

Quantifying the uncertainties in life cycle greenhouse gas emissions for UK wheat ethanol

This content has been downloaded from IOPscience. Please scroll down to see the full text.

2013 Environ. Res. Lett. 8 015024

(<http://iopscience.iop.org/1748-9326/8/1/015024>)

View [the table of contents for this issue](#), or go to the [journal homepage](#) for more

Download details:

IP Address: 144.173.57.70

This content was downloaded on 06/06/2016 at 11:09

Please note that [terms and conditions apply](#).

Quantifying the uncertainties in life cycle greenhouse gas emissions for UK wheat ethanol

Xiaoyu Yan^{1,2} and Adam M Boies¹

¹ Department of Engineering, University of Cambridge, Trumpington Street, Cambridge CB2 1PZ, UK

² Environment and Sustainability Institute, University of Exeter, Penryn, Cornwall TR10 9EZ, UK

E-mail: xiaoyu.yan@alumni.qmul.net

Received 30 November 2012

Accepted for publication 8 February 2013

Published 27 February 2013

Online at stacks.iop.org/ERL/8/015024

Abstract

Biofuels are increasingly promoted worldwide as a means for reducing greenhouse gas (GHG) emissions from transport. However, current regulatory frameworks and most academic life cycle analyses adopt a deterministic approach in determining the GHG intensities of biofuels and thus ignore the inherent risk associated with biofuel production. This study aims to develop a transparent stochastic method for evaluating UK biofuels that determines both the magnitude and uncertainty of GHG intensity on the basis of current industry practices. Using wheat ethanol as a case study, we show that the GHG intensity could span a range of 40–110 gCO₂e MJ⁻¹ when land use change (LUC) emissions and various sources of uncertainty are taken into account, as compared with a regulatory default value of 44 gCO₂e MJ⁻¹. This suggests that the current deterministic regulatory framework underestimates wheat ethanol GHG intensity and thus may not be effective in evaluating transport fuels. Uncertainties in determining the GHG intensity of UK wheat ethanol include limitations of available data at a localized scale, and significant scientific uncertainty of parameters such as soil N₂O and LUC emissions. Biofuel policies should be robust enough to incorporate the currently irreducible uncertainties and flexible enough to be readily revised when better science is available.

Keywords: life cycle, greenhouse gas emissions, uncertainty, biofuel, ethanol, wheat

 Online supplementary data available from stacks.iop.org/ERL/8/015024/mmedia

1. Introduction

Lack of viable alternatives to reduce transport greenhouse gas (GHG) emissions, a desire for energy security and economic demands for increased markets for domestically produced crops have led to significant emphasis on the production and use of liquid transport fuels from biomass. Ethanol and biodiesel are the largest biofuels produced globally due to their compatibility with existing vehicles and their relatively mature production technology. Worldwide

fuel-ethanol production rapidly increased from 17 to 86 billion litres and biodiesel from 1 to 21 billion litres between 2000 and 2011 due to government support such as mandates, subsidies and tax benefits. Biofuel production is expected to increase to more than 220 billion litres if mandates currently in place around the world are met (REN21 2012). Within the EU biofuel usage is governed by the Renewable Energy Directive (RED), which requires 10% of road transport fuels by energy to be sourced from biofuels by 2020. The RED targets have been met almost exclusively through direct substitution of ethanol and biodiesel with gasoline and diesel. While, ethanol is mainly produced from corn in the US and sugarcane in Brazil, accounting for 63 and 24% of global production in 2011, respectively, wheat is a major feedstock



Content from this work may be used under the terms of the [Creative Commons Attribution 3.0 licence](http://creativecommons.org/licenses/by/3.0/). Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.

used in other top ethanol producers such as the EU, China and Canada (Balat and Balat 2009, Yan 2012). Ethanol production from wheat in the EU increased from 0.53 to 1.74 billion litres between 2000 and 2011 (40% of total production in 2011) and is forecasted to reach 2.2 billion litres by 2013 (Flach *et al* 2012). Wheat is a particularly attractive ethanol feedstock for north-European countries, as it is the highest yielding cereal crop (6.8 tonnes ha⁻¹ in 2010) and represents over half of all cereal production (27.2 megatonnes in 2010). Within northern-Europe the UK represents over half of all wheat production (27.2 megatonnes in 2010) and achieves the second highest yields (7.7 tonnes ha⁻¹ in 2010) (FAOSTAT 2012).

While Europe has set common RED objectives, the manner in which individual countries meet their objectives and production of the biofuels remain distinct. In the UK, the Renewable Transport Fuel Obligation (RTFO) came into effect in 2008 and is the principle legislation driving biofuel consumption. The RTFO obligates fossil fuel suppliers to blend 5% biofuel by volume within road transport fuels by 2013. To meet RTFO objectives more than a billion litres of biofuels have been consumed within the UK annually since 2008, with the majority of these met by imports. Ethanol produced from UK wheat jumped to 120 million litres during the 2010/11 RTFO year (DfT 2011) as the UK's first and the Europe's largest wheat ethanol plant, Ensus, came into production in early 2010 with an annual capacity of 400 million litres. Another large wheat ethanol plant in the UK with an annual production capacity of 420 million litres is expected to be operational in late 2012 (Vivergo 2012) while a smaller one with an annual production capacity of 200 million litres is under construction (Vireol 2012). This indicates that wheat ethanol production in the UK could increase substantially in the next few years. These three ethanol plants could potentially produce ~1.0 billion litres of ethanol annually, ~5.1% of the UK petrol vehicle fuel use in 2011 by volume or ~3.4% by energy.

While wheat ethanol is poised to dominate the ethanol market within the UK and EU, relatively few studies have examined the GHG intensity of the fuels. The majority of life cycle analysis (LCA) studies (academic and private) to date are based on deterministic models that include non-homogenous system boundaries, adopt different methods of dealing with co-products, use hypothetical processing technologies, use differing soil N₂O emission factors and omit the effect of land use change (LUC). Not surprisingly the GHG intensities of wheat ethanol from past studies range in value from 14 to 128 gCO₂e MJ⁻¹, see table S1 in the supporting information (available at stacks.iop.org/ERL/8/015024/mmedia) (Bernesson *et al* 2006, Klemetsson and Smith 2011, LowCVP 2004, Mortimer *et al* 2004, Mosier *et al* 2009, Richards 2000, Scacchi *et al* 2010, Weinberg and Kaltschmitt 2013). Despite this divergence in results, there is none of them giving an indication of which GHG intensity is more likely.

Despite the lack of uncertainty studies for wheat ethanol, LCA practitioners have begun to incorporate the inherent uncertainties of input parameters using stochastic modelling

methods for other fuels. Such studies have typically found GHG intensities for biofuels to be highly uncertain, mainly because of the uncertainties in key parameters such as indirect LUC and soil N₂O emissions (Boies *et al* 2011, Mullins *et al* 2011, Plevin *et al* 2010). One study on EU wheat ethanol has adopted the stochastic methodology (Malça and Freire 2012) and reported GHG intensities from slightly negative (net sequestering) to greater than 300 gCO₂e MJ⁻¹ depending on LUC assumptions and co-product methods. However, the results from this study are not suitable for regulatory purposes as Malça and Freire (2012) have failed to properly justify the probability distributions used for many input parameters and rely on different scenarios for direct LUC without giving clear indication of which scenario is most likely.

Despite the lack of academic consensus, European governments have recognized the need for controls on GHG intensity. Biofuel suppliers need to demonstrate compliance with the RED GHG savings requirements in order to for their biofuels to be accounted towards meeting the RTFO obligation. The requirements are at least 35% GHG savings, rising to at least 50% from 2017 and 60% from 2018 (DfT 2012a). To determine the GHG intensity of fuels the RTFO developed a fuel carbon calculator which is a deterministic LCA model where inputs are intended to contain high GHG intensity default values to encourage self-reporting by biofuel suppliers. While widely used within the fuel industry, this carbon calculator suffers from key inadequacies including omission of indirect LUC emissions, poor treatment of uncertainty and a rigid method of dealing with biofuel co-products.

The objectives of this study are to develop a transparent method for evaluating UK biofuels that determines both the magnitude and uncertainty of GHG intensity. Using UK wheat ethanol as a case study, we compare deterministic GHG intensity results using RTFO inputs with our stochastic outcomes to determine whether the default values are conservative enough to encourage self-reporting by fuel producers. Key sources of uncertainties in determining the GHG intensity based on currently available knowledge and data are discussed. Finally, different methods of attributing emissions to co-products are evaluated and the resulting GHG intensity probability distributions are compared to determine their applicability for use as a standard.

2. Method and data

Our analysis adopts the attributional LCA method and is based on the current practices of the wheat ethanol industry in the UK. The life cycle stages considered include agriculture (wheat and straw cultivation and harvest), wheat transport and handling, biorefinery (ethanol and co-product production), ethanol distribution and potential land use change. The efficiency of ethanol combustion and resulting effects on vehicle performance are analysed in a separate study (Yan *et al* 2012); in this analysis we assume complete combustion whereby the CO₂ emitted is initially absorbed from the atmosphere during wheat growing. The GHG intensity of wheat ethanol is derived by aggregating the life cycle GHG

emissions for direct energy and material inputs at each stage normalized to per MJ final fuel energy produced. For non-CO₂ GHG emissions we consider CH₄ and N₂O, with all emissions converted to CO₂ equivalents (CO₂e) based on their 100-year global warming potential (23 gCO₂e/gCH₄ and 296 gCO₂e/gN₂O).

Our LCA model uses Oracle Crystal Ball (Oracle 2012) to perform Monte Carlo simulation with 10 000 iterations per simulation is used to assess the uncertainty in the final GHG intensity. Sources of uncertainty in LCA can be broadly classified into parameter uncertainty (input data), normative choice and model uncertainty (mathematical relationships) (Lloyd and Ries 2007). As the mathematical relationship in an LCA model is relatively simple (linear and additive), model uncertainty is considered to be minimum. For normative choice, a major issue yet to be resolved for attributional LCA is choosing appropriate method(s) of dealing with the co-products in the biofuel production system. Possible methods include the substitution (or displacement) method where emission burdens of producing the products displaced by biofuel co-products are credited to the biofuel and the allocation methods where emissions are allocated between biofuels and co-products based on a common metric such as mass, energy content and market value. These methods all have advantages and drawbacks and can in some cases produce significantly different results (Wang *et al* 2011). To assess the uncertainty induced by different choices, we use the energy allocation, economic (or market value) allocation and substitution methods in our analysis to deal with the straw, DDGS and electricity co-produced in the wheat ethanol pathway.

This study addresses parameter uncertainty arising from a variety of different origins, including statistical uncertainty, temporal/spatial variability, data limitation and scientific uncertainty. Statistical uncertainty refers to the uncertainty induced by estimating the population means from samples. These are usually recorded for parameters that have large samples collected through surveys. Temporal or spatial variability includes parameters that vary by times or regions and can be measured such as wheat yield and agro-chemical inputs. Data limitation includes parameters that have only limited data available and the uncertainties of which can, at least in theory, be reduced through further data collection/reporting or analysis. Scientific uncertainty includes parameters that are currently highly uncertain with the best available science such as soil N₂O emission from fertilizer use and the carbon emission from land use change. A set of model runs are designed to assess the impact of these different sources on the overall uncertainty in the GHG intensity and are described in more detail below. The Baseline run serves as a benchmark and is a deterministic or point estimate of the GHG intensity where the mean or most likely values for all the parameters are used. Other runs include different sets of parameters for uncertainty analysis while keeping the rest fixed as in the Baseline. Detailed input data for all runs are presented in the supporting information (see tables S2 and S3 available at stacks.iop.org/ERL/8/015024/mmedia).

2.1. Baseline (point estimate)

UK average values for the year 2010 are used for grain yield and agro-inputs. Seeding rate is assumed to be 180 kg ha⁻¹, the average of the 175 and 185 kg ha⁻¹ cited in Berry *et al* (2008) and Mortimer *et al* (2004) respectively. Manufacture or embedded GHG emissions for agro-inputs are taken from the literature (AEA 2010, Audsley *et al* 2009, DfT 2012b, Williams *et al* 2006). Nitrogen (N) fertilizers applied to UK wheat are estimated to be 78% of ammonium nitrate and 22% of urea based on the quantity of different N fertilizers consumed (BSFP 1998–2011) and their nutrient contents (Defra 2010). Diesel fuel use by farm machinery is not usually recorded and is often estimated based on characteristics of the machinery used and the time needed to complete each type of field operation (such as ploughing and harvesting). A UK average value of 112 l ha⁻¹ estimated by AEA (2010) is used.

Soil N₂O emissions are estimated following the IPCC Tier 1 methodologies. These include direct emissions from N inputs (N fertilizer applied and N in the crop residues returned to the soil) and indirect emissions through atmospheric deposition of N volatilized as NH₃ and NO_x and through the nitrate leaching effect (IPCC 2006). N₂O emissions from cultivating organic soils (or histosols) are also taken into account and are calculated to be 47.1 kgCO₂e ha⁻¹ based on the regional emissions estimated by AEA (2010) weighted by the wheat production of each region. There is a growing concern that the soil N₂O emission rate might be significantly underestimated using the bottom-up IPCC methodologies and the implications for biofuel GHG intensity calculations can be substantial (Crutzen *et al* 2008, Klemetsson and Smith 2011, Mosier *et al* 2009). However, the higher emission rates estimated by the global top-down methodology needs to be validated by field measurements before they can be used in a localized analysis. A revisit of the soil N₂O emission rates is necessary when new evidence is available.

LUC emissions are one of the major issues surrounding biofuels yet to be resolved. These emissions are inherently uncertain, as they cannot be directly measured or verified and are commonly estimated using complex general or partial equilibrium models. The majority of the work in this area has been focused on US corn ethanol where the estimated LUC emissions vary by an order of magnitude (Boies *et al* 2011). Estimates for wheat ethanol from several recent EU biofuel studies also differ significantly, ranging from 14 to 139 gCO₂e MJ⁻¹ (Edwards *et al* 2010). These studies were reviewed by the International Council on Clean Transportation (Malins 2012) and the most recent study by the IFPRI (Laborde 2011) was considered to represent the 'best available scientific evidence'. Therefore, the result for EU wheat ethanol from this study, 14.4 gCO₂e MJ⁻¹ (including both direct and indirect emissions), was used in our analysis. This value is rather low compared with other biofuels mainly because the co-produced DDGS displaces soy meal imports from South America when used as animal feed and hence reduce LUC caused by soybean production. Other methodologies have produced, in our view, overly optimistic results, such as the recent UK Department for Transport study

using a 'casual descriptive' methodology, resulting in net LUC emissions for EU wheat ethanol that were negative as a result of the displacement of soybean production in South America by DDGS (E4tech 2010). Due to the lack of rigour within this and similar studies, such results were not included.

Most of the biorefinery data were provided by Ensus (Lywood 2011). The wheat-to-ethanol conversion efficiency is higher than those cited in earlier studies (LowCVP 2004, Richards 2000) but is typical for modern EU wheat bioethanol plants (Lywood 2011). A natural gas turbine CHP with an overall efficiency of 90% and an electricity-to-heat ratio of 0.5 is used to supply the process heat and electricity demand. Electricity surplus is sold to the grid. GHG emissions embedded in chemicals input and from plant construction and maintenance are taken from (Mortimer *et al* 2004).

Most of the data for transport and handling of wheat and ethanol are from the RTFO default values (DFT 2012b). Transport of wheat from farm to biorefinery is by lorry and the distance is 75 km (Lywood 2011). Transport of ethanol from biorefinery to depot (Ensus to Stanlow) is by boat of 5000 tonne size (Lywood 2011) and the distance is estimated by the authors to be ~400 km. Transport distance for straw from farm to use is set at 50 km, which reflects the use of straw within a closer proximity due to the low energy density. The GHG intensities for energy carriers are assumed to be 90.2 gCO₂e MJ⁻¹ diesel fuel, 65.8 gCO₂e MJ⁻¹ natural gas (Edwards *et al* 2011) and 589.8 gCO₂e kWh⁻¹ electricity consumed (AEA 2012).

For energy-based allocation of emissions between ethanol and co-products, the energy contents of different products are needed. These are taken as the lower heating values (LHV) for wheat, straw, ethanol and DDGS and 1 MJ MJ⁻¹ for electricity. Market prices are needed for market value-based allocation of emissions. Monthly average prices for feed wheat and wheat straw are available from Defra statistics (Defra 2012a) and the average prices in 2010 are used to derive the wheat/straw price ratio. There are no publicly available information on the prices of fuel ethanol and DDGS in the UK and the average prices during 2008–2011 provided by Ensus (Lywood 2011) are used. The price for electricity is taken as the mean value of annual average price paid by the manufacturing industry during 2008–2011 (DECC 2012).

The substitution method tends to better reflect the actual effects of co-products compared with the allocation methods and is the preferred option in many academic studies and regulatory frameworks (Wang *et al* 2011). The primary use of wheat straw collected is currently for animal bedding in the UK while a small amount is also used for energy generation and in the mushroom industry (Copeland and Turley 2008). The only straw-fired power plant in the UK, the Ely Biomass Power Station, consumes 0.2 million tonnes of straw annually or ~3% of total wheat straw collected. This percentage is used in this analysis. We assume the production of electricity from straw will replace equal parts coal- and natural gas-fired electricity generation and determine the emissions credit based on the displaced emissions less the non-CO₂ GHG emissions from straw combustion. The GHG intensity for coal

used in power generation is 111.1 gCO₂e MJ⁻¹ coal (AEA 2012). No emission credit is assigned to the straw used in the livestock and mushroom industries as the substitution effect is unclear. A separate case is considered where the straw is not taken into account in order to compare our results with studies where straw is not considered.

The electricity surplus generated at the biorefinery is sold to the grid and is thus assumed to displace grid electricity. The emission credit is 547 gCO₂e kWh⁻¹ electricity generated (the difference between the emission factors for electricity consumed and generated is due to transmission and distribution losses) (AEA 2012). The substitution effect of DDGS as animal feed is accounted for but remains wrought with uncertainty. Although many previous LCA studies have used a simple substitution ratio between DDGS and the products assumed to be displaced such as soy meal, in reality this effect is much more complex and not directly measurable. A study based on digestible nutritional values shows that 1 tonne of wheat DDGS could displace 0.386 tonne of feed wheat and 0.594 tonne of soy meal (Lywood *et al* 2009). Another study suggests that 1 tonne of wheat DDGS would displace 0.33 tonne of soy meal at current inclusion levels in the EU feed market but potential exists for this substitution ratio to increase as the inclusion limits are expected to increase when larger quantities of high quality DDGS are available (Weightman *et al* 2011). A more recent UK-specific study commissioned by the International Council on Clean Transportation have developed a detailed feed formulation model and estimated that wheat DDGS in the UK will replace different mixtures of barley, wheat, soy meal and sunflower meal, among some other feed components at different DDGS prices (Hazzledine *et al* 2011). Their results show that 1 tonne of DDGS would displace 0.11 tonne of barley, 0.37 tonne of soy meal and 0.27 tonne of sunflower meal at £180 (~\$288) per tonne DDGS (the average price during 2008–2011). The value for soy meal displacement is close to that used in the LUC study by the IFPRI (Laborde 2011), where 1 tonne of DDGS was assumed to displace 0.07 tonne of wheat, 0.35 tonne of soy meal, 0.04 tonne of sunflower meal and 0.14 tonne of rapeseed meal. To be consistent with the LUC emissions used in our analysis, we assume 1 tonne of DDGS will displace 0.07 tonne of wheat and 0.35 tonne of soy meal following the IFPRI study. The displacement of sunflower and rapeseed meal is not considered as these are co-products from sunflower and rapeseed production (main products are sunflower and rapeseed oil), unlike soy meal which is the main product of soybean production. GHG emissions for wheat production are 307 kgCO₂e/tonne from our analysis based on the substitution method for co-produced straw. GHG emissions for soy meal production from South America were estimated to be 721 and 344 kgCO₂e/tonne when palm oil and rapeseed oil were assumed to be the marginal oil displaced by the co-produced soy oil (Dalgaard *et al* 2008). Given the challenge in determining which oil is the marginal oil in reality (Dalgaard *et al* 2008), we use the average value of 533 kgCO₂e/tonne for South America soy meal production.

2.2. Run 1 (statistical uncertainty)

Parameters that have statistical data available are included for uncertainty analysis in this run. Normal distributions based on the mean and standard errors reported are used to account for the statistical uncertainties for grain yield and application rates of N, phosphorus (P) and potassium (K) fertilizers as well as pesticides (mean and standard errors are not available for sulfur (S) fertilizer and lime).

2.3. Run 2 (temporal variability)

Parameters that have time series data available are included to assess the effects of temporal variability. UK average grain yield data are available from 1885 onwards (Defra 2012b). Significant increases in yields were achieved during the second half of the 20th century due to innovations in nutrient supply, crop protection and plant breeding (Dungait *et al* 2012). However, this increasing trend seems to have slowed in recent years (see figure S1 available at stacks.iop.org/ERL/8/015024/mmedia) with large variations recorded, in particular the notable drops in 2001, 2007 and 2012, mainly due to the adverse impacts of weather (Defra 2012c). A normal distribution based on the mean and standard deviation of the data over the 22-year period 1991–2012 is used to characterize the temporal variability in yields. Monthly average prices for feed wheat and wheat straw are available from 2001 onwards (Defra 2012a). A distribution fitted to the available data is used to characterize the temporal variability in the wheat/straw price ratio, which will affect the results only when co-product allocation based on market value is used.

UK average application rates for fertilizers, including N, P, K and S, are available from 1994 onwards (BSFP 1998–2011). The application rates for N fertilizer are relatively stable between 1994 and 2011 (see figure S2 available at stacks.iop.org/ERL/8/015024/mmedia), a trend since 1983 after the large increases during the 1969–1983 period (Chalmers 2001). A normal distribution based on the mean and standard deviation derived from the data over the 18-year period 1994–2011 is used to characterize the temporal variability in N application rates. The application rates for P and K fertilizers have been decreasing while that for S fertilizer has been increasing over the period 1994–2011 (see figure S3 available at stacks.iop.org/ERL/8/015024/mmedia). Application rates for all fertilizers dropped significantly in 2008 and 2009 when fertilizer prices were at historical high levels before recovering in the following years (BSFP 2011). The long-term decreases in P and K application rates reflect the need to reduce the P and K surplus in UK soils (Chalmers 2001, Dungait *et al* 2012). The increase in S application rate was necessary to compensate the reduced deposition of atmospheric S due to major reduction in anthropogenic emissions of sulfur dioxide in recent years (BSFP 2011). However, it is unclear whether or for how long these trends will continue into the future. Therefore, temporal variability is not considered for P, K and S fertilizers and deterministic values are used. Lime application rates (BSFP 1998–2011) and pesticide usage (PUSR 1998–2010) are available from

1998 and 1992 onwards respectively and uniform distributions based on the minimum and maximum values recorded are used to characterize their temporal variability.

2.4. Run 3 (temporal and spatial variability)

The annual average grain yield data are available for the Nomenclature of Territorial Units for Statistics level 1 regions of England and the rest of the UK as a whole for the 14-year period 1999–2012 (Defra 2012b). Yields in all regions varied over time and the differences in the average yields over the 14-year period between different regions are not statistically significant except for the North West where yields were notably and consistently lower than other regions (see figure S4 available at stacks.iop.org/ERL/8/015024/mmedia). Therefore, it is considered reasonable to treat these data points as random. A distribution fitted to the regional average values excluding those for the North West is used to characterize the temporal and spatial variability in yields, accounting for 98% of UK wheat production. The region-specific farm machinery fuel uses were estimated by AEA (2010) taking into account regional differences in factors such as field size and soil type. A triangular distribution is used based on the UK average, minimum and maximum values reported in this study. The data in the fertilizer and pesticide surveys were not sufficiently robust to estimate regional differences in fertilizer and pesticide application rates. Therefore, spatial variability for all agro-inputs is not considered and the only differences between Run 3 and 2 are grain yield and farm machinery diesel use.

2.5. Run 4 (data limitation)

Most LCA input parameters are quantities that could be robustly measured or reported (as opposed to parameters that do not have direct methods of measurement), but in practice are not collected in a coherent manner. For parameters that have only one value available such as the grain/aboveground biomass dry mass ratio (used to derive straw yield from grain yield) and transport and handling data, uniform distributions based on a $\pm 10\%$ range of the available values are used to represent the uncertainty. For parameters that have two or more values, uniform distributions are chosen based on available information. Triangular distributions are used for parameters with most likely, minimum and maximum values available such as the CH₄ and N₂O emission factors for straw burned for power generation (IPCC 2006) and the GHG intensities for diesel and natural gas (Edwards *et al* 2011).

One of the most important parameters is the quantity of GHG emissions released in ammonium nitrate fertilizer production as the process is energy intensive and generates N₂O emissions. The AEA (2010) regional biofuel report suggests that N fertilizer manufacturing plants in the UK and the countries from which the UK imports most of its N fertilizers are fitted with N₂O abatement technology which enables a reduction in N₂O emissions of up to 70–85%. The embedded GHG emissions in ammonium nitrate fertilizer of 2.9 kgCO₂e kg⁻¹ N⁻¹ used in the Baseline is derived from

plants fitted with N₂O abatement technology. However, there are no peer-reviewed scientific studies to confirm these claims. Given that the embedded GHG emissions in ammonium nitrate fertilizer can be as high as 7.2 kgCO₂e kg⁻¹ N⁻¹ (Williams *et al* 2006), we use a uniform distribution with minimum and maximum values of 2.9 and 7.2 to represent the uncertainty in this parameter.

Another important input parameter is the share of collected straw used for power generation. A uniform distribution is used where the minimum value is 3%, the value used in the Baseline reflecting current straw usage UK power stations. Two new straw-fired power plants and a few smaller straw CHP stations that are expected to be operational in the near future (Brigg Renewable Energy Plant 2012, Sleaford Renewable Energy Plant 2012, Copeland and Turley 2008) will increase the share of straw used for energy to 0.787 million tonnes or ~12% of total straw collected. This is used as the maximum value.

A uniform distribution is used to represent the variability of the wheat-to-ethanol conversion efficiency using the minimum and maximum values reported (Bernesson *et al* 2006, LowCVP 2004, Lywood 2011, Mortimer *et al* 2004, Richards 2000, Scacchi *et al* 2010, Weinberg and Kaltschmitt 2013). The overall efficiency of 90% for the biorefinery gas turbine CHP in the Baseline is high compared with the 2011 UK average gas turbine CHP efficiency of ~80% (DECC 2012) and the 84–85% used in previous studies (LowCVP 2004, Mortimer *et al* 2004). A uniform distribution is used to represent the variability of the CHP efficiency with a minimum value of 80% and a maximum value of 90%.

2.6. Run 5 (scientific uncertainty IPCC)

Scientifically uncertain parameters are those that are not well-known despite effort for better quantification and parameters whose uncertainty is likely to remain large. These include soil N₂O emissions, LUC emissions and the substitution effects of DDGS. The triangular distributions used in our model to represent the uncertainties in soil N₂O emission related parameters are based on the uncertainty guideline given by the IPCC (2006). Uncertainty in N₂O emissions from cultivating organic soils is characterized by a discrete distribution based on the regional emissions estimated by AEA (2010) and their wheat production weighted probability.

The IFPRI LUC study (Laborde 2011) has carried out stochastic simulations to assess the uncertainty ranges of the LUC (direct and indirect) emission estimates caused by the uncertainties in a few key parameters. A normal distribution based on their results for wheat ethanol, a mean of 13.6 and standard deviation of 3.1 gCO₂e MJ⁻¹, are used in our model to represent the uncertainty in wheat ethanol LUC emissions. Their results, however, are optimistic estimates of the true uncertainty as some large sources of uncertainties, such as the carbon stock of new land brought into cultivation and the uncertainty about future agricultural practices, were not included in the stochastic simulations (Laborde 2011). The UK wheat LUC emissions are less than those of studies of US corn ethanol where total LUC emissions

have been found to range from 70 to 168 gCO₂e MJ⁻¹ by Plevin (2010). Although, regulatory frameworks have used significantly lower LUC emissions levels for US corn ethanol (30 gCO₂e MJ⁻¹ by CARB and 34 gCO₂e MJ⁻¹ by USEPA), comparisons of such values to UK wheat ethanol LUCs are not valid as they do not represent the best understanding of scientific uncertainty. Future work is necessary to refine the UK wheat ethanol LUC uncertainty range.

The uncertainty in the substitution emission credit for DDGS is represented by a uniform distribution with a minimum and maximum value of 114 and 301 kgCO₂e/tonne. The minimum value is based on the substitution ratio estimated by Weightman *et al* (2011), 0.33 tonne of soy meal per tonne DDGS, and GHG emissions of 344 kgCO₂e/tonne for soy meal while the maximum value is based on the substitution ratios estimated by Hazzledine *et al* (2011), 0.11 tonne of barley (assuming the emissions associated with barley production are the same with wheat) and 0.35 tonne of soy meal per tonne DDGS and GHG emissions of 721 kgCO₂e/tonne for soy meal.

2.7. Run 6 (scientific uncertainty UK-DNDC)

This run is analogous to Run 5 except that the direct soil N₂O emissions and their uncertainties are derived based on the preliminary results from the UK-DNDC model (AEA 2010). This model is a version of the process-based model DNDC with UK-specific data on soil characteristics, crops, daily weather, livestock and farming at a county-scale to provide county-scale estimate of direct soil N₂O emissions. N₂O emissions from crop residues returned to the soil and from cultivating organic soils are taken into account in the model. A triangular distribution approximated to the wheat production weighted probability of regional emission factors derived from UK-DNDC is used (see figure S5 available at stacks.iop.org/ERL/8/015024/mmedia). This approach reflects the uncertainty faced by ethanol producers when the origin of the feedstock wheat is unknown. The UK-DNDC is a deterministic model that is continuing to be developed and will be validated by future field work (AEA 2010).

2.8. Run 7 (all IPCC)

Run 7 is a combination of the Runs 3, 4 and 5, i.e., it includes all sources of parameter uncertainty with the soil N₂O emissions estimated based on the IPCC Tier 1 methodology.

2.9. Run 8 (all UK-DNDC)

Run 8 is analogous to Run 7 except that the direct soil N₂O emissions are estimated based on results from the UK-DNDC model.

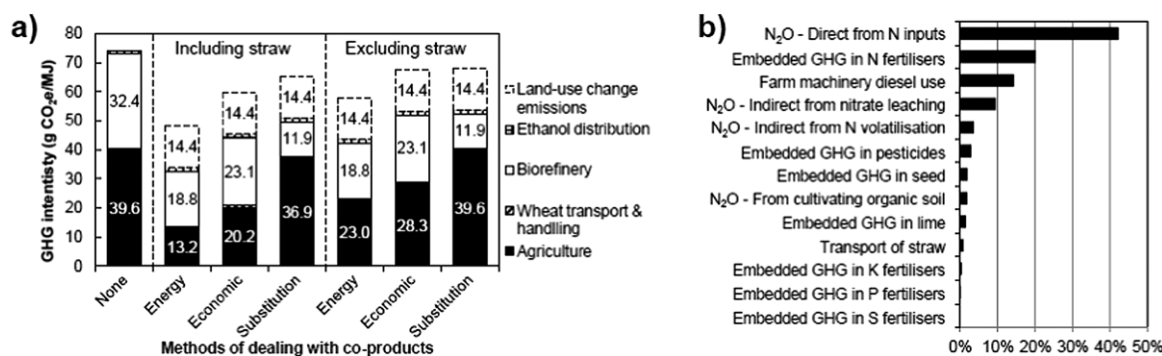


Figure 1. (a) Deterministic evaluation of UK wheat ethanol GHG intensity. (b) Contributions to the agriculture GHG emissions from different sources.

2.10. Run 9 (all UK-DNDC + wheat sourcing)

This run examines ethanol produced from wheat sourced in specific regions rather than using national averages, and thereby the geographic effects of feedstock uncertainty. The feedstock used in UK ethanol production is feed wheat produced in the North East, Yorkshire, East Midlands and Eastern (Lywood 2011) and is used here as an illustration. A distribution fitted to the average feed wheat yields in these regions over the 14-year period 1999–2012 is used to characterize the temporal and spatial variability in yields. The yields for feed wheat are estimated based on the shares of the wheat crop area in the UK used for milling and feed wheat (BSFP 2011) and the fact that yield is ~8.5% higher for feed wheat than milling wheat (AEA 2010). The N fertilizer application rates for feed wheat are lower than those for milling wheat. A normal distribution derived from the feed wheat-specific N application rates over the 18-year period 1994–2011 (BSFP 1998–2011) is used to characterize the temporal variability. A triangular distribution approximated to the wheat production weighted probability of soil N₂O emission factors for the target regions derived from the UK-DNDC is used here (see figure S6 available at stacks.iop.org/ERL/8/015024/mmedia). A uniform distribution is used for the farm machinery diesel use.

3. Results and discussions

The GHG intensity results for UK wheat ethanol in the Baseline run are shown in figure 1(a). When co-products and LUC emissions are not taken into account, the GHG intensity is 74 gCO₂e MJ⁻¹. The agriculture and biorefinery stages account for most of the emissions while wheat transport, handling and ethanol distribution contribute very little. Soil N₂O emissions and embedded emissions in N fertilizers account for 57% and 20% of the agriculture emissions, respectively (see figure 1(b)). The GHG intensity will reduce to 34–51 gCO₂e MJ⁻¹ when co-products including straw are considered, representing a 39%–60% reduction in GHG emissions compared with the fossil fuel benchmark in the RTFO (currently set as 84 gCO₂e MJ⁻¹, the average GHG intensity of gasoline and diesel supplied in the EU) (DfT 2012a). The energy allocation method results in the lowest

GHG intensity, because 43% of the agriculture emissions are allocated to straw and 42% of the agriculture emissions allocated to wheat and the biorefinery emissions are allocated to DDGS and surplus electricity. The economic allocation method results in higher GHG intensity as less GHG emissions are allocated to co-products based on market values. The substitution method gives the highest GHG intensity mainly because of the high agriculture GHG intensity as emission credits are only assigned to the 3% of the collected straw used for energy generation. On the other hand, biorefinery GHG intensity is the lowest for the substitution method because the emission credits assigned to the DDGS and surplus electricity are quite high given the large emissions from soy meal production in South America and the relatively high GHG intensity of the UK electricity grid.

When straw is excluded, the GHG intensity will increase by 3–10 gCO₂e MJ⁻¹ but the order of emissions for all co-product methods still holds. The LUC emissions are included in this analysis despite their omission in many studies, the EU and UK regulatory frameworks. These emissions will add 14 gCO₂e MJ⁻¹ to the GHG intensity, reducing the potential GHG offsets to 22%–43%.

When LUC emissions and straw are excluded, the energy allocation method results in a GHG intensity of 44 gCO₂e MJ⁻¹, which is the same as the RTFO default value for wheat ethanol when natural gas CHP is used for process energy supply (DfT 2012b). However, this is only coincidence as the RTFO default value is derived based on European data at the agriculture stage (lower yields and agro-input application rates), a conservation factor of 1.4 for biorefinery energy use and a combination of the energy allocation and substitution methods to deal with the biorefinery co-products. When the substitution method is used, the deterministic GHG intensity of 51 gCO₂e MJ⁻¹ from this analysis is in agreement with those from earlier studies (51–55 gCO₂e MJ⁻¹ by LowCVP (2004) and 51 gCO₂e MJ⁻¹ by Weinberg and Kaltschmitt (2013)).

Results for all other runs where different set of parameters were included for uncertainty analysis are shown in figure 2. The median values for GHG intensities derived in Runs 1, 2 and 3 are very close to the point estimates in Baseline. Run 1 suggests that the statistical uncertainties in UK average wheat yields and agro-input application rates are quite small

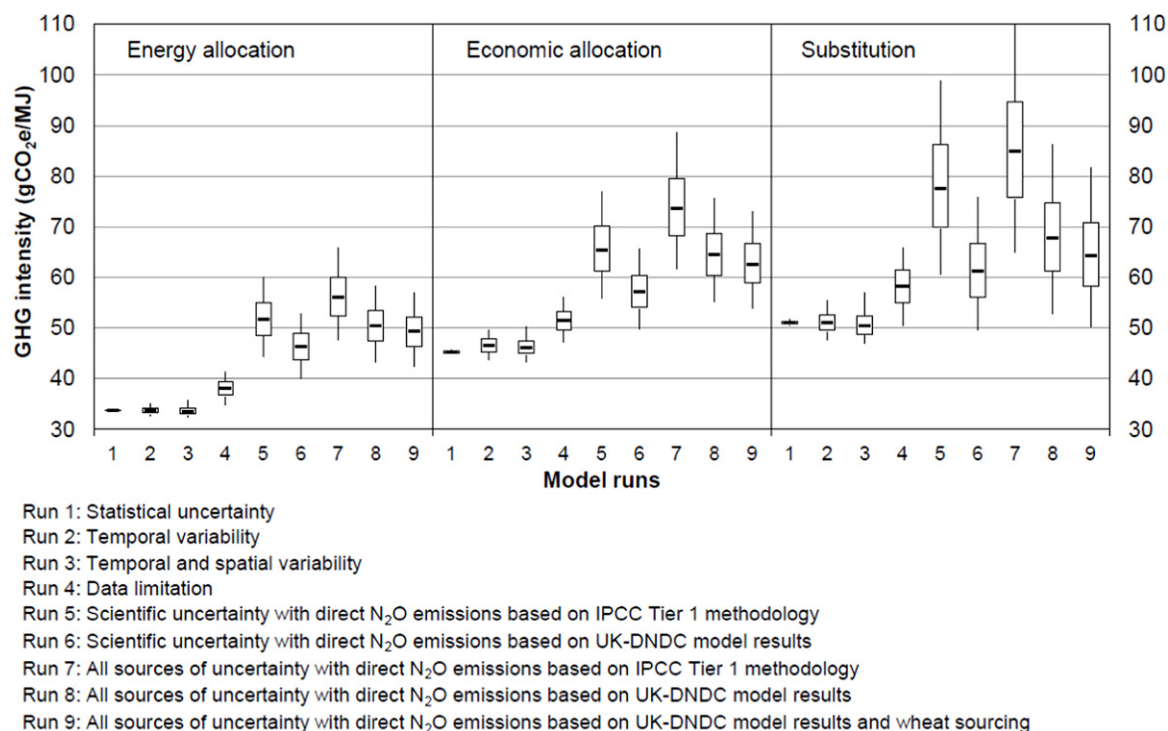


Figure 2. GHG intensity for UK wheat ethanol in Runs 1–9 (the bottom and top of the box are the 25th and 75th percentile, the band inside the box is the 50th percentile and the ends of the whiskers are the 5th and 95th percentile).

and would have little effects on the uncertainty in GHG intensity. The uncertainty ranges in Run 2 increase modestly due to the temporal variability in some parameters. With energy allocation and substitution methods the uncertainty is mainly attributed to grain yield (contribution to variance (CtV) 88%), followed by N fertilizer application rates (CtV 9%) and lime application rates (CtV 2%). When the economic allocation method is used, the uncertainty is mainly attributed to the temporal variability in the grain/straw price ratio (CtV 51%), followed by grain yield (CtV 43%) and N fertilizer application rates (CtV 4%). The uncertainty ranges in Run 3 increase slightly compared with those in Run 2 because of the larger variability in regional grain yields and the inclusion of the regional variations in farm machinery diesel use. Changes in the causes of uncertainty for energy allocation and substitution methods are small as variations in farm machinery diesel use contribute little (CtV 2%). The uncertainty for the economic allocation case is now mainly attributed to grain yield (CtV 51%), followed by the grain/straw price ratio (CtV 44%).

In Run 4, the GHG intensities and their uncertainty ranges both increase noticeably. The median values for GHG intensities increase to 38, 52, and 58 gCO₂e MJ⁻¹ for the energy allocation, economic allocation and substitution methods, respectively. This is mainly because the deterministic values for the embedded GHG in fertilizers used in Runs 1, 2 and 3 are the lowest values in the uniform distributions used in Run 4 and those for biorefinery CHP efficiency and wheat-to-ethanol conversion efficiency are the highest. A number of parameters have contributed to the increased uncertainty ranges (see figure 3(a)). The most important

parameters are embedded GHG in ammonium nitrate fertilizer and biorefinery process heat demand when allocation methods are used. The amount of DDGS produced, CHP efficiency, wheat-to-ethanol conversion efficiency, grain/aboveground biomass dry mass ratio and the share of straw collected are also major contributors to the overall uncertainty and for the economic allocation method, the prices of ethanol and DDGS. For the substitution method, the contribution to uncertainty is mainly dominated by the embedded GHG in ammonium nitrate fertilizer and the share of straw used for energy generation, followed by and wheat-to-ethanol conversion efficiency.

The GHG intensities and their uncertainty ranges increase substantially when the scientific uncertainties and LUC emissions are included in Run 5. The median values for GHG intensities increase to 52, 66, and 78 gCO₂e MJ⁻¹ while the 90% confidence intervals expand to 44–60, 56–77 and 61–99 gCO₂e MJ⁻¹ for the energy allocation, economic allocation and substitution methods, respectively. The direct soil N₂O emissions from N inputs and LUC emissions dominate the contribution to uncertainty regardless of the method used to deal with co-products (see figure 3(b)). The effect of the uncertainty in the GHG credit for DDGS as animal feed appears to be relatively small. When the UK-DNDC modelling results instead of the IPCC Tier 1 methodologies are used in Run 6 to estimate direct soil N₂O emissions, the increases in the GHG intensities and their uncertainty ranges are considerably lower. The median values are 46, 57, and 61 gCO₂e MJ⁻¹ while the 90% confidence intervals are 40–53, 50–66 and 50–76 gCO₂e MJ⁻¹ for

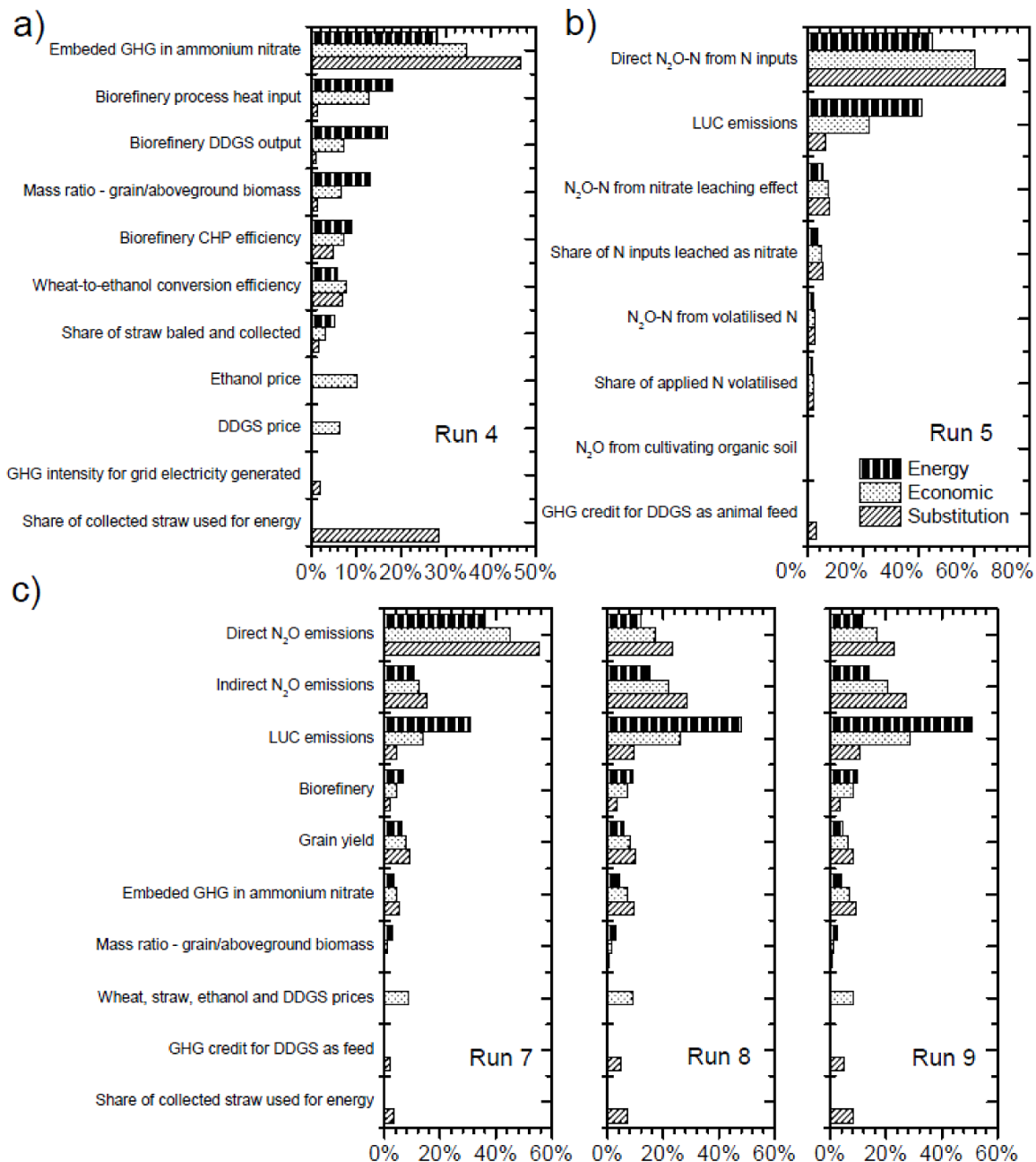


Figure 3. Contribution to variance for the most important parameters assessed (covering at least 95% of the total contribution to variance) for: (a) Run 4; (b) Run 5; and (c) Runs 7, 8 and 9.

the energy allocation, economic allocation and substitution methods, respectively.

When incorporating all sources of uncertainties in Run 7 (soil N₂O emissions following IPCC Tier 1 methodologies), the median values for GHG intensities increase to 56, 74, and 85 gCO₂e MJ⁻¹ while the 90% confidence intervals expand to 48–66, 62–89 and 65–110 gCO₂e MJ⁻¹ for the energy allocation, economic allocation and substitution methods, respectively. When the UK-DNDC results instead of the IPCC Tier 1 methodologies are used in Run 8 to estimate direct soil N₂O emissions, there are reductions of 10%, 12% and 20% in the median values and reductions of 18%, 24% and 26% in the ranges of the 90% confidence intervals for the energy allocation, economic allocation and substitution methods,

respectively. Using data on grain yield, N application rates, direct N₂O emissions and farm machinery diesel use for feed wheat from targeted regions in Run 9 only achieves a further 2–5% reduction in the median values and 4–6% reduction in the ranges of the 90% confidence intervals.

The scientific uncertain parameters are the dominating sources of uncertainty in Runs 7, 8 and 9, with N₂O emission related parameters and LUC emissions together accounting for 76–78%, 65–71% and 61–75% of CtV for the energy allocation, economic allocation and substitution methods respectively while biorefinery parameters only account for 7–10%, 4–8% and 2–4% (see figure 3(c)). Other important sources of uncertainty include variability in grain yield and the uncertainty in the embedded GHG in ammonium nitrate

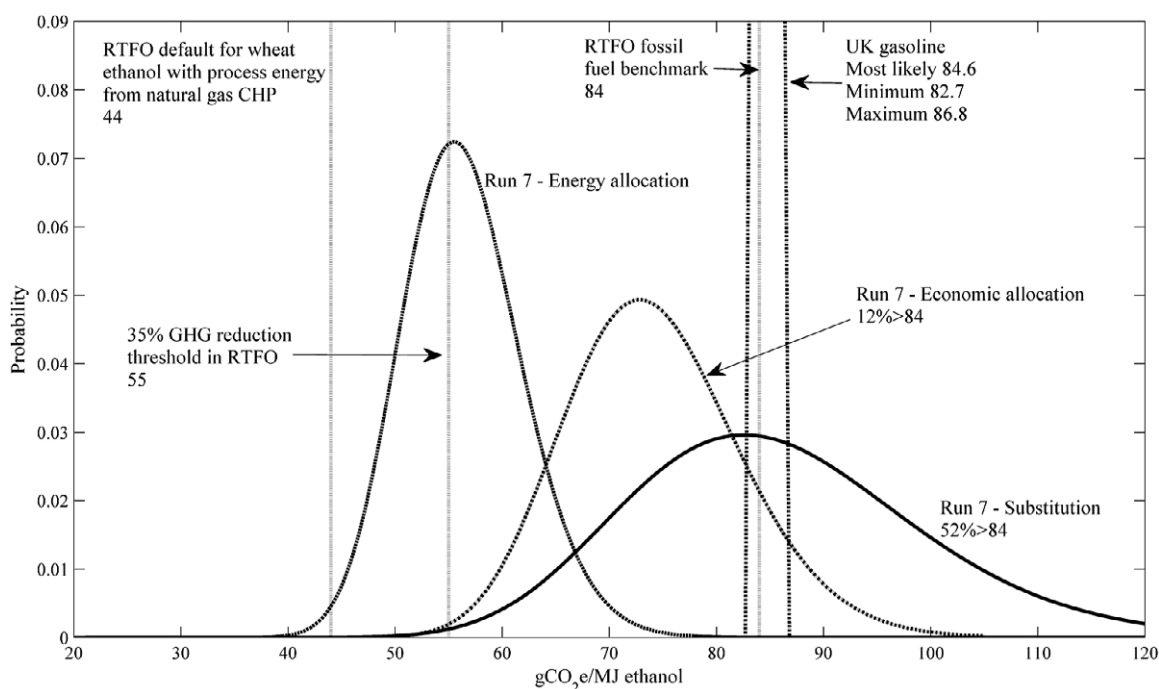


Figure 4. GHG intensities for gasoline and wheat ethanol with vertical lines representing deterministic values used in the RTFO and probability distributions representing results from stochastic model runs in this study.

fertilizer. In addition, variability in market prices and the share of collected straw used for energy generation will play a role for the economic allocation and substitution methods, respectively. We also test the effect of the uniform distributions based on a $\pm 10\%$ range used for parameters with data limitations. It is found that even when the $\pm 10\%$ range was increased to $\pm 20\%$, the CtV for these parameters would not surpass those for N_2O emission related parameters and LUC emissions (see table S4 available at stacks.iop.org/ERL/8/015024/mmedia).

As outputs from the UK-DNDC model are currently not sufficiently rigorous to be used as a replacement of the IPCC Tier 1 methodology, we compare the probability distributions of wheat ethanol GHG intensities from Run 7 with the deterministic values used in the RTFO and the probability distributions of UK gasoline GHG intensity. As can be seen from figure 4, when the economic allocation and substitution methods are used, wheat ethanol is highly unlikely (probability of less than 1%) to meet the 35% GHG reduction threshold set in the RTFO. For the substitution method there exists a 52% probability that the GHG intensity of wheat ethanol is greater than RTFO fossil fuel benchmark. A comparable analysis for UK gasoline GHG intensity does not currently exist, however based on a triangular distribution of gasoline GHG intensity (AEA 2012, Edwards *et al* 2011), there is a non-negligible probability that the GHG intensity of wheat ethanol is greater than that gasoline. These probabilities are not reflected in either the economic or energy allocation methods, and therefore the applicability of such methods in determining the representative risk of biofuel GHG intensity exceeding displaced fossil fuels remains uncertain. These findings imply that the risks of policy failure for the RTFO are significant when LUC emissions and various sources of

uncertainties are considered. Using stochastic methods to quantify these risks will help base policy designs on scientific evidence and establish more appropriate emission reduction targets (Mullins *et al* 2011).

Our analysis suggests that the RTFO uses a default GHG intensity for wheat ethanol that failed to capture the risks of LUC, the benefits of straw as a co-product and the variations due to different methods of dealing with the co-products. Moreover, there are still considerable uncertainties in determining the GHG intensity of UK wheat ethanol based on currently available knowledge and data. The uncertainties mainly stem from those parameters that are highly uncertain with the best science currently available such as soil N_2O emissions. When all other sources of uncertainties are removed through more data collection and reporting as in Run 5, the GHG intensity still spans over ranges (90% confidence intervals) that are 30–49% of the median. Research in the US and have shown that similar ranges exist for corn ethanol but that the median values of wheat ethanol GHG intensity are lower: 55–95 $gCO_2e MJ^{-1}$ for wheat ethanol compared to 113 (Boies *et al* 2011) to $>400 gCO_2e MJ^{-1}$ (Plevin 2010) for US corn ethanol. Despite lower GHG intensities, wheat ethanol producers in the UK will have very limited ability to reduce the uncertainty in the GHG intensity of its ethanol. Even if the ethanol producers source their feedstock wheat from specific regions, the resulting reduction in the uncertainty is insignificant. In addition, assigning different GHG intensity values to ethanol produced from wheat grown in different regions is not appropriate. This is because incentivizing ethanol production from ‘low-carbon’ wheat is unlikely to be effective in reducing GHG emissions unless other uses of wheat such as animal feed are subject to the same incentives.

Our results have also highlighted the differences in the way various sources of parameter uncertainties propagate through the stochastic LCA model when different methods are used to deal with the co-products. The uncertainty ranges for the GHG intensity are much larger for the substitution method than the allocation methods and are larger for economic than for energy allocation (see figure 2). Besides the additional uncertainties induced by market mechanisms (prices and substitution effects) in the economic allocation and substitution methods, this is primarily because the uncertainties in most parameters (analogous to emissions) will be 'shared' with co-products when the allocation methods are used. This is also reflected in the observations that the contributions to overall uncertainty from agriculture related parameters such as N₂O emissions, grain yield and the embedded GHG in ammonium nitrate fertilizer exhibit the same patterns as the uncertainty ranges when different methods are used to deal with the co-products. Therefore, although the energy allocation method might be preferred from a regulation point of view (as is currently adopted in the EU biofuel regulatory framework), it could significantly underestimate the magnitude and uncertainties in the GHG intensity of wheat ethanol.

One limitation to these results is that potential correlations between parameters are not considered in the stochastic simulations. This is mainly because of the aggregated nature of the datasets available. Further research is needed to examine the impact of correlations between key parameters such as nitrogen application rate, grain yield, grain price, farm machinery fuel use and ethanol conversion efficiency when disaggregated data is available. While this effect may serve to overestimate the uncertainty range of GHG emissions resulting from N₂O emissions, these effects are likely small compared to omissions that would serve to increase the uncertainty range of LUCs.

4. Conclusions

This study provides a comprehensive assessment of the magnitude and uncertainties in the GHG intensity of UK wheat ethanol based on current industry practices. When LUC emissions are not included, our deterministic estimates of the GHG intensity are 34–51 gCO₂e MJ⁻¹ depending on methods used for dealing with co-products and are broadly in agreement with results from earlier studies and values used in existing regulatory frameworks. However, by ignoring LUC emissions and the uncertainties in input parameters, the deterministic methodology could significantly underestimate the real GHG intensity. Our stochastic results show that GHG intensity can span a range of 40–110 gCO₂e MJ⁻¹ when LUC emissions and various sources of uncertainty are taken into account. This suggests that the current deterministic regulatory framework underestimates the likelihood of wheat ethanol GHG intensity and thus may not be effective in reducing biofuel GHG intensity.

The considerable uncertainties in determining the GHG intensity of UK wheat ethanol based on currently available knowledge and data mainly stem from those scientific

parameters such as soil N₂O emission rates and LUC emissions, rather than process parameters that are not well reported. As a result, biofuel producers have a limited ability to reduce the uncertainty in the GHG intensity of their products. Therefore, in addition to incentives to encourage producers to collect and report more data, biofuel policies should be robust enough to incorporate the currently irreducible uncertainties and flexible enough to be readily revised when better science is available.

Although the substitution method is the preferred option from a scientific perspective to account for biofuel co-products in attributional LCA, it is most challenging to implement mainly because of the difficulties in estimating various substitution effects. In addition, it results in the highest biofuel GHG intensities and uncertainty ranges. Not surprisingly, the energy allocation method is the preferred option by the industry and policy makers even though it could significantly underestimate the true GHG intensities and the associated uncertainties. The economic allocation method provides a compromise that results in GHG intensities closer to those by the substitution method yet remain relatively simple to implement. The economic allocation method better reflects the real-world effects of co-products when compared with energy allocation method, as the substitution effects are dependent on the economic values of products. Moreover, by monitoring the trends in market prices and revising results accordingly, the economic allocation method could better reveal the complex and rapidly-changing market dynamics that drive production practices.

References

- AEA 2010 Regional emissions from biofuels cultivation *Final Report to the Department for Transport*
- AEA 2012 *2012 Guidelines to Defra/DECC's GHG Conversion Factors for Company Reporting*
- Audsley E, Stacey K F, Parsons D J and Williams A G 2009 Estimation of the greenhouse gas emissions from agricultural pesticide manufacture and use *Report*
- Balat M and Balat H 2009 Recent trends in global production and utilization of bio-ethanol fuel *Appl. Energy* **86** 2273–82
- Bernesson S, Nilsson D and Hansson P A 2006 A limited LCA comparing large- and small-scale production of ethanol for heavy engines under Swedish conditions *Biomass Bioenergy* **30** 46–57
- Berry P M, Kindred D R and Paveley N D 2008 Quantifying the effects of fungicides and disease resistance on greenhouse gas emissions associated with wheat production *Plant Pathol.* **57** 1000–8
- Boies A M, McFarlane D, Taff S, Watts W F and Kittelson D B 2011 Implications of local lifecycle analyses and low carbon fuel standard design on gasohol transportation fuels *Energy Policy* **39** 7191–201
- Brigg Renewable Energy Plant 2012 www.briggprep.co.uk/default.htm (accessed 19.10.12)
- BSFP 1998–2011 *The British Survey of Fertiliser Practice—Fertiliser Use on Farm Crops for Crop Year 1998–2011* (www.defra.gov.uk/statistics/foodfarm/enviro/fertiliserpractice)
- BSFP 2011 *The British Survey of Fertiliser Practice—Fertiliser Use on Farm Crops for Crop Year 2011* (www.defra.gov.uk/statistics/foodfarm/enviro/fertiliserpractice)

- Chalmers A G 2001 A review of fertilizer, lime and organic manure use on farm crops in great Britain from 1983 to 1987 *Soil Use Manag.* **17** 254–62
- Copeland J and Turley D 2008 National and regional supply/demand balance for agricultural straw in great Britain *Report Prepared for the National Non-Food Crops Centre. Agri-Environment and Land Use Strategy Team* (York: Central Science Laboratory)
- Crutzen P J, Mosier A R, Smith K A and Winiwarter W 2008 N₂O release from agro-biofuel production negates global warming reduction by replacing fossil fuels *Atmos. Chem. Phys.* **8** 389–95
- Dalgaard R, Schmidt J, Halberg N, Christensen P, Thrane M and Pengue W A 2008 LCA of soybean meal *Int. J. Life Cycle Assess.* **13** 240–54
- DECC 2012 *Digest of United Kingdom Energy Statistics 2012* (London: TSO)
- Defra 2010 *Fertiliser Manual (RB209)* 8th edn (Norwich: The Stationery Office)
- Defra 2012a *Feeding Stuff Prices* (www.defra.gov.uk/statistics/foodfarm/farmgate/commodity/)
- Defra 2012b *UK Cereal and Oilseed Areas, Yields and Production—Dataset* (www.defra.gov.uk/statistics/foodfarm/landuslivestock/farmstats/)
- Defra 2012c *Observatory Monitoring Framework—Indicator Data Sheet*
- DfT 2011 *RTFO Year 3 Verified Report: 15 April 2010–14 April 2011—Verified Data for the 2010/11 Obligation Year*
- DfT 2012a *RTFO Guidance Part Two: Carbon and Sustainability Guidance—RTFO Year 5: 15 April 2012 to 14 April 2013 Version 5.0*
- DfT 2012b *Post-RED Implementation Guidance for Year 5 of the RTFO—Detailed Carbon Intensity Data—Version 5.0*
- Dungait J A J *et al* 2012 Advances in the understanding of nutrient dynamics and management in UK agriculture *Sci. Total Environ.* **434** 39–50
- E4tech 2010 A causal descriptive approach to modelling indirect land use change impacts of biofuels *Research Report*
- Edwards R, Larivé J-F and Beziat J-C 2011 *Well-to-Wheels Analysis of Future Automotive and Powertrains in the European Context* (Ispra: Joint Research Centre, Institute for Energy)
- Edwards R, Mulligan D and Marelli L 2010 *Indirect Land Use Change from Increased Biofuels Demand: Comparison of Models and Results for Marginal Biofuels Production from Different Feedstocks* (Ispra: Joint Research Centre, Institute for Energy)
- FAOSTAT 2012 *Food and Agriculture Organization of the United Nations* (www.fao.org)
- Flach B, Bendz K and Lieberz S 2012 *EU-27 Biofuels Annual 2012* No. NL2020 (Washington, DC: US Department of Agriculture)
- Hazzledine M, Pine A, Mackinson I, Ratcliffe J and Salmon L 2011 Estimating displacement ratios of wheat DDGS in animal feed rations in great Britain *Working Paper 2011-8* (Washington, DC: International Council on Clean Transportation)
- IPCC 2006 *2006 IPCC Guidelines for National Greenhouse Gas Inventories, Prepared by the National Greenhouse Gas Inventories Programme* ed H S Eggleston, L Buendia, K Miwa, T Ngara and K Tanabe (Japan: IGES)
- Klemetsson A K and Smith K A 2011 The significance of nitrous oxide emission due to cropping of grain for biofuel production: a Swedish perspective *Biogeosciences* **8** 3581–91
- Laborde D 2011 *Assessing the Land Use Change Consequences of European Biofuel Policies* (Washington, DC: International Food Policy Institute (IFPRI))
- Lloyd S M and Ries R 2007 Characterizing, propagating, and analyzing uncertainty in life-cycle assessment—a survey of quantitative approaches *J. Indust. Ecol.* **11** 161–79
- LowCVP 2004 *Well-to-Wheel Evaluation for Production of Ethanol from Wheat—a Report by the LowCVP Fuels Working Group, WTW Sub-Group No. FWG-P-04-024*
- Lywood W 2011 personal communications
- Lywood W, Pinkney J and Cockerill S 2009 Impact of protein concentrate coproducts on net land requirement for European biofuel production *GCB Bioenergy* **1** 346–59
- Malça J and Freire F 2012 Addressing land use change and uncertainty in the life-cycle assessment of wheat-based bioethanol *Energy* **45** 519–27
- Malins C 2012 A model-based quantitative assessment of the carbon benefits of introducing iLUC factors in the European Renewable Energy Directive *GCB Bioenergy* at press (doi:10.1111/j.1757-1707.2012.01207.x)
- Mortimer N D, Elsayed M A and Horne R E 2004 *Energy and Greenhouse Gas Emissions for Bioethanol Production from Wheat Grain and Sugar Beet* (Sheffield: Sheffield Hallam University)
- Mosier A R, Crutzen P J, Smith K A and Winiwarter W 2009 Nitrous oxide's impact on net greenhouse gas savings from biofuels: life-cycle analysis comparison *Int. J. Biotechnol.* **11** 60–74
- Mullins K A, Griffin W M and Matthews H S 2011 Policy implications of uncertainty in modeled life-cycle greenhouse gas emissions of biofuels *Environ. Sci. Technol.* **45** 132–8
- Oracle 2012 *Oracle Crystal Ball* (www.oracle.com/us/products/applications/crystalball/index.html)
- Plevin R J 2010 Life cycle regulation of transportation fuels: uncertainty and its policy implications. Energy and resources *PhD Thesis* University of California, Berkeley
- Plevin R J, O'Hare M, Jones A D, Torn M S and Gibbs H K 2010 Greenhouse gas emissions from biofuels' indirect land use change are uncertain but may be much greater than previously estimated *Environ. Sci. Technol.* **44** 8015–21
- PUSR 1998–2010 *Pesticide Usage Survey Report—Arable Crops in Great Britain, 1998–2010* (London: Food & Environment Research Agency)
- REN21 2012 *Renewables 2012 Global Status Report* (Paris: REN21 Secretariat)
- Richards I R 2000 *Energy Balances in the Growth of Oilseed Rape for Biodiesel and of Wheat for Bioethanol* (Rendlesham: Levington Agriculture Ltd)
- Scacchi C C O, Gonzalez-Garcia S, Caserini S and Rigamonti L 2010 Greenhouse gases emissions and energy use of wheat grain-based bioethanol fuel blends *Sci. Total Environ.* **408** 5010–8
- Sleaford Renewable Energy Plant 2012 www.sleafordrep.co.uk/ (accessed 19.10.12)
- Vireol 2012 www.vireol.com/ (accessed 3.9.12)
- Vivergo 2012 www.vivergofuels.com/ (accessed 31.8.12)
- Wang M, Huo H and Arora S 2011 Methods of dealing with co-products of biofuels in life-cycle analysis and consequent results within the US context *Energy Policy* **39** 5726–36
- Weightman R M, Cottrill B R, Wiltshire J J J, Kindred D R and Sylvester-Bradley R 2011 Opportunities for avoidance of land-use change through substitution of soya bean meal and cereals in European livestock diets with bioethanol coproducts *GCB Bioenergy* **3** 158–70
- Weinberg J and Kaltschmitt M 2013 Greenhouse gas emissions from first generation ethanol derived from wheat and sugar beet in Germany—analysis and comparison of advanced by-product utilization pathways *Appl. Energy* **102** 131–9
- Williams A G, Audsley E and Sandars D L 2006 Determining the environmental burdens and resource use in the production of agricultural and horticultural commodities *Defra Project Report IS0205* (Bedford: Cranfield University and Defra)
- Yan X 2012 Bioethanol and biodiesel as alternative transportation fuels in china: current status, future potentials, and life cycle analysis *Energy Sources A* **34** 1067–75
- Yan X, Inderwildi O R, King D A and Boies A M 2012 The effects of ethanol on vehicle energy efficiency and the implications on ethanol life cycle analysis *Environ. Sci. Technol.* at press