a performance-based energy efficiency indicator (EPI) for the US food processing sector using linear regression models. Due to lack of data and the diversity involved in food processing, the author adopted a more segmented approach using primary data for specific sectors in the food processing industry, as opposed to modelling the entire processing industry. The study is based on primary energy sources and calculates an EPI for each sector by comparing the actual energy consumption of each processing plant. The optimum scenario is obtained following a stochastic frontier regression analysis, which applies the ordinary least-square regression method to the standard linear regression model. The model predicted R^2 coefficients of 0.8 to 0.96 and variances varying between 0.06 and 0.6. The benefits of using the EPI are that it allows industry leaders to benchmark the performance of various plants and to simply assess the average performance of the sectors, crucial for effective policy designs. However, the large data requirements, the diversity in processing methods and the need for constant updating of the database (due to technical and business innovations) pose limitations in the implementation of such models for longer term.

Tassou *et al.* [48] employed a regression model to analyse the electrical energy intensity variation with respect to the sales area of UK retail buildings. The study predicted the efficacy of using simple models when the modeller has a firm idea of the influential variables of the system. The authors separated a sample of 2,570 UK food retail buildings based on the sales areas: convenience stores, supermarkets, superstores and hypermarkets. Power law models were employed for each type of store, observing that the electrical energy intensity reduces with increasing sales area, with the relative rate of energy intensity reduction decreasing as the store sales area increases above 2000 m^2. The standard deviations in the models were found to be higher for small stores (22 to 24%) compared to larger stores (15%). A general relationship was also developed, which showed that the potential for energy savings is higher for small stores, especially if the refrigeration energy consumption is reduced to the mean energy intensity for each category.

Amundson *et al.* [49] outlined the major steps for developing linear regression models for monitoring and reporting energy savings. The stepwise procedure is illustrated in Figure 2. The authors employed this procedure to develop a model characterising the effects of time resolution on the model coefficients for a large food processing plant and a 'high-tech' factory. The independent variables were the ambient temperatures, production periods etc., whilst total electrical energy consumption was the dependent variable. The authors assessed the fitness of their models using the R^2, coefficient of variation of the root mean square error (CV-RMSE) and model residuals, and quantified the validity of the models using fractional uncertainties. It was observed that the employment of daily resolution improves the uncertainty levels in the models, but the increase in

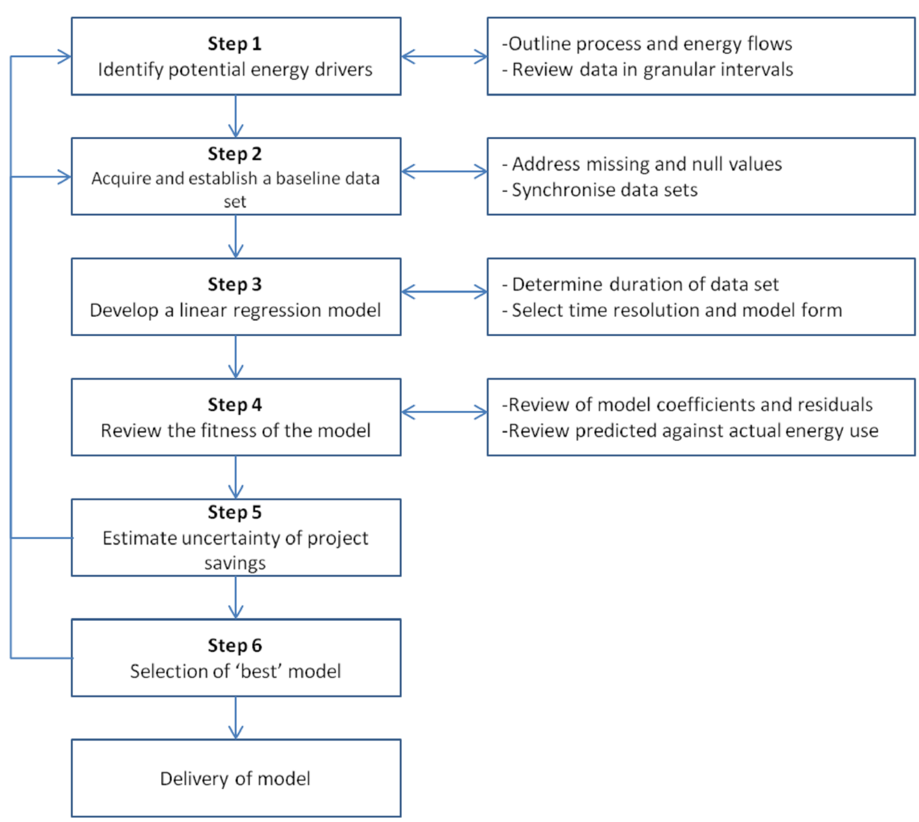

Figure 2 Development process of linear regression model for monitoring and reporting energy savings for industrial maintenance and operation [49].

hardware and software requirements and the additional time and complexity of smaller time resolutions should be justifiable. The selection of a suitable model was found to be subject to the opinions of the modeller and the user reaching a compromise.

Regression models are found to represent a simplistic approach to a complex system, by using a set of influential variables. It is important that these models do not only relate these variables but to also include the effects of causality in the representation. The use of regression models (mainly linear regression models) extends in various disciplines (energy, GHG emissions and costs analyses [50]) because of their relative ease of use and assessment of the model errors. The particularities of this approach are evaluated in the 'Results and discussion' section.

'Top-down' approach

Top-down approaches refer to the decomposition of a scenario into a set of equations where the 'required parameter' is obtained from a combination of the variables considered as 'underlying causes' [51]. The choice of factors depends both on a conceptual model and on data availability. There are two types of equations used in such macroeconometric models: stochastic (or behavioural) and identities. Stochastic equations are estimated from historical data, whilst identities are equations that hold by definition, i.e. they are always true [52]. The variables can be separated into endogenous variables (variables explained in the model) and exogenous (variables imposed on the model) [52], and the model generally applies to an annual basis/time-step. A top-down model can apply to a whole economy or a section of an economy [53]. This section does not attempt to detail the workings of such models, but rather to portray their practicality, benefits and limitations with respect to their use in the food and energy (and/or GHG emissions) chain.

Input-output model

Economic input-output analysis can be regarded as a collection of the aggregated (intermediate and final) value or amount of goods and services that flows in an economic system and/or as an analytical technique describing and predicting the behaviour of that economic system [54]. The data are usually presented in tabular form and can be obtained from national statistical offices on a yearly basis. Generally, governmental input-output (IO) tables are quantified in terms of monetary value and must therefore be adequately converted energy/emissions values [55,56]. This is accomplished by following the principle of conservation of embodied energy to create a hybrid monetary-energy table. This principle states that the energy burnt or dissipated by a sector of the economy is passed on, embodied in the product [55]. Since final demand is considered the output of an economy in economic IO analysis, conservation of embodied energy implies that all energy entering an economy is entirely embodied in the final market sales of goods and services [2]. The energetic IO process separates the economy into energy and non-energy sectors and tracks the flow of energy for each sector. It assumes linear homogeneous production technologies, where the output of a sector varies linearly with the production inputs. As such, the concept of energy intensity is often employed [55].

Canning *et al.* [2] employed the IO analysis of the national US food system to trace the energy flow of roughly 400 industries, using data obtained from two federal sources. The study aimed at understanding the factors influencing the US food-energy system over three time periods (1997, 2002, 2007) using a structural decomposition analysis (SDA) and a supply chain analysis (SCA). The SDA evaluated the effects of changes in US population, food-related budget, product mix and food system technologies, whilst the SCA provided a more in-depth analysis of the changes, in terms of the contribution of agriculture, processing, packaging, transportation, retail, food service and household operations to the aggregate change in energy flows. The authors acknowledge that although the boundary of IO analysis is the domestic food system, imported and waste flows are crucial in evaluating the performance of the food chain. Thus, imported embedded energies were obtained by assuming the state of technologies in other countries to be similar US technologies, and waste energy flows were estimated from EPA statistics. The authors observed that energy-intensive technologies accounted for half of the food-related energy increase over the years, whilst the rest was due to increase in population, prepared food and eating out. Household operations accounted for the highest energy use, whilst food processing showed the largest increase from 2002 to 2007, as both households and foods service sectors outsourced manual food preparation and cleanup activities to the manufacturing sector, which relied on energy-intensive technologies.

Zhang *et al.* [57] employed multi-regional input-output model to track the embodied energy for various sectors in China in 2007. A wide range of data were obtained from the Chinese Academy of Science and the National Bureau of Statistics of China, where the linkage between each region and the economy was made by considering the direct primary energy use and imported embodied energies. Amongst the sectors considered, the food production and processing industry accounted for 4.5% of the total Chinese embodied energy use. The study not only showed the potential of IO analyses in terms of flexibility and the number of variables that can be incorporated into the model, but also depicted the statistical knowledge requirements to develop such complex models. Bekhet and Abdullah [58] studied the agricultural energy chain in Malaysia, in an attempt to reduce food imports, minimise energy consumption and increase the yield of the agricultural industry. The authors employed secondary data from National Statistical Databases, considering three energy industries. The study showed a more significant increase in the dependence of the agricultural industry on petrol and coal, compared to the other energy industries, although agriculture is a relatively weak energy consumer. The fisheries sector was found to be the largest consumer of energy, followed by forestry and logging and oil palm estates. The authors acknowledge that because IO data are normally obtained at 5-year intervals, the study fails to identify the changes in energy consumption using a time-series approach, but nonetheless suggest that electricity and gas should be promoted, instead of petrol.

Although the concept of IO analysis was developed for national economic systems, the principles have been extended to specific products. Essengun *et al.* [59,60] explored the energy flow of dry apricot and tomato production in Turkey, by collecting primary energy input, quantities and costs of inputs and outputs. The authors employed various multipliers to construct a relatively simple model that allows the modeller to track the energy and monetary flows in the agricultural production. Such model determined the energy efficiency and intensity of the production and suggested different energy improvement measures. Kuswardhani *et al.* [61] studied the energy and economic IO of greenhouse and open-field production in Indonesia. The authors obtained primary data from surveys and used appropriate conversion factors to obtain the energy values. The study identified the linkages between energy input and crop yield for greenhouse and open-field production, and depicted the energy efficiency ratio of different products. A number of other studies also employed simple adaptation of IO analysis for the agricultural sector [62-68]. The primary motivation for choosing the product-specific IO method was the flexibility in collecting primary data, determining energy efficiency ratios and extending the analysis to cost-benefit analyses.

This section has shown that food-energy IO analyses have not only been used at the national or regional level, but also at a more product-specific level. The approaches to IO energy analyses have been to convert national IO tables' monetary values to energy values (using hybrid tables) or to directly employ energy values (or closely related energy parameters). When using the national hybrid monetary-energy IO models, structural decomposition analysis (SDA) has been used to study the sources of changes obtained from IO analysis over different time periods [2,69-72], whilst supply chain analysis (SCA) explores the contributions of different stages of food production to the overall energy flow [2]. The analysis of embodied (i.e. direct and indirect) energy flows has been found to identify and optimise low energy-efficient processes and to propose improvements at both the energy and cost/profitability levels.

Index decomposition analysis models

An index decomposition analysis model refers to the definition of a governing function that relates the aggregate to a pre-defined number of decomposed factors, in order to measure the impact or weight of these factors on the aggregate, over specific time periods. The two most popular approaches for energy analyses are based on the Divisia index and the Laspeyres index where the choice is problem dependent [73]. The Laspeyres index measures changes in an aspect over time by letting the related variables change, but fixing all other variables at the base period values [74]; the Divisia index uses a weighted sum of logarithmic growth rates, where the weights are the components' share in the aggregated value [73].

Hammond and Norman [75] examined the causes and weights of the effects that resulted in the reduction in carbon emissions in the UK manufacturing sector, between 1990 and 2007. They adopted the log mean Divisia index (LMDI) approach, on the basis that LMDI has no residuals and the additive method is easier to interpret. Secondary data were obtained from various sources, and the changes in carbon emissions were decomposed in terms of changes in production volume, inter-sector structure, secondary energy intensity, fuel mix and carbon emission factor. Furthermore, in order to ensure the changes are associated with the correct effects, the manufacturing sector was divided into subsectors, which include the manufacture of food and beverages. The individual energy efficiency was taken to be inversely proportional to the energy-intensity effects, which does not imply that improvements in the energy-intensity effects are due to technological effects, unless the energy system is disaggregated to high enough level [76]. The results showed that improvements in energy intensity were the main cause of reduction in carbon emissions in UK manufacturing - whereby more efficient technology, better control and housekeeping, moving towards an increased use of electricity and natural gas, and inter-sector structural change are believed to have contributed to lower energy consumption during the period.

Hasanbeigi *et al.* [77] decomposed the Chinese manufacturing industry using the additive LMDI approach, for both past (1995 to 2010) and future years (2010 to 2020). The authors assumed a constant share of the value-added for each sector, and the future energy projections assumed to be cumulatively decreasing based on the government's reduction targets. The decomposition analysis investigated the effects of aggregate activity, sectoral structure and energy intensity. The additive LMDI approach was selected as it leaves no residuals, and the study showed that the food and beverage sector had the second largest sector rise in value-added from 1995 to 2010, whilst primary energy use remained relatively constant and the energy intensity decreased for the same period. The forecasted energy intensity for the food sector was found to decrease at a lower rate for the period of 2010 to 2020. The decomposition analysis showed that if China intends to meet its goal of re-structuring its economy and moving towards less energy-intensive and polluting sectors, then specific scenarios should be followed. The forecasted decomposition analysis therefore aided evaluation of the impact of the different scenarios on both primary energy use and value-added, at a more disaggregated level.

Generally, the log mean Divisia index model was found to be the most commonly used method [73] for economy, industry or sector level analyses, where the main effects are often separated into production volume, inter-sector structure, energy intensity, fuel mix and/or carbon emission factor. A finer disaggregation level of the dataset allows a more accurate evaluation of the relative impacts of the disaggregated effects, whereby the IEA identified the disaggregated energy indicator hierarchy as shown Figure 3. Furthermore, physical intensities (material, energy and emissions) are suitable, but not preferred for holistic industry decompositions, because of the large varieties in physical units involved. Instead, it is recommended that the energy and GHG intensities be based on monetary units [78].

In general, the Divisia index model was used in decomposition studies ranging from specific industries, such as the manufacturing industry - which includes food manufacturing [80-83], the agricultural industry [84], the service industry [85], to whole economy decompositions [86-90]. The Laspeyres index approach was less popular, employed mainly by the International Energy Agency (IEA), due of its ease of use and to ensure consistency in IEA publications (ETO/ESD/LTO, 2007; [79]). The reasons for the lower popularity of the Laspeyres approach were as follows: the model produces residuals when the aggregate values are calculated [74], the choice between the additive or multiplicative Laspeyres model affects the final results of the analysis [91] and the generally lower accuracy of the model compared to the Divisia index method [73].

Dynamic models

Dynamic models incorporate time into the breakdown of a structural framework using systems of difference or differential equations, in an attempt to provide future expectations/impacts of various policies [92]. These models are more complex and detailed than static models, as they involve assumptions on the rate of economic growth, time preferences, population growth rates, inflation rates, depreciation rates etc. [92,93]. Researchers to date have adopted dynamic models in different ways and for different applications, but application to the food-energy chain has been limited.

Irz *et al.* [17] studied the dynamics of price formation of food commodities with respect to agricultural, energy and labour commodity prices, for the case of Finland, by considering attributed relating to the demand and supply sides of the Finnish economy. The

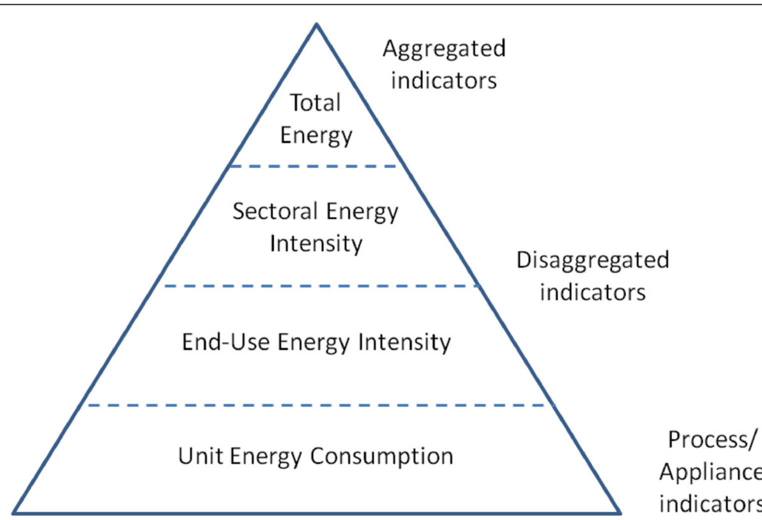

Figure 3 **Disaggregated energy indicator hierarchy (adapted from [79]).**

authors employed a co-integration analysis using both stochastic and identity sets of equations. The conceptual framework was based on the equilibrium of agricultural, labour and energy commodities for the supply side and disposable income and demographic distribution for the demand side. However, Finland was assumed to have a negligible demographic distribution and disposable income was ignored, due to the unavailability of data. Hence, the empirical model only explained the relationship between food prices and agricultural, energy and labour commodity. The authors studied the system dynamics using a time-series approach by testing for the presence of unit roots and using the Johansen approach to study long-term equilibrium. The causality aspect of the model was analysed using Granger causality tests. The outcome of the model was a long-run relationship of food prices with respect to the other commodity prices, assuming linear growth. The study showed that farm prices represent the main determinant of food prices, followed by wages in food retail and the price of energy. It should however be noted that technological change is implicitly proxied in the time-trend series. Other studies with similar conclusions can be found in Lambert and Miljkovic [18] and Baek and Koo [94].

MAgPIE is a nonlinear recursive dynamic optimisation model, developed by Potsdam Institute for Climate Impact Research Land-use group (PIK [95]). The model requires a set of exogenous demand parameters for each time-step and the yield growth from agriculture is obtained in relation to investment forecasts. The model predicts the impacts of agriculture on land use and GHG emissions. Applications of this model can be found in Dietrich *et al.* [96], Schmitz *et al.* [97] or Popp *et al.* [98].

Hence, dynamic models can be used to study the transient impacts of specific parameters on the economy, but require validation with historical data. The lack of application of dynamic top-down models related to the food-energy chain can be attributed to the fact that the dynamic behaviour and different timeframes (between production and consumption and waste) associated with food is difficult to be forecasted on an aggregated basis due to the large variance in types of food products and technological processes. Furthermore, the level of assumptions that may be required to decompose aggregated energy data for specific food sectors may themselves become a source of question, especially when the temporal aspect is considered. Hence, for such forecasting purposes, hybrid models (such as IO-based LCI or MARKAL-MACRO models) may be more suitable as they allow a higher disaggregation level in terms of technologies and/or food products. Thus, the following section explores the use of hybrid approaches.

Hybrid approach

A hybrid modelling approach seeks to combine both bottom-up and top-down approaches to allow the modeller to analyse specific details of processes and consider the entire supply chain simultaneously [99]. In the case of the food chain, hybrid IO and LCA were found to be most commonly used in assessing energy and carbon footprints. IO tables provide complete and aggregated data within national boundaries, whilst process-based LCI provide detailed and accurate process information. Suh and Huppes [100] identified three approaches to hybrid IO-LCI methods:

1. Tiered hybrid analysis employs process-based LCI data for consumption, waste and upstream activities, whilst the remaining information is obtained from the economic IO-based LCI. Although a simple and fast approach, limitations are (i) the demarcation between process-based and IO-based LCI should be carefully selected, (ii) double counting may occur and (iii) there is no feedback between the two approaches.
2. IO-based hybrid analysis requires the disaggregation of the industry sectors in the IO table into subsectors and employs the tiered hybrid method for product life cycles outside the IO table boundary. The interactive relationship between pre-consumer stages and the rest of the product life cycles is often difficult to model.
3. Integrated hybrid analysis: is a matrix representation of the physical product system, whereby the IO table is connected upstream and downstream of the matrix. The linkages between the product system and the economy can be obtained in terms of purchases and sales records from LCI. This approach puts LCI at the core of the hybrid model and allows full interactions between the individual processes and industries in a consistent framework.

Elgimez *et al.* [101] employed an IO-based LCI hybrid approach to study the sustainability impact of the US food manufacturing sector. The study consisted of disaggregating the industry into 33 sub-sectors (or product systems), which allowed the consideration of both the direct and indirect effects at a more detailed level than using IO only. In addition to the IO-LCI model, this study also included a data envelopment analysis (DEA) model which evaluated the impact of the sectors through a sustainability performance index (SPI), to allow comparative study. The authors therefore adopted a two-stage hierarchical process where the IO-LCI model provided the environmental outputs, which are then fed to the DEA model to evaluate the SPI of each sub-sector. The authors obtained the imported footprints assuming the same level of technology as the US food manufacturing industry and ignored the regional variations associated with carbon emissions due to the regional homogeneity obtained in IO tables. The study concluded that 19 of the 33 food manufacturing sub-sectors are inefficient and that fisheries and animal slaughtering, rendering and processing are the dominant 'carbon footprint' sectors in the US food manufacturing industry.

Virtanen *et al.* [102] studied the GHG emissions of the Finnish food-chain using process-based LCA and an IO-based LCA hybrid model. The process-based LCA was obtained from 30 typical lunch plates, used to augment the national IO tables. The hybrid IO-LCA model was derived from a combination of economic input-output tables associated with environmental emissions, LCI of agricultural sub-sectors and related emissions and publicly available LCI and conversion factors for imports (ignoring waste and disposal). Particular emphasis was placed on the agricultural industry because of its relatively high emissions. As a result, this industry was further disaggregated to 44 sub-sectors, with emissions obtained from the ENVIMAT model. The authors observed from the IO-LCI model that the Finnish food chain accounts for 14% of the Finnish GHG emissions, with agriculture accounting for 69% and the energy industry 12%.

Weber and Matthews [23] studied the effects of food miles on the US environmental impact of food. An IO-based hybrid model was employed, where the disaggregation of the transportation sector was done with life cycle information from secondary sources. A commodity-based functional unit of ton-km was employed, where the model assumed that all users of a commodity require the same amount of ton-km per dollar purchase of a commodity, where energy use and carbon emissions were obtained by assuming standard fuel conversion factors. The authors identified limitations of grouping different goods and time lag of data in the IO-LCA model which increase uncertainties in the analysis. Nonetheless, the study depicted that holistic transportation contributes an average of 11% for life cycle GHG emissions and that red meat is more energy-intensive than other food products. The study concluded that dietary shift is a more energy efficient means than 'buying local' in the US.

Wood *et al.* [103] employed an IO-based LCA hybrid approach to study the comparative energy, water, land and GHG emissions impacts of organic farming and conventional farming in the Australian food chain. The authors conducted a survey of organic farmers to obtain primary data for a process-based LCA for organic farming, whilst conventional farming data were deduced from IO tables. Farm operations were obtained from LCAs and the remaining indirect effects from IO tables. The authors used the SCA decomposition of the hybrid IO-LCA table to obtain the various energy and emissions contributions of the agricultural industry, assuming homogeneous organic farm operations across the industry. The results showed that total embodied energy is generally lower for organic produce, compared to conventional produce, and synthetic chemicals and fertilisers are a major source of energy use, where organic agriculture would reduce these impacts.

In the context of the food and energy/emission chain, the use of hybrid IO tables and LCA models has been found to focus on emissions, rather than energy, because of the relatively higher importance placed by environmental policies on emissions. As such, most hybrid IO-LCA models generally include the details from LCI mainly to the agricultural and manufacturing sections of the food chain, thereby providing more details for these sectors where a majority of the emissions take place in the food chain [101-103]. These models have been used as they allow further disaggregation of the conventional economic IO models (as well as including up- and down-stream analyses, beyond the IO model boundary) and incorporate the economy-wide effects to the segregated LCA models. The level of analysis is therefore enhanced, allowing for the detection of environmental hot-spots and better implementation of environmental policies.

Results and discussions

This paper describes different modelling approaches used in the food chain. These approaches are differentiated as bottom-up, top-down and hybrids, which are qualitatively evaluated as follows, in relation to their applicability to modelling the energy and emissions flow in the food chain.

LCA models provide a process or product based analysis of emissions and energy use in the food-chain using a cradle-to-grave approach. Owing to the complexity of the food chain and the high level of detail possible from LCA, efficiency hot-spots can be identified, therefore targeting actions for improvements [29]. Whilst LCA is good at identifying the intricacies and complex nature of the food chain, this very complexity presents an obstacle to the development of specific recommendations for the future [24]. The level of details required limits the accuracy of this approach and increases the associated uncertainties when such data are not available. Furthermore, it is important to have a standard procedure through which life cycle impacts are measured, with the system boundaries, assumptions, uncertainties and the definition of the functional units of the different studies clearly specified [31,104]. LCAs need to include ways of measuring outputs that are not only multiple but also intangible - such as social aspects of the chain [24] - and to consider the integration of individualistic models as components to holistic models. Nonetheless, current academic and grey literatures, although performed on a relatively random basis, can provide qualitative assessments of energy and GHG emissions, as well as opportunities for improvements in specific cases [27].

As opposed to LCA models, MARKAL and its submodels are mainly employed at the national and regional levels, to analyse the implications of different national technology mix ([105]; Teri [106]). The national models and the disaggregated impacts of a particular sector are dependent on the level of detail obtained from the country's MARKAL databases. There are uncertainties when analysing future energy scenarios with regard to the discount rates. The two theoretical concepts of social time preference and social opportunity cost tend to show a divergence in the choice of discount rates between the values adopted by the private sector and the government (Rath-Nagel and Stocks [39]). Hence, different discount rates are often used for different situations and countries (3% for Switzerland, 5 to 10% for the USA, 10% for China or 10% for the UK) [105,107]. A high discount rate value shows high uncertainty in the energy impacts of a new technology [105].

In most cases, except when the main variables are definite, the development of regression models is an iterative process, requiring a large amount of data and an understanding of the engineering and statistical processes involved. The underlying assumption of linear regression models is that the residuals (difference between predicted and actual data) follow a normal distribution from the mean. This helps to identify outliers (which distort the regression model), model weaknesses and process changes [49]. As such, the judgement of the modeller is crucial in determining the 'best' representative model; e.g. Spyrou *et al.* [46] considered outliers to be at three standard deviations. Further to the residuals, the fitness and model coefficients are crucial. The use of various indicators such as R^2, variations of root mean square errors, p-value, auto-correlation coefficients, standardised (β) coefficient and fractional uncertainties have been found to be common. Although there are limitations associated with the 'error indicators' [49,108], the final adoption of a regression model will depend on a compromise between the judgement of the modeller and the satisfaction of the user.

IO models are static linear equilibrium models, where the national IO system boundary for the food-energy chain starts from energy production up to final consumption of food, hence requiring simplifying assumptions to consider the impacts of imports and wastes in the chain. Economic IO tables are usually several years old and in some cases at large time intervals and are mainly used to analyse past energy flows as opposed to predicting these flows. They are therefore not convenient for time-series-type analyses. The results obtained from economic IO analyses are usually exhaustive and applicable to large-scale questions, which are less useful for micro questions [55]. Nonetheless, such an aggregated method usually performed using data from single sources, reduce ambiguities related to acquiring data from different sources. It can also account for the aggregated inter-regional and socio-economic aspects of the chain [109]. When used in the simpler product-specific manner, the efficiency of IO models can be improved when primary data are collected. Furthermore in such studies, the conversion of monetary values to energy values is often not required, eliminating the assumption of sector homogeneity, as energy values are not determined from homogeneous energy prices.

The unique feature of index decomposition analysis (IDA) to provide macro results based on myriad detailed energy indicators gives policymakers quick access to findings from technical data [77]. In IDA analyses, there are issues of data quality, level of sector disaggregation, measurement of output/activity levels and the choice of indicators which would affect the quality and validity of the decomposition results [73] - these are however only dependent on the datasets being used and independent of the actual methodology. Only direct effects can be evaluated with IDA models [110], as opposed to structural decomposition analysis (SDA) that can evaluate embodied effects. An advantage of IDA over SDA is the lower data requirement. However, this is also a disadvantage, since IDA is capable of less detailed decompositions of the economic structure [75,110].

The comparative aspects of the aforementioned models are presented in Table 1. This comparison has been done in a qualitative manner with respect to the ease of use, benefits, limitations and the assumptions of the models to provide information in the choice of a specific modelling method. Table 1 generally shows that the benefits of one approach are the limitations of the other approach, for instance; bottom-up approaches provide the benefits of high level of detail for a specific product/ sector, whilst top-down approaches have limitations in the disaggregation of the economy to a sector/ product level. This therefore led to the development of the commonly used hybrid IO-LCI models.

Such hybrids allow the following: further disaggregation of the economic IO model, incorporate the up- and downstream analyses and include economy-wide effects to segregated LCA models. The level of analysis is therefore enhanced, allowing for the detection of environmental hot spots and better implementation of environmental policies. Hybrid IO-LCA analyses can pose problems with regard to temporal discrepancies. IO tables are usually published at typically long time intervals (1 to 5 years), making the information in the energy/emission IO tables usually older than a process-based LCA [100] and creating complexities in the clear demarcation of IO and process-

Table 1 Qualitative evaluation of 'bottom-up' and 'top-down' modelling approaches referred in this paper

Models	Brief description	Common benefits	Common limitations	Common assumptions
Bottom-up approaches				
LCA models	A process or product based evaluation method of the energy use and GHG emissions, typically using a 'cradle to grave' approach	- Measure high quality of energy and GHG emissions data	Level of detail required increases the complexity of data collection	- Secondary to primary energy conversion factors
		- Capture the intricacies and complex nature of the food-energy chain	- Analysis is usually very specific to country and product/process	- Transportation distances and fuels
		- Allow the identification of energy and GHG emission hot-spots	- Information from different sources cannot be combined, unless uncertainties and assumptions are clearly specified	- Imported energies and GHG emissions
			- Choice of functional units and demarcations between system add complexity to the method	- Agricultural sector energies and GHG emissions
			- Ignores the holistic industry impact on the product/process, i.e. static model	- Waste disposal and storage emissions
			- LCA needs constant update	
MARKAL and sub-models	- Demand-driven multi-period linear programming and cost optimisation tools	- Technologies and processes can be explicitly modelled in detail	- Results depend on the accuracy of demand-inputs and description of technological processes	- Description of technological processes
	- Simultaneously assess the impact of several technologies through the partial equilibrium of demand and supply of energy	- Currently being employed in various energy research studies, and various extensions/innovations of the model are being developed	- Discount rates of technologies impact the partial equilibrium when forecasting energy demands	- Discount rates and future energy demands
		- Allows the explicit modelling of the evolution of demand and energy prices	- Does not have information feedback to the wider economy	
			- MARKAL databases have to be regularly updated	
Regression models	Find the causal relationship between the dependent and independent variables in the food-energy chain	- Relatively easy to use and construct	- Require large amount of data to ensure proper correlations	- Determination of errors, and validity of models are subjective to modeller
		- Provide a simplistic description of problem, and allows quick approximations of different policies	- Provide only a quantitative evaluations, and does not show the factors causing the inefficiencies (depends on the level of disaggregation of the model)	- General assumptions relate to the energy consumption and GHG emissions in the data collection phase of the study
			- Assumptions are implicit in the model, hence constant updates required	- Data points outside three standard deviations require further investigation

Table 1 Qualitative evaluation of 'bottom-up' and 'top-down' modelling approaches referred in this paper *(Continued)*

Top-down approaches				
Economic Input-output (IO) models	Provide the aggregated monetary/energy flow through an economy	- Analyse the impact of the entire economy on each industry, and inter-industry relationships	- Stop at the point of purchase, and ignore waste and imports	- Employ the principle of embodied energy to convert monetary to energetic values
		- Data are usually obtained from same sources, which provides consistency in analyses	- Aggregated data analysis prevents detection of specific energy/environmental hot-spots	- Economic IO analysis requires energy/GHG assumptions for wastes and imports
		- Quantify the impact/weight of each sector, and therefore allows identification of low-performing sector	Frequency of national IO tables is low	- Linear production technologies [2]
				- No capacity constraints [111]
				- Sector homogeneity [111]
				Usually assume a constant level of technologies for future analyses [2,111]
				- Import emissions usually based on domestic production technologies [2]
Index decomposition analysis models (IDA)	Decompose aggregate energy and GHG emissions data into pre-defined factors to measure the relative impacts over specific time periods has been used for: (i) energy demand and supply, (ii) energy-related gas emissions, (iii) material flows and dematerialisation, (iv) national energy efficiency trend monitoring and (v) cross-country comparisons [70]	- Method is relatively quick and simple to implement	- Require an adequate level of disaggregation, else actual effects are not clearly identified	Energy and GHG intensities are usually based on monetary outputs, as opposed to physical outputs
		- LMDI approach has no residuals in decomposition process	- Laspeyres index is simple to implement, but calculates with residuals	
		Provide quick access to assessing the overall impact of policy measures on the economy		
Dynamic models	Aim at predicting future energy and GHG expectations of the food-energy chain	Can provide indication of future energy and policy expectations	- Technological effects are often implicitly accounted in models	- Economic growth rates
			- Can require significant level of assumptions, which questions the validity of such models	- Time preferences
			- Studies related to the food chain are scarce	- Population growth rates
				Inflation and depreciation rates

based LCA models. From the various literatures reviewed in this paper, it is apparent that the IO-based hybrid approach has been most popular for the food chain, due to the easy availability of national IO tables and extensive amount of LCA studies. However, it is not that one hybrid model outperforms another. The choice of a particular approach is dependent on a variety of criteria such as the following: data requirements, uncertainty of source data, upstream system boundary, technological system boundary, geographical system boundary, available analytical tools, time and labour intensity, simplicity of application, required computational tools and goal and scope of the model [100]. Generally, the use of hybrid IO-LCI models has been found to focus on emissions due to the high importance placed by environmental policies. As such, most hybrid IO-LCA models focus on the agricultural and manufacturing sectors where most emissions take place [101-103]. Other hybrid models such as the MARKAL/TIMES-MACRO model from the IEA exist and are worth examining in the context of the food chain.

Conclusion

This paper presents a review of modelling approaches for the energy and GHG emissions in the food chain. These methods can be classified as follows: bottom-up, top-down and hybrid approaches. The impetus for this study stems from the need to accurately model the holistic food-energy chain, in order to effectively design and implement policies to tackle the food-energy-climate nexus and food security issues. Top-down approaches have been found to consider the impact of the economy on the food-chain and be used to develop national policy measures. However, the limited level of disaggregation due to unavailability of data and the homogenisation of the economy when using top-down models are drawbacks, which do not help in the identification of energy/environmental hot-spots. On the other hand, bottom-up approaches generally provide a high level of detail and capture the intricacies of the food-energy system. However, their specificity to products/processes limits their application to holistic systems if the individual bottom-up models do not follow a standardised procedure. Hence, the predominant trend has been towards hybrid models, which seek to combine the advantages of both bottom-up and top-down approaches. Furthermore, although three hybrid modelling approaches (tiered hybrid, IO-based hybrid, integrated hybrid) have been identified, the IO-based hybrid has been more commonly used in the food-chain.

The choice of one modelling approach over another depends on a variety of criteria including data requirements, uncertainty, technological systems to be modelled, available analytical tools, time and labour intensity amongst others. It should also be noted that the same modelling approach may lead to different results depending on the assumptions made. As a result, the method (i.e. the mathematics and economics), assumptions and limitations of a particular model should be clearly stated in every study. A simple and quick model (such as regression models) may be useful in obtaining a rough indication of policy impacts for specific cases, but when used for the holistic food-energy chain may increase errors and uncertainties due to the complexity of the food chain.

The modelling of the agriculture and waste parts of the food chain was found to involve relatively more assumptions than the other sectors. This is particularly the case for modelling the GHG emissions because of the need to account for biological processes in agriculture and waste management, based on various conversion factors which increase the probability of inaccuracies in the model. Generally, these inaccuracies can be quantified in various forms, such as R^2 in regression models or relative-percentages in other models.

Most modelling approaches and studies to date consider both the energy and GHG emission aspects of the food-chain. However, in the majority of cases, the emphasis has been on the estimation of GHG emissions and their impact on climate change. Although GHG emissions and energy impacts are complementary in some sections of the food chain, their holistic interdependence is not uniform. Hence, the energy part of the nexus is equally important, especially as the food chain becomes more complex, food security becomes more prominent, and food and fossil fuels decouple as more renewable energy systems are implemented in the chain. This study serves as a background to the application of holistic and integrated approaches to modelling the energy and GHG emissions of the food chain. Such approaches have the potential to better represent energy technologies, can integrate different modelling methodologies and can incorporate social, demographic, economic and climate considerations in a holistic context to predict both short- and long-term impacts. Although the application of dynamic models to the food chain was found to be scare, the importance of considering the temporal impact of policy is crucial and requires further research.

Abbreviations

CHP: combined heat and power systems; CLEWS: climate, energy, water and land use strategies; DECC: UK Department of Energy and Climate Change; DEFRA: UK Department of Environment, Food and Rural Affairs; EC: European Commission; EPA: United States Environmental Protection Agency; EPI: energy performance indicator; F&D: food and drink industry; FAO: Food and Agriculture Organisation of the United Nations; GHG: greenhouse gas; IDA: index decomposition analysis; IEA: International Energy Agency; IO: input-output; ISO: International Organization for Standardization; LCA: life cycle assessment; LCIs: life cycle inventories; LMDI: log mean Divisia index; MAgPIE: model of agricultural production and its impact on the environment; MARKAL: market allocation model; PAS: publicly available specification; SCA: supply chain analysis; SDA: structural decomposition analysis; SIC: standard industry classification; UNEP: United Nations Environment Programme; WFP: World Food Programme.

Competing interests
The authors declare that they have no competing interests.

Authors' contributions
Dr. BLG carried out the review of different modelling techniques presented in this paper, structured and drafted the manuscript. Prof. SAT was involved in finalising the format and content of the manuscript, as well as putting the paper into the overall context of the food chain. Both authors read and approved the final manuscript.

Acknowledgements
This study is a result of funding from the Research Councils UK to set up the RCUK National Centre for Sustainable Energy Use in Food Chains (CSEF), grant no. EP/K011820/1. We would like to acknowledge the contributions of the EPSRC, ESRC and 'Manufacturing the Future' and those of the industry and academic partners in CSEF.

Received: 31 August 2014 Accepted: 16 January 2015
Published online: 26 February 2015

References

1. Food and Agriculture Organisation (FAO) (2011) Energy-smart food for people and climate. Issue paper, © FAO 20112
2. Canning P, Charles A, Huang S, Polenske KR, Waters A (2010) Energy use in the US food system. United States Department of Agriculture Economic research report No. 94
3. DEFRA (2013) Food Statistics Pocketbook, 2013, 71 pgs. https://www.gov.uk/government/statistics/food-statistics-pocketbook-2013. Accessed on 12 June 2014
4. Lobell DB, Schlenker W, Costa-Roberts J (2011) Climate trends and global crop production since 1980. Science 333(6042):616–620
5. Roberts MJ, Schlenker W, Eyer J (2011) Agronomic weather measures in econometric models of crop yield with implications for climate change. Am J Agric Econ 95(2):236–436, United Nations Environment Programme (UNEP) (2011) Towards a green economy: pathways to sustainable development and poverty eradication - a synthesis for policy makers. United Nations Environment Programme www.unep.org/greeneconomy
6. United Nations Environment Programme (UNEP) (2011) Towards a green economy: pathways to sustainable development and poverty eradication - a synthesis for policy makers. United Nations Environment Programme www.unep.org/greeneconomy
7. Clinton Global Initiative (CGI) (2012) http://www.clintonglobalinitiative.org/aboutus/tracks.asp, Accessed on 02 January 2014
8. Grace Communications Foundation (2013) http://gracelinks.org/1309/renewable-energy-at-the-nexus. Accessed on 29 Nov 2013
9. Mistry P, Misselbrook T (2005) Assessment of methane management and recovery options for livestock manures and slurries. DEFRA report: AC0402
10. Krozer Y (2013) Cost and benefit of renewable energy yin the European Union. Renew Energy 50:68–73
11. Parida B, Iniyan S, Goic R (2011) A review of photovoltaic technologies. Renew Sust Energ Rev 15(3):1625–1636
12. International Energy Agency - IEA (2012) World Energy Outlook 2012: Renewable energy outlook. http://www.worldenergyoutlook.org/media/weowebsite/2012/WEO2012_Renewables.pdf. Accessed on 29 Nov 2013
13. World Food Programme (WFP) (2013) http://www.greeningtheblue.org/what-the-un-is-doing/world-food-programme-wfp, Accessed on 29 November 2013
14. Maggio G, Cacciola G (2012) When will oil, natural gas and coal peak? Fuel 98:111–123
15. Kim GR (2010) Analysis of global food market and food-energy price links - based on systems dynamics approach, Hankuk Academy of Foreign Studies, South Korea, Scribd, 18 pages. http://www.systemdynamics.org/conferences/2009/proceed/papers/P1332.pdf, Accessed on 5 December 2013
16. Heinberg R, Bomford M (2009) The food and farming transition - towards a post-carbon food system, Post Carbon Institute, Sebastopol, California. 39 pages. http://www.postcarbon.org/publications/food-and-farming-transition/, Accessed on 21 December 2013
17. Irz X, Niemi J, Liu X (2013) Determinants of food price inflation in Finland - the role of energy. Energy Policy 63:656–663
18. Lambert DK, Miljkovic D (2010) The sources of variability in US food prices. J Policy Model 32:210–222
19. Ciaian P, Kancs D'A (2011) Interdependencies in the energy-bioenergy-food price systems: a cointegration analysis. Resour Energy Econ 33(1):326–348
20. Seck GS, Guerassimoff G, Maizi N (2013) Heat recovery with heat pumps in non-energy intensive industry: a detailed bottom-up model analysis in the French food and drink industry. Appl Energy 111:489–504
21. Welsch M, Hermann S, Howells M, Rogner HH, Young C, Ramma I, Bazilian M, Fischer G, Alfstad T, Gielen D, Le Blanc D, Röhrl A, Steduto P, Müller A (2014) Adding value with CLEWS - modelling the energy system and its interdependencies for Mauritius. Appl Energy 113:1434–1445
22. Tukker A, Jansen B (2006) Environment impacts of products - a detailed review of studies. J Ind Ecol 10(3):159–182
23. Weber CL, Matthews HS (2008) Food-miles and the relative climate impacts of food choices in the United States. Environ Sci Technol 42(10):3508–3513
24. Garnett T (2013) Three perspectives on sustainable food security: efficiency, demand restraint, food system transformation. What role for LCA? Journal of Cleaner Production. In Press, doi:10.1016/j.jclepro.2013.07.045
25. Bazilian M, Rogner H, Howells M, Hermann S, Arent D, Gielen D, Steduto P, Mueller A, Komor P, Tol RSJ, Yumkella KK (2011) Considering the energy, water and food nexus: towards an integrated modelling approach. Energy Policy 39:7896–7906
26. Ingram JSI, Wright HL, Foster L, Aldred T, Barling D, Benton TG, Berryman PM, Bestwick CS, Bows-Larkin A, Brocklehurst TF, Buttriss J, Casey J, Collins H, Crossley DS, Dolan CS, Dowler E, Edwards R, Finney KJ, Fitzpatrick JL, Fowler M, Garrett DA, Godfrey JE, Godley A, Griffiths W, Houlston EJ, Kaiser MJ, Kennard R, Know JW, Kuyk A, Linter BR et al (2013) Priority research questions for the UK food system. Food Sec 5:617–636
27. Garnett T (2011) Where are the best opportunities for reducing greenhouse gas emissions in the food system (including the food chain)? Food Policy 36(Sup 1):S23–S32
28. Dron D (2012) Sustainable food, a component of the green economy. In: Corson MS, van der Werf HMG (eds) Proceedings of the 8th International Conference on Life Cycle Assessment in the Agri-Food Sector (LCA Food 2012), 1–4 October 2012, Saint Malo. France. INRA, Rennes, pp 1–7
29. Mistry P, Cadman J, Miller S, Ogilvie S, Pugh M (2007) Resource use efficiency in food chains: priorities for water, energy and waste opportunities., An AEA Energy and Environment Report to Defra No. AEAT/ENV/R/2457 (ED05226)
30. DEFRA report No. FO 0103 (2008) Comparative Life cycle assessment of food commodities procured for UK consumption through a diversity of supply chains., Report by AEA, Cranfield University, Ed Moorhouse, Paul Watkiss Associates, AHDBMS, Marintek, submitted to DEFRA
31. Fisher K, James K, Sheane R, Nippress J, Allen S, Cherruault JY, Fishwick M, Lillywhite R, Sarrouy C (2013) An initial assessment of the environmental impact of grocery products. Report submitted to the Product Sustainability Forum (PSF), Code: RPD002-004
32. Lillywhite R, Sarrouy C, Davidson J, May D, Plackett C (2013) Energy dependence and food chain security. DEFRA report FO0415
33. PAS 2050 (2008) Guide to PAS 2050: how to assess the carbon footprint of goods and services., © Crown 2008 and Carbon Trust 2008, ISBN 978-0-580-64636-2
34. PAS 2050:2011 (2011) The guide to PAS 2050:2011, how to carbon footprint your products, identify hotspots and reduce emissions in your supply chain, © British Standards Institution 2011, ISBN 978-0-580-77432-4
35. Holmes M, Wiltshire J, Wynn S, Lancaster D (2010) PAS 2050 informing Low carbon procurement: pilot study - food, ADAS report to DEFRA
36. Tassou SA, Hadawey A, Marriott D (2008) Greenhouse gas impacts of food retailing. DEFRA report No. FO405
37. DEFRA report No. FO 0409 (2008) Understanding the GHG impacts of food preparation and consumption in the home., A report by Campden & Chorleywood Food Research Association, Food Process Innovation Unit (Cardiff Business School), Food Refrigeration & Process Engineering Research Centre (University of Bristol)
38. Ecoinvent (2013), The ecoinvent database, Available at http://www.ecoinvent.org/database/, Accessed on the 22 January 2014
39. Rath-Nagel S, Stocks K (1982) Energy modelling for technology assessment: the MARKAL approach. Omega Int J Manag Sci 10(5):493–505

40. Loulou R, Goldstein G, Noble K (2004) Documentation for the MARKAL Family of Models, Energy Technology Systems Analysis Programme. http://www.etsap.org/tools.htm
41. Loulou R, Remne U, Kanudia A, Lehtila A, Goldstein G (2005) Documentation for the TIMES Model PART 1, Energy Technology Systems Analysis Programme. http://www.etsap.org/tools.htm
42. Remme U (2012) Capacity building through energy modelling and systems analysis. Presentation slides from the IEA Experts' Group on R&D Priority-Setting and Evaluation Developments in Energy Education: Reducing Boundaries. Copenhagen 9-10 May 2012. Accessible from http://www.iea.org/media/workshops/2012/egrd/Remme.pdf. Accessed on 01 February 2015
43. Gerlagh T and Gielen DJ (1999) MATTER 2.0: A module characterisation for the agriculture and food sector. ECN-C-99-048, http://www.iea-etsap.org/web/reports/c99048s.html, Accessed on 5 December 2013
44. International Energy Agency - IEA (2011) http://www.iea-etsap.org/web/Times.asp. Accessed on 19 October 2014
45. Ramcharan R (2006) Regressions: why are economists obsessed with them? Finance and Development: a quarterly magazine of the IMF, Vol. 43, No.
46. Spyrou MS, Shanks K, Cook MJ, Pitcher J, Lee R (2014) An empirical study of electricity and gas demand drivers in large food retail buildings of a national organisation. Energy Buil 68:172–182
47. Boyd GA (2011) Development of performance-based industrial energy efficiency indicators for food processing plants. Report to the US Environmental Protection Agency ENERGY STAR Programme, obtained from http://www.energystar.gov/buildings/tools-and-resources/read-about-food-processing-plant-epis, 05 December 2013
48. Tassou SA, Ge Y, Hadawey A, Marriott D (2011) Energy consumption and conservation in food retailing. Appl Therm Eng 31(2–3):147–156
49. Amundson T, Brooks S, Eskil J, Martin S, Mulqueen S (2013). Elements of defensible regression-based energy models for monitoring and reporting energy savings in industrial energy efficiency operation and maintenance projects. In proceedings of the 2013 ACEEE Summer Study on Energy Efficiency in Industry, 25 July 2013, Paper no. 192
50. Esmaeili A, Shokoohi Z (2011) Assessing the effect of oil price on world food prices: application of principal component analysis. Energy Policy 39 (2):1022–1025
51. Seibel (2003) Decomposition analysis of carbon dioxide-emission changes in Germany - conceptual framework and empirical results, Federal statistical office of Germany: Environmental economic accounting division. © European Communities, ISBN 92-894-5167-X, 32 pp
52. Fair RC (2004) Estimating how the macroeconomy works. ISBN: 0-674-01546-0, The President and Fellows of Harvard College, Cambridge, Massachusetts, London, England
53. Dagoumas A, Barker T, Scrieciu S, Stretton S (2009) Top-down technological modelling of stabilisation pathways: UKERC scenarios for the UK to 2050 using E3MG-UK. IOP Conference Series. Earth Environ Sci 6:272003, doi:10.1088/1755-1307/6/7/272003
54. Christ CF (1955) A review of input-output analysis. In Input-output analysis: an appraisal. Princeton University Press (ISBN: 0-870-14173-2), pp. 137–182. Available at www.nber.org/chapters/c2866, Accessed on 21 December 2013
55. Bullard CW, Herendeen RA (1975) The energy cost of goods and services. Energy Policy 3(4):268–278
56. Casler S, Wilbur S (1984) Energy input-output analysis: a simple guide. Resour Energy 6(2):187–201
57. Zhang B, Chen ZM, Zia XH, Xu XY, Chen YB (2013) The impact of domestic trade on China's regional energy uses: a multi-regional input-output modelling. Energy Policy 63:1169–1181
58. Bekhet HA, Abdullah A (2010) Energy use in agriculture sector: input-output analysis. Int Bus Res 3:3
59. Essengun K, Erdal G, Gunduz O, Erdal H (2007) An economic analysis and energy use in stake-tomato production in Tokat province of Turkey. Renew Energy 32(11):1873–1881
60. Essengun K, Gunduz O, Erdal G (2007) Input-output energy analysis in dry apricot production of Turkey. Energy Convers Manag 48(2):592–598
61. Kuswardhani N, Soni P, Shivakoti GP (2013) Comparative energy input-output and financial analyses of greenhouse and open field vegetables production in West Java, Indonesia. Energy 53:83–92
62. Franzluebbers AJ, Francis CA (1995) Energy output: input ratio of maize and sorghum management systems in eastern Nebraska. Agric Ecosyst Environ 53(3):271–278
63. Pahlavan R, Omid M, Akram A (2012) Energy input-output analysis and application of artificial neural networks for predicting greenhouse basil production. Energy 37(1):171–176
64. Ren LT, Liu ZX, Wei TY, Xie GH (2012) Evaluation of energy input and output of sweet sorghum grown as a bioenergy crop on coastal saline-alkali land. Energy 47(1):166–173
65. Ozkan B, Ceylan RF, Kizilay H (2011) Energy inputs and crop yield relationships in greenhouse winter crop tomato production. Renew Energy 36(11):3217–3221
66. Bojacá CR, Casilimas HA, Gil R, Schrevens E (2012) Extending the input-output energy balance methodology in agriculture through cluster analysis. Energy 47(1):465–470
67. Michos MC, Mamolos AP, Menexes GC, Tsatsarelis CA, Tsirakoglou VM, Kalburtji KL (2012) Energy inputs, outputs and greenhouse gas emissions in organic, integrated and conventional peach orchards. Ecol Indic 13(1):22–28
68. Salehi M, Ebrahimi R, Maleki A, Mobtaker HG (2014) An assessment of energy modelling and input costs for greenhouse button mushroom production in Iran. J Clean Prod 64:377–383
69. Rormose P, Olsen T (2005) Structural decomposition analysis of air emissions in Denmark 1980-2002, 15th International Conference on Input-output Techniques Beijing, China June 27 to July 1, 2005., Accessible from http://iioa.org/conferences/15th/pdf/roermose_olsen.pdf. Accessed on 01 February 2015
70. Wachsmann U, Wood R, Lenzen M, Schaeffer R (2009) Structural decomposition of energy use in Brazil from 1970 to 1996. Appl Energy 86 (4):578–587
71. Nie H, Kemp R (2013) Why did energy intensity fluctuate during 2000-2009? A combination of index decomposition analysis and structural decomposition analysis. Energy Sustain Dev 17:482–488
72. Cao S, Xie G, Zhen L (2010) Total embodied energy requirements and its decomposition in China's agricultural sector. Ecol Econ 69:1396–1404
73. Ang BW (2004) Decomposition analysis for policymaking in energy: which is the preferred method? Energy Policy 32:1131–1139
74. Cahill CJ, Gallachoir BPO (2012) Combining physical and economic output data to analyse energy and CO2 emissions trends in industry. Energy Policy 49:422–429
75. Hammond GP, Norman JB (2012) Decomposition analysis of energy-related carbon emissions from UK manufacturing. Energy 41:220–227
76. Jenne CA, Cattell RK (1983) Structural change and energy efficiency in industry. Energy Econ 5(2):114–123
77. Hasanbeigi A, Price L, Fino-Chen C, Lu H, Ke J (2013) Retrospective and prospective decomposition analysis of Chinese manufacturing energy use and policy implications. Energy Policy 63:562–574
78. Reddy BS, Ray BK (2010) Decomposition of energy consumption and energy intensity in Indian manufacturing industries. Energy Sustain Dev 14(1):35–47
79. Taylor PG, D'Ortigue OL, Francoeur M, Trudeau N (2010) Final energy use in IEA countries: the role of energy efficiency. Energy Policy 38:6463–6474
80. Jeong K, Kim S (2013) LMDI decomposition analysis of greenhouse gas emissions in the Korean manufacturing sector. Energy Policy 62:1245–1253
81. Hasanbeigi A, Rue du Can S, Sathaye J (2012) Analysis and decomposition of the energy intensity of California industries. Energy Policy 46:234–245
82. Salta M, Polatidis H, Haralambopoulos D (2009) Energy use in the Greek manufacturing sector: a methodological framework based on physical indicators with aggregation and decomposition analysis. Energy 34:90–111
83. Bhattacharya SC, Ussanarassamee A (2005) Changes in energy intensities of Thai industry between 1981 and 2000: a decomposition analysis. Energy Policy 33:995–1002
84. Robaina-Alves M, Moutinho V (2014) Decomposition of energy-related GHG emissions in agriculture over 1995-2008 for European countries. Appl Energy 114:949–957
85. Mairet N, Decellas F (2009) Determinants of energy demand in the French service sector: a decomposition analysis. Energy Policy 37(7):2734–2744
86. Mulder P, de Groot HLF (2013) Dutch sectoral energy intensity developments in international perspective, 1987–2005. Energy Policy 52:501–512
87. Md S, Alam K (2013) Changes in energy efficiency in Australia: a decomposition of aggregate energy intensity using logarithmic mean Divisia approach. Energy Policy 56:341–351
88. Inglesi-Lotz R, Pouris A (2012) Energy efficiency in South Africa: a decomposition exercise. Energy 42(1):113–120

89. Balezentis A, Balezentis T, Streimikiene D (2011) The energy intensity in Lithuania during 1995-2009: A LMDI approach. Energy Policy 39:7322–7334
90. Ediger VS, Huvaz O (2006) Examining the sectoral energy use in Turkish economy (1980-2000) with the help of decomposition analysis. Energy Convers Manag 47(6):732–745
91. Ang BW, Huang HC, Mu AR (2009) Properties and linkages of some index decomposition analysis methods. Energy Policy 37:4624–4632
92. Paltsev S (2004) Moving from static to dynamic general equilibrium economic models (notes for a beginner in MPSGE), MIT joint program on the science and policy of global change, technical note 4 (June 2004)
93. Rout UK, Voβ A, Singh A, Fahl U, Blesl M, Gallachoir BPO (2011) Energy and emissions forecast of China over a long-time horizon. Energy 36:1–11
94. Baek J, Koo WW (2010) Analyzing factors affecting U.S. food price inflation. Can J Agric Econ 58(3):303–320
95. PIK Landuse Group (2011), MAgPIE Mathematical description, obtained from http://www.pik-potsdam.de/research/sustainable-solutions/research/landuse-group/magpie-mathematical-description. Accessed on 14 December 2013
96. Dietrich JP, Schmitz C, Lotze-Campen H, Popp A, Müller C (2014) Forecasting technological change in agriculture—an endogenous implementation in a global land use model. Technol Forecast Soc Chang 81:236–249
97. Schmitz C, Biewald A, Lotze-Campen H, Popp A, Dietrich JP, Bodirsky B, Krause M, Weindl I (2012) Trading more food: implications for land use, greenhouse gas emissions, and the food system. Glob Environ Chang 22 (1):189–209
98. Popp A, Lotze-Campen H, Bodirsky B (2010) Food consumption, diet shifts and associated non-CO2 greenhouse gases from agricultural production. Glob Environ Chang 20(3):451–462
99. Acquaye AA, Wiedmann T, Feng K, Crawford RH, Barrett J, Kuylenstierna J, Duffy AP, Lenny Koh SC, McQueen-Mason S (2011) Identification of "carbon hot-spots" and quantification of GHG intensities in the biodiesel supply chain using hybrid LCA and structural path analysis. Environ Sci Technol 45 (6):2471–2478
100. Suh S, Huppes G (2005) Methods for life cycle inventory of a product. J Clean Prod 13(7):687–697
101. Elgimez G, Kucukvar M, Tatari O, Bhutta MKS (2014) Supply chain sustainability assessment of the US food manufacturing sectors: a life cycle based frontier approach. Resour Conserv Recycl 82:8–20
102. Virtanen Y, Kurppa S, Saarinen M, Katajajuuri JM, Usva K, Mäenpää I, Mäkelä J, Grönroos J, Nissinen A (2011) Carbon footprint of food - approaches from national input-output statistics and a LCA of a food portion. J Clean Prod 19 (16):1849–1856
103. Wood R, Lenzen M, Dey C, Lundie A (2006) A comparative study of some environmental impacts of conventional and organic farming in Australia. Agric Syst 89(2–3):324–348
104. Garnett T (2006) Fruit and vegetables and UK greenhouse gas emissions: exploring the relationship., Produced as part of the work of the food climate research network, FCRN working paper 06–01 Rev. A
105. Goldstein G and Tosato GC (2008) Global energy system and common analyses: Final report of Annex X (2005-2008). International Energy Agency (IEA), http://www.etsap.org/FinReport/ETSAP_AnnexX_FinalReport-080915.PDF. Accessed on 5 December 2013
106. The Energy and Research Institute (Teri), Government of India (2006) National energy map for India: technology vision 2030. Press, TERI. ISBN 81-7993-099-8
107. Strachan N, Anandarajah G, Pye S, Usher W (2010) UK Energy-economic modelling. An overview of the UK MARKAL/TIMES family., Presentation at the UCL Energy Institute, University College London, July 2010
108. Reddy TA, Claridge DE (2000) Uncertainty of "measured" energy savings from statistical baseline models. HVAC&R Res 6(1):3–20
109. Martinez SH, Jv E, Cunha MP, Guilhoto JJM, Walter A, Faaij A (2013) Analysis of socio-economic impacts of sustainable sugarcane-ethanol production by means of inter-regional input-output analysis: demonstrated for Northeast Brazil. Renew Sust Energ Rev 28:290–316
110. Hoekstra R, van der Bergh JJCJM (2003) Comparing structural and index decomposition analysis. Energy Economics 25(1):39–64
111. Karkacier O, Goktolga ZG (2005) Input-output analysis of energy use in agriculture. Energy Convers Manag 46:1513–1521