MA22 THE VARIABILITY AND DRIVERS OF THE CARBON FOOTPRINT OF CANE SUGAR

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Abstract

The carbon footprint (GHG emissions) of sugar is of increasing interest to sugar users and consumers. This study considers the potential variability on a global basis of the carbon footprint of cane sugar, and investigates the key drivers affecting this variability.

A mathematical model was built to represent the production of sugar from field to market. Key input values were replaced by ranges to reflect the variability and uncertainty associated with the diversity of sugar production scenarios worldwide. Monte Carlo simulation was carried out to simulate the effect of these variations on the model outputs, which were assessed against the Bonsucro method (with modifications and additions) for estimating GHG emissions.

The carbon footprint of field-to-gate raw sugar ranged between 217 and 809 g CO_{2eq} per kg sugar in 90% of simulations. The biggest drivers were the country of origin, agricultural methods, power production/export and process energy efficiency. Production of plantation white sugar and transport to a local market added another 100-150 g CO_{2eq}/kg, split between transport and processing emissions.

The carbon footprint of field-to-market factory-refined sugar ranged between 329 and 1121 g CO_{2eq}/kg. The increase from raw sugar was mainly due to increased fossil fuel usage, and the biggest driver was process energy efficiency. The carbon footprint associated with shipping raw sugar from port, refining at a destination refinery, and transporting to market ranged between 465 and 660 g CO_{2eq}/kg. The biggest driver was refinery energy efficiency. Finally, the carbon footprint of field-to-market destination-refined sugar ranged between 621 and 1459 g CO_{2eq}/kg in 90% of simulations, of which the distance from factory to port was an additional significant driver.

The potential variability in cane sugar carbon footprint has been shown to be large, depending on where and how it is produced. However, by focussing on areas such as irrigation, agricultural chemicals, cane yields, power generation and export, process energy efficiency and cane burning, it is realistic to achieve a negative carbon footprint for field-to-market refined sugar: a net emissions credit of

260 g CO_{2eq}/kg was simulated, improving to 565 g CO_{2eq}/kg with trash recovery and to 1470 g CO_{2eq}/kg with biomass gasification.

Introduction

The GHG emissions resulting from production of sugar in the context of global warming are of increasing interest and importance to consumers. This impact is most appropriately measured via the estimation of the overall greenhouse gas (GHG) emissions resulting from sugar production, or its “carbon footprint”. A growing number of manufacturers and retailers are estimating and publicly stating the carbon footprint associated with various products, including beet and cane sugar, while consumer awareness is likely to create pressure on more cane sugar manufacturers, refiners and retailers to publish similar information. This paper has the following aims:

1. To estimate the potential global variability in carbon footprint of cane sugar.
2. To identify the key drivers affecting this variability.
3. To explore the potential for manipulating these drivers to minimise carbon footprint.

Five scenarios were investigated in this study:

Scenario 1: Field-to-factory-gate raw sugar
Scenario 2: Field-to-market plantation white sugar
Scenario 3: Field-to-market refined sugar (refinery annexed to factory)
Scenario 4: Raw sugar port to refined sugar market (i.e. raw sugar transport and refining)
Scenario 5: Field-to-market refined sugar (refinery separate from factory)

Following these investigations, three further scenarios were modelled to investigate the potential to achieve low-emissions refined sugar:

Scenario 6: Low emissions refined sugar
Scenario 7: Very low emissions refined sugar
Scenario 8: Extremely low emissions refined sugar

Method of Analysis

Modelling

Estimation of the carbon footprint involved firstly creating a model of the system under analysis. This was carried out using SugarCaneModel, a technical and economic modelling tool for the cane sugar industry. SugarCaneModel builds mass and energy balances for the processes and utilities involved, i.e. agriculture, raw sugar processing, ethanol production, sugar refining, steam/power production, and transport.

A key feature of SugarCaneModel is that it allows the modelling of uncertainty via Monte Carlo simulation methods. Monte Carlo simulation can be described simplistically as incorporating three steps:

1. Replace any model input parameter which is subject to inherent uncertainty with a range of values represented by a probability distribution.
2. Recalculate the model over and over again, each time using a different set of random inputs as sampled from the probability distributions.

3. Aggregate the results from each recalculation and generate probability distributions for each output value.

Monte Carlo simulation provides two key benefits. Firstly, and most importantly, it provides a range of outcomes from which the probability that they will occur can be calculated. This contrasts with traditional static modelling, in which fixed input values give a single fixed output value. In a world dominated by variability and uncertainty, this fixed output reflects only one of a myriad of possible outcomes. Secondly, it provides transparency for the key input parameters driving the variability of the outputs, via sensitivity analysis. These characteristics of Monte Carlo simulation are ideally suited to this study, which is aiming to analyse variability across a diverse range of scenarios, and to identify the key drivers.

In this study, key model inputs (listed in tables below) were designated as being variable and replaced by probability distributions. Three different distribution types were used: discrete, PERT, and uniform. These distributions are described briefly below.

Discrete distributions

Discrete distributions are simple: there are a finite number (typically two or three) of values that the input can take and the probability of each value occurring is defined. For example, in the model, the molasses produced from a sugar factory is either processed into ethanol or sold directly. The probability of the molasses being processed into ethanol was set at 30%. Therefore, for every 1000 simulations of the model, roughly 300 will involve a molasses distillery and, in the other 700, the molasses will be sold directly.

Uniform distributions

Uniform distributions are also simple, and are defined by two values: a minimum and a maximum. In a uniform distribution, there is an equal probability of any value occurring between the minimum and maximum. For example, in the model, the boiler steam pressure varies between 20 and 100 bar, with equal probability of any value in that range occurring.

PERT distributions

The most common distribution used in this study was the PERT distribution. PERT distributions are defined by three values: minimum, maximum, and most likely. For example, for irrigated fields, the water application was allowed to vary between 0 and 4000 mm, with a most likely value of 500. In a PERT distribution, there is a higher probability of values around the most likely value being selected, and a lower probability of values around the minimum and maximum. This is illustrated in Figure 1, which shows the actual probability distribution used in the model. The vertical axis represents probability.

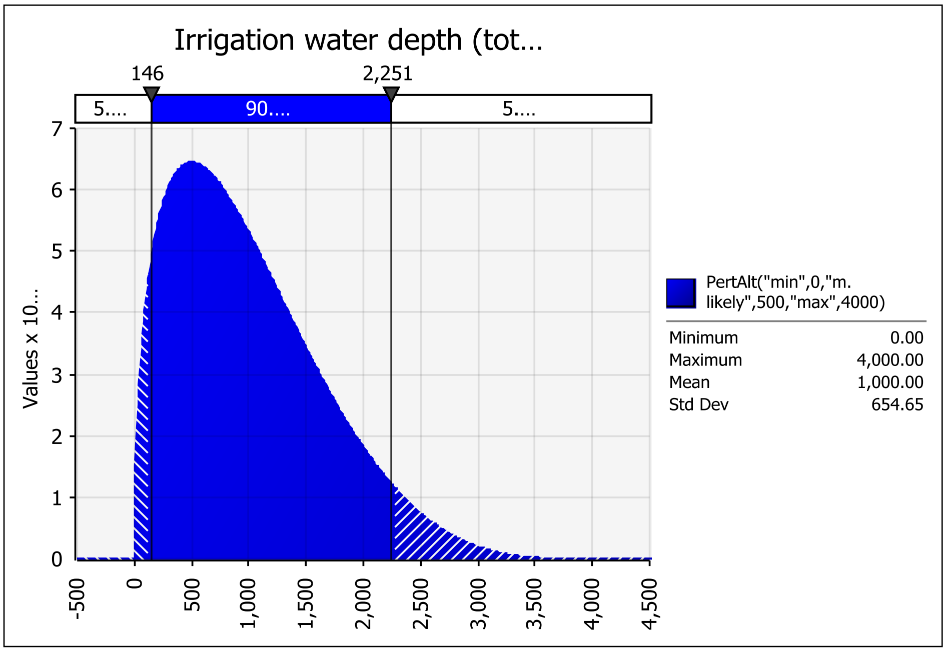

Fig. 1 – PERT distribution example: irrigation water usage (mm)

Method of assessing GHG emissions

The GHG emissions (carbon footprint) for various production systems were estimated by taking the outputs from SugarCaneModel and applying the method published and applied by Bonsucro (2011) to accredit sugar producers under the Bonsucro Certification System, the first global metric standard for sugarcane. The method (details can be obtained from the Bonsucro website) is a field-to-gate analysis which accounts for direct and indirect energy use and GHG emissions in the following areas:

- Agriculture (irrigation, chemical use, cane burning[1], transport fuel use, field residues)
- Fossil fuels burnt
- Electricity imports/exports[2]
- Process chemicals used
- Allocation to co-products (e.g. molasses, ethanol)

In addition to the methodology and data published by Bonsucro, the following assumptions and data were used for GHG emissions estimation:

1. Transport of products was included (where applicable), with road transport assumed and diesel used as fuel.
2. Sea transport of raw sugar for refining was included (where applicable), with emissions factors from Defra (2011)[3].
3. Emissions factors from electricity generation were taken from IEA (2011), with 2007-2009 averages used. IEA data were used as the range of countries included is wider than the range given in the Bonsucro standard. For destination refineries, the Bonsucro

[1] CH_4 and N_2O emissions.
[2] Export of electricity achieves a credit in terms of energy and emissions saved, according to the displacement of energy in that country. The Bonsucro method uses the grid average emissions to calculate the credit. There is an argument that this is conservative as in reality electricity exports are likely to replace marginal energy production, which is likely to be from fossil fuels. However, at present the Bonsucro method follows the EU Renewable Energy Directive in this respect.
[3] 5.7 gCO_2eq per tonne km for a 35 000-59 999 dwt bulk carrier, 55% loaded.

average (i.e. non-country-specific) emissions factor for electricity generation (150 g CO_{2eq}/MJ) was used.
4. Cane stalks left on the field after harvest contain 0.1% nitrogen, as stated after 12 months growth by Bakker (1999).
5. Cane trash (tops and leaves) left on the fields after harvest contains 0.5% nitrogen. This is an approximation from data from Pankhurst (2005) and Bakker (1999).
6. Filter mud returned to the fields contains 5% nitrogen on a dry basis, as stated by Smith-Baez (2008).
7. The concentration of $CaCO_3$ in agricultural lime was assumed to be 65%.
8. Waste-water treatment and raw water intake was included, with emission factors from Defra (2011).[4]
9. It is assumed that in none of the scenarios modelled was non-agricultural land converted to agricultural use after 1 January 2008.

Scenario 1: Field-to-factory-gate raw sugar

The first scenario modelled was raw sugar production. The model incorporated cane growing, harvest, transport to factory and production into raw sugar, molasses and/or ethanol. The GHG emissions were calculated on a cradle-to-gate basis, i.e. excluding any transport of raw sugar from the factory. 3000 model simulations were run, and the basis for each was 20 000 hectares of land. The same input dataset was used for each simulation, with selected inputs allowed to vary randomly from simulation to simulation according to defined probability distributions. The full input dataset is too lengthy to be reproduced here but is available on request. The variable inputs are listed in Tables 1 and 2. Table 1 contains the discrete variable inputs, while Table 2 contains the continuous variable inputs (for uniform or PERT distributions).

Table 1 – Variable (discrete) model inputs: field-to-factory-gate raw sugar

Parameter	Value/Range
Country of origin	[5]
% of simulations (non-Brazil) with irrigated fields	80%
% of simulations (Brazil) with irrigated fields	10%
% of simulations with irrigation via diesel pumps (i.e. not electric)	70%
% of simulations with cane trash recovered and used for additional fuel	2%
% of simulations with coal as supplementary fuel (remainder is fuel oil)	50%
% of simulations where power exported to grid (if available)[6]	30%
% of simulations with some electrification of mill/preparation drives	40%
% of simulations with filter mud re-used on fields[7]	80%
% of simulations with a distillery[8]	30%
% of simulations with distillery vinasse processed in digestor for biogas production (remainder is applied to cane fields)	10%

[4] 0.70 gCO_2eq per kg wastewater and 0.34 gCO_2eq per kg raw water intake.
[5] The country of origin varies according to the relative % of harvested area amongst the top 25 sugarcane producers according to 2010 data from FAO. For example, in 2010, Brazil harvested ~9 million ha, around 42% of the total from the top 25 producers. Therefore, in each simulation, there is a 42% probability that Brazil is the country of origin.
[6] If trash recovered and used for fuel, then power is automatically exported
[7] Otherwise, filter mud is disposed as a solid waste to landfill
[8] If a distillery is included, then 100% of molasses is processed in the distillery into ethanol

Table 2 – Variable (continuous) model inputs: field-to-factory-gate raw sugar

Parameter	Value/Range	Distribution
Cane yield (t/ha)	±25%[9]	PERT
% of cane fields planted mechanically	20% (0-100%)	PERT
Litres of tractor fuel used per ha planted mechanically	35 (25-50)	PERT
Irrigation water usage (mm/y) – if fields irrigated	500 (0-4000)	PERT
Irrigation pumping head (m)	30 (20-50)	PERT
Irrigation diesel pump thermal efficiency	31% (26-35%)	PERT
Amount of nitrogen required as fertiliser (kg/ha)[10]	75 (45-300)	PERT
Amount of P_2O_5 required as fertiliser (kg/ha)	90 (45-180)	PERT
Amount of K_2O required as fertiliser (kg/ha)	100 (50-200)	PERT
Amount of lime applied in the fields (kg/ha)	1000 (500-2000)	PERT
Amount of herbicide applied in the fields (kg/ha)[11]	2.2 (1.1-3.3)	PERT
Pol % in cane stalk	14% (11-15%)	PERT
Fibre % in cane stalk	13.3% (11-15%)	PERT
Purity (sucrose) of cane stalk	90% (85-92.5%)	PERT
% of cane burnt prior to harvest	65% (0-100%)	PERT
% of trash recovered if trash recovery operated[12]	50% (30-80%)	PERT
% of fields mechanically harvested	40% (0-100%)	PERT
Average distance from field to mill (km)	10 (1-20)	PERT
Mill sucrose extraction	95% (88-98%)	PERT
Mill imbibition water on fibre	200% (100-300%)	PERT
Bagasse moisture	50% (45-55%)	PERT
% of drives electrified in factories with electrification	75% (25-100%)	PERT
Energy usage in mill drives (kWh/te fibre)	83 (70-131)	PERT
Energy usage in cane preparation drives (kWh/te fibre)	67 (36-107)	PERT
Process energy efficiency	[13]	PERT
Boiling house process efficiency	[14]	PERT
Boiler steam pressure	20-100 bar	Uniform
Power generation turbine overall efficiency	70% (50-80%)	PERT
% of clear juice sent to distillery (if included)	50% (0-100%)	PERT
Ethanol yield in distillery fermentation (% of stoichiometric)	89% (88%-92%)	PERT

Correlations were included in the model to link the variability of the fertiliser input parameters (N, P_2O_5 and K_2O required) and irrigation water usage with the variability in cane yield, i.e. if the irrigation water usage or fertiliser parameters varied upwards, the cane yield was likely to also vary upwards. Similar correlations were included to link imbibition water usage, mill extraction and bagasse moisture.

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[9] The cane yield varies with the country of origin, according to the average yields for 2010 from FAO data (e.g. Brazil average in 2010 was 70.4 t/ha). This value is then allowed to vary ±25%.

[10] If the filter mud and/or distillery vinasse is returned to the cane fields, their nutrients count against the required fertiliser components, i.e. the amount of fresh fertiliser required is reduced.

[11] Herbicide is only applied if the trash blanket remaining on the fields after harvest is less than 7.5 t/ha

[12] Trash is only recovered from fields mechanically harvested

[13] The variability of process energy efficiency is applied in the model via an Energy Efficiency Factor. This factor was set at 5 and allowed to vary between 1 and 10. These values roughly correspond with a factory process steam-on-cane of 45% (varying between 33% and 65%), with the other inputs at average values.

[14] The variability of boiler house process efficiency is applied in the model via a Process Efficiency Factor. This factor was set at 2 and allowed to vary between 0.5 and 4. These values roughly correspond with a Boiler House Recovery (BHR) of 89% (varying between 84% and 92.5%), with the other inputs at average values.

Results

Figure 2 below shows the distribution of the results from the 3000 model simulations. The horizontal axis is the g CO_{2eq}/kg sugar, and the vertical axis represents frequency, i.e. there is a greater frequency of results around the 300-500 g region than lower or higher values. The chart shows that the mean carbon footprint was 441 g CO_{2eq}/kg sugar, and the median was 390. It shows that 90% of the simulations had carbon footprints between 217 and 809 g CO_{2eq}/kg sugar. A small number of simulations (0.5%) had negative carbon footprints, with 1% having values above 1200 g CO_{2eq}/kg sugar.

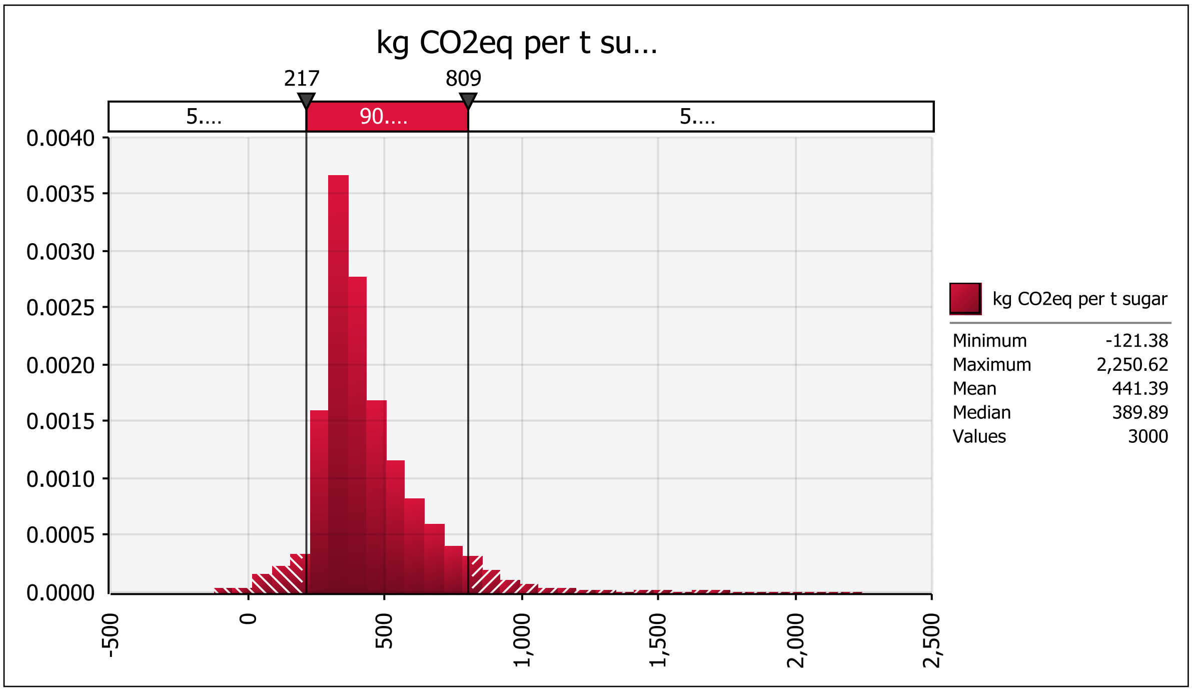

Fig. 2 – Carbon footprint variability: field-to-factory-gate raw sugar

The breakdown of the carbon footprint by category is illustrated by the table in Appendix 1, which shows the mean results for each of the scenarios. This shows that the majority of emissions result from the agricultural phase, with smaller amounts from cane transport (5-10%) and processing (15-20%). The total emissions due to cane production (up to the mill gate) are 630 g CO_{2eq}/kg sugar. The emissions due to electricity are shown as negative due to the average power export. The appropriate share of total emissions is allocated to co-products either by market value (for molasses) or by energy content (for ethanol). Of the agricultural emissions, the biggest contributor is nitrogen for fertilisation, followed by irrigation, cane burning and lime application. Of the processing emissions, the biggest contributors are caustic soda usage and bagasse burning.

Comparison with other published carbon footprint estimates

Comparing carbon footprint estimates from different sources is difficult due to the variability in methods used. Klenk *et al.* (2012) recently carried out a literature review of published carbon footprint estimations for cane sugar, only including estimates where the methodology was stated. Four estimates for raw sugar production (cradle-to-gate) were included, with values ranging between 210 and 550 g CO_{2eq}/kg sugar. One of those estimates was by Rein (2010), who developed the Bonsucro accounting method. Rein's estimate, 307 g CO_{2eq}/kg sugar, was based on a "typical" sugar mill, producing sugar and molasses and exporting some power. As a method of validation, the model used in this paper was tested against the inputs used by Rein, with similar results. Rein (2011) later stated that values for raw sugar could be expected to be between 200 and 500 g CO_{2eq}/kg sugar, and more recently Rein (2012) cited various estimates between 203 and 800 g CO_{2eq}/kg sugar.

Figure 2 shows similarity to these previous published estimates. The 90% band is similar to the 203-800 range reported by Rein (2012). The mean and median are higher than Rein's 2010 estimate of 307 g CO_{2eq}/kg sugar. In fact, three quarters of the simulations resulted in values above 307 g CO_{2eq}/kg sugar. Around two thirds of the simulations resulted in values within the 200-500 range suggested by Rein (2011) and reported by Klenk *et al.* (2012).

Renouf *et al*. (2010) assessed the carbon footprint of Australian sugarcane production based on data from the state of Queensland, with Monte Carlo simulation to account for variability. In 95% of cases, the carbon footprint was between 66.4 and 114.5 kg CO_2 per tonne cane delivered to mill. At an assumed sugar yield (kg raw sugar per kg cane) of 12.5%, this equates to 531 to 916 g CO_{2eq}/kg sugar. The mean emissions from Appendix 1 are 630 g CO_{2eq}/kg sugar, i.e. within that range.

Sensitivity analysis

Figure 3 shows the top-ranked variable inputs in terms of the effect their variability had on the overall carbon footprint, i.e. it shows which inputs the carbon footprint was most sensitive to. The horizontal bars give an indication of the magnitude of the changes in carbon footprint caused by variations in each input. For example, variations in the cane yield caused the carbon footprint to fluctuate over a range of around 160 g CO_{2eq}/kg sugar. It should be noted that the sensitivity is a result of the importance of the parameter <u>and</u> the variability assigned to it (see Table 2).

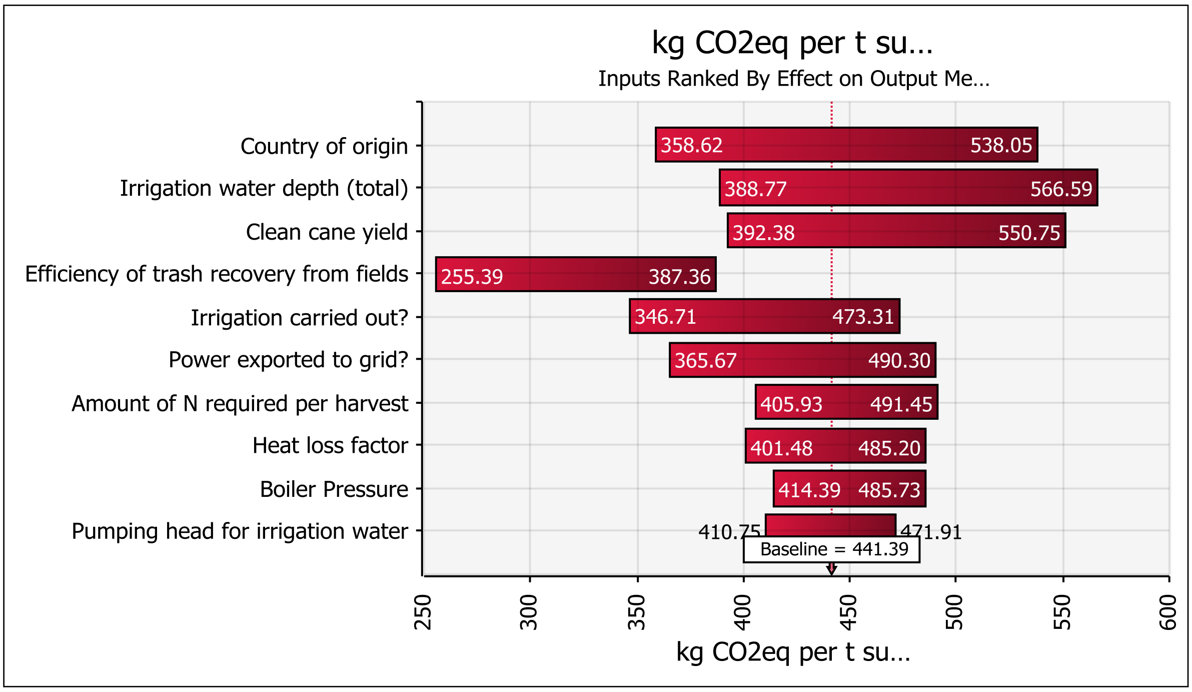

Fig. 3 – Sensitivity analysis: field-to-factory-gate raw sugar

The key drivers as shown in Figure 3 are in the areas of agriculture (cane yield, irrigation and fertilisation), power production/export and process energy efficiency. The top-ranked input is the country of origin, which causes a number of impacts in the model: (a) it affects the likely cane yield, (b) it affects the likelihood of irrigation (in the case of Brazil), and (c) it affects the GHG emissions credit allocated to power export (see the Bonsucro standard for more detail). The presence of trash recovery efficiency is interesting, as trash recovery was only carried out in 2% of simulations. This indicates the potential importance of trash recovery, which is explored further in scenarios 7 and 8.

Scenario 2: Field-to-market plantation white sugar

The second scenario modelled was the production of plantation white sugar, including product transport (sugar, molasses and ethanol) to market. Plantation white sugar is here defined as white sugar produced in a sugar factory (as distinct from 'refined' sugar) and intended for direct consumption in local markets. The model was generally the same as scenario 1, except that juice and syrup sulfitation were included, the boiling scheme was modified, and transport of products was included. The additional variable inputs were as shown in Table 3 below.

Table 3 – Additional variable model inputs: field-to-market plantation white sugar

Parameter	Value/Range	Distribution
Juice sulfur usage (ppm to cane equivalent)	500 (300-600)	PERT
Syrup sulfur usage (ppm to cane equivalent)	100 (50-200)	PERT
Average road distance to market (km): sugar	100 (50-300)	PERT
Road distance to market (km): molasses	100 (10-500)	PERT
Road distance to market (km): ethanol	100 (10-500)	PERT
Road freight fuel efficiency (tonne.km per litre)	21 (16-26)	PERT

Results

The distribution of the results from the 3000 model simulations generally mimicked that of the raw sugar scenario in Figure 2, except that the carbon footprint is around 100-150 g CO_{2eq}/kg sugar higher. The mean, median, minimum, maximum and 5% and 95% percentiles from the 3000 model simulations are shown in Appendix 2, with the equivalent values for each of scenarios 1 to 5. As before, Appendix 1 shows the breakdown of the carbon footprint by category. This shows that the biggest contributor to the increase is product transport (50%), followed by increased chemical usage (30%) and increased net energy usage (20%).

Scenario 3: Field-to-market refined sugar (refinery annexed to factory)

The third scenario modelled was the production of refined sugar in a refinery annexed to a factory, including product transport (sugar, molasses and ethanol) to market. The model was generally the same as scenario 1 except that all raw sugar produced was processed into refined sugar and transport of products was included (similar to scenario 2). The refinery processes were assumed to include melting; phosphatation clarification; filtration, powdered activated carbon (PAC) or ion exchange (IER) with brine recovery; crystallisation; and drying. The heat energy to the refinery was provided by bleeding factory evaporator vapour where available. The additional variable inputs are shown in Table 4.

Table 4 – Additional variable model inputs (refinery annexed to factory)

Parameter	Value/Range	Distribution
Sugar colour to refinery (IU) [15]	1000 (800-1200)	PERT
Decolourisation by PAC or IER	50%/50%	Discrete
IER colour removal per cycle (BV.IU) [16]	22 500 (20 000-30 000)	PERT
PAC dose rate (% to sugar throughput)	0.1% (0.05-0.2%)	PERT

Results

Figure 4 shows the distribution of the results from the 3000 model simulations, and Appendix 2 compares the results with the other scenarios 1-5.

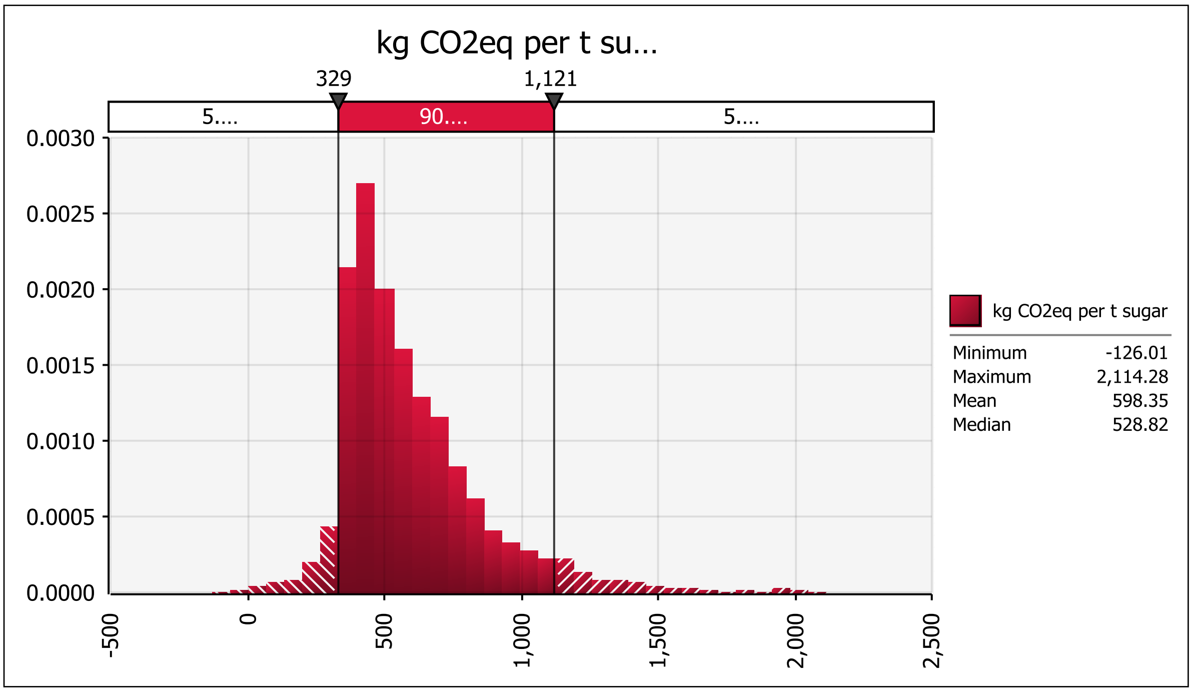

Fig. 4 – Carbon footprint variability: field-to-market refined (refinery annexed to factory)

Compared to the plantation white scenario, the carbon footprint is around 50 (between 0 and 160) CO_{2eq}/kg sugar higher. Appendix 1 shows that the mean increase in carbon footprint is mostly due to an increase in fossil fuel usage, mitigated by a reduction in chemical usage.

Sensitivity analysis

Figure 5 shows the sensitivity analysis chart. The top-ranked input is the heat loss factor, i.e. the process energy efficiency of the factory and refinery. This is a logical result: for raw sugar production alone, a factory can often afford to be energy inefficient and still be self-sufficient in steam from bagasse; whereas the addition of an annexed refinery makes it more important to focus on factory energy efficiency.

[15] ICUMSA colour units
[16] Bed volumes processed multiplied by average colour removal (IU)

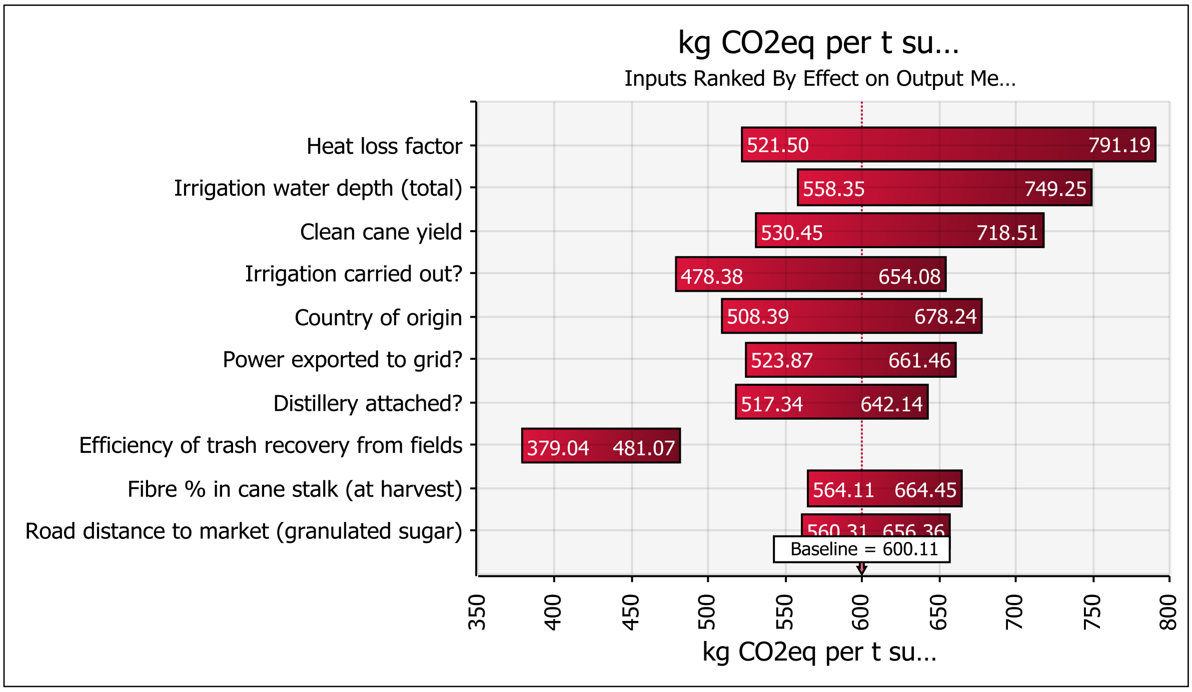

Fig. 5 – Sensitivity analysis: field-to-market refined sugar (refinery annexed to factory)

Scenario 4: Raw sugar port to refined market (i.e. raw shipping, refining and transport)

The fourth scenario modelled was raw sugar refining in a destination refinery, including shipping by sea of raw sugar to the refinery, and product transport (refined sugar and molasses) to market. The starting point for each simulation was 1 million tonnes of raw sugar at a port in the country of origin. Variable inputs are listed in Tables 5 and 6 below.

Table 5 – Variable (Discrete) Model Inputs: Destination Refinery

Parameter	Value/Range
% of simulations processing VHP quality sugar (remainder use affination)	50%
% of simulations with phosphatation (remainder have carbonatation)	60%
% of simulations with bone char/GAC[17]/IER for decolourisation	20%/30%/50%
% of simulations including export of surplus power to grid	20%
% of simulations using coal/oil/gas as fuel	30%/10%/60%

Table 6 – Variable (Continuous) Model Inputs: Destination Refinery

Parameter	Value/Range	Distribution
Raw (non-VHP) sugar colour to refinery (IU)	3000 (1500-5000)	PERT
VHP sugar colour to refinery (IU)	1000 (500-1200)	PERT
Refinery energy efficiency	[18]	PERT
Refinery process efficiency	[19]	PERT
Power generation turbine overall efficiency	70% (50-80%)	PERT

[17] Granular activated carbon.
[18] The variability of process energy efficiency is applied in the model via an Energy Efficiency Factor. This factor was set at 1 and allowed to vary between 0 and 5. These values roughly correspond with an exhaust steam usage of 1.09 t/t sugar (varying between 0.9 and 1.45).
[19] The variability of process efficiency is applied in the model via a Sugar Loss Factor. This factor was set at 1 and allowed to vary between 0.5 and 4. These values roughly correspond with an overall sucrose yield of 98% (varying between 99% and 96%).

Carbonatation lime dosing (ppm CaO to DS[20] in feed)	6000 (4500-9000)	PERT
Bone char burn rate (kg per kg DS in feed)	10% (5-15%)	PERT
GAC burn rate (kg per kg DS in feed)[21]	0.8% (0.4-1.4%)	PERT
IER colour removal per cycle (BV.IU)	22 500 (20 000-30 000)	PERT
Raw sugar sea shipping distance to refinery (km)	8000 (2000-20000)	PERT
Average road distance to market (km): refined sugar	100 (50-300)	PERT
Average road distance to market (km): molasses	100 (10-500)	PERT
Road freight fuel efficiency (tonne.km per litre)	21 (16-26)	PERT

Results

Figure 6 shows the distribution of the results from the 3000 model simulations, and Appendix 2 compares the results with the other scenarios 1-5. Appendix 1 shows that around 75% of the carbon footprint is due to fossil fuel usage, with the remainder split between product transport, raw sugar shipping and process chemicals.

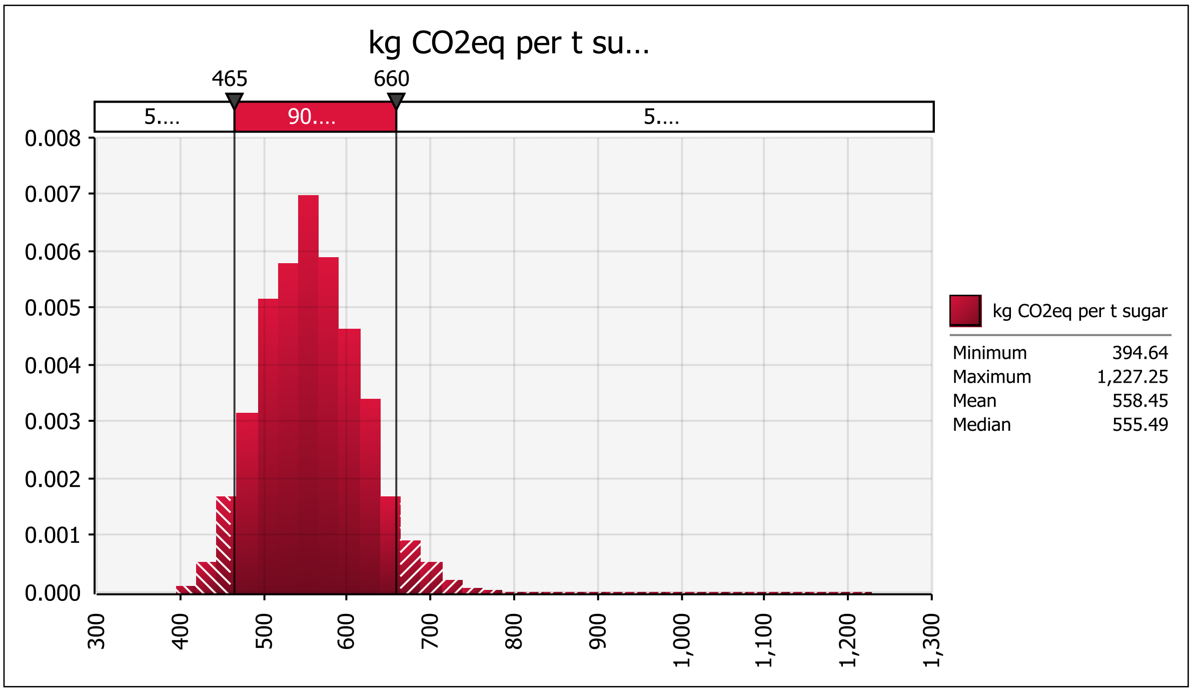

Fig. 6 – Carbon footprint variability: raw sugar port to refined market

Comparison with other published estimates

Rein (2011) estimated a value of 417 g CO_{2eq}/kg sugar for refining alone (i.e. excluding transport). Rein also reported values for raw sugar transport to a destination refinery of 48 (Thailand to Japan) and 140 kg CO2eq/t sugar (Mauritius to Europe), although it is not clear if these include overland transport from factory to port. These values are of the same order as the results shown above and in Appendix 1.

Sensitivity analysis

Figure 7 shows the sensitivity analysis chart. The top-ranked input is the heat loss factor, i.e. the refinery energy efficiency. This is logical as the majority of emissions are due to fossil fuel usage. Other key drivers are transport distances and efficiencies, power

[20] Dry solids
[21] kg of GAC sent to kiln for regeneration per kg of sugar (dry solids) processed

generation and process configuration. Of the options included, the configuration with the lowest carbon footprint is VHP sugar refined using phosphatation and either IER or GAC.

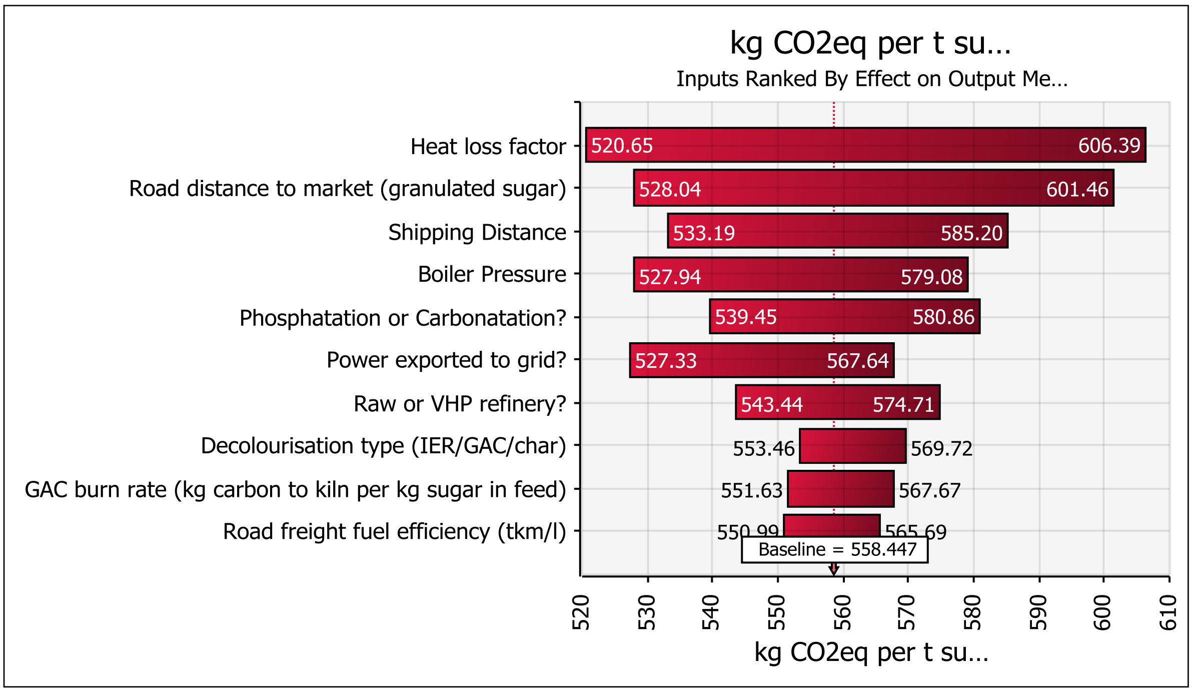

Fig. 7 – Sensitivity analysis: raw sugar port to refined market

Scenario 5: Field-to-market refined sugar (refinery separate from factory)

The fifth scenario modelled included raw sugar production (as scenario 1), transport to a refinery, refining and product transport (as scenario 4). The refinery could be either within the country of origin or in the country of destination. The starting point for each simulation, as in scenario 1, was 20 000 ha of sugarcane production. The additional or modified variable inputs are:

Table 7 – Additional variable model inputs (scenario 5)

Parameter	Value/Range	Distribution
Refinery located with road distance of factory	15%	Discrete
Road distance from factory to refinery (km)	50 (0-200)	PERT
Road distance from factory to port (km)	400 (10-1000)	PERT

Results

Figure 8 shows the distribution of the results from the 3000 model simulations, and Appendix 2 compares the results with the other scenarios 1-5. Appendix 1 shows that around half of the emissions are due to agriculture, with around 40% from processing (mainly fossil fuel usage in refining) and the remainder in transport. Road transport contributes around double the emissions of sea transport.

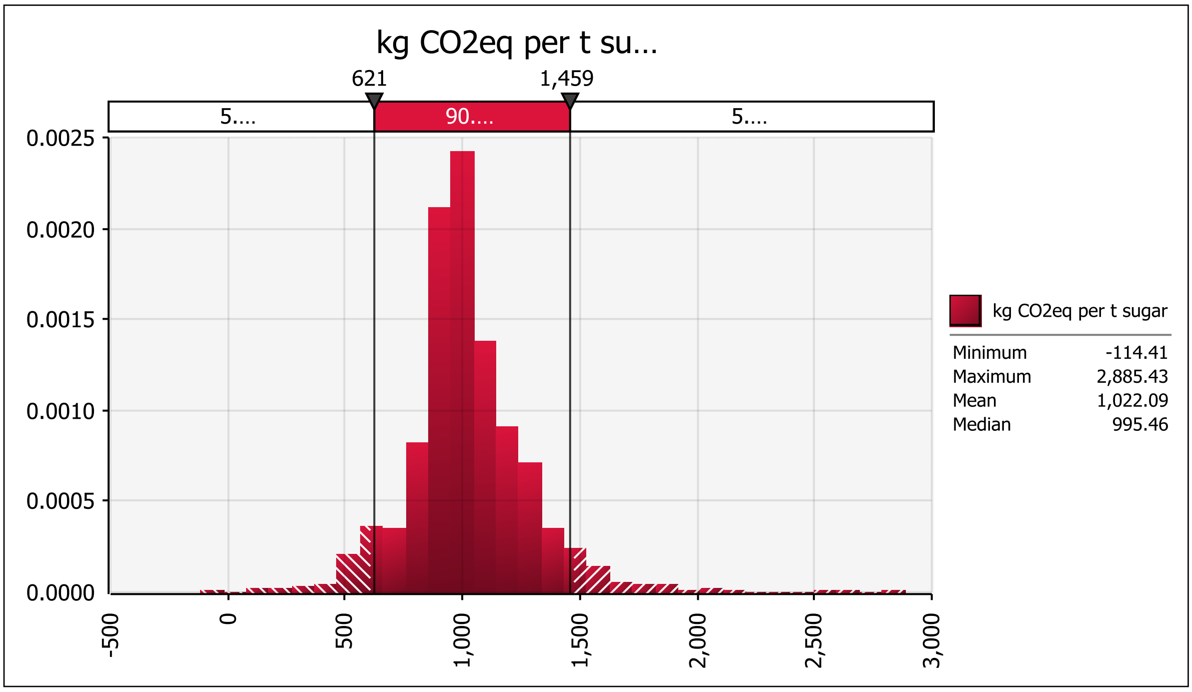

Fig. 8 – Carbon footprint variability: field-to-market refined (refinery separate from factory)

Comparison with other published estimates

The literature survey in Klenk *et al.* (2012) included two estimates for raw sugar shipped and refined in another country: 630 and 534 g CO_{2eq}/kg sugar. Rein (2012) reported an estimate of 570 g CO_{2eq}/kg sugar in the US. Tate & Lyle (2009) reported a carbon footprint of 380 g CO_{2eq}/kg retail sugar (field-to-use), while Florida Crystals (2008) reported carbon-neutral refined sugar (i.e. carbon footprint of zero). These values are all at the lower end of the distribution in Figure 8.

Sensitivity analysis

Figure 9 shows the sensitivity analysis chart. The highest-ranked input is the road distance from factory to port (as this was defined in Table 7, it is highly variable). The other inputs are dominated by agriculture, power production and energy efficiency.

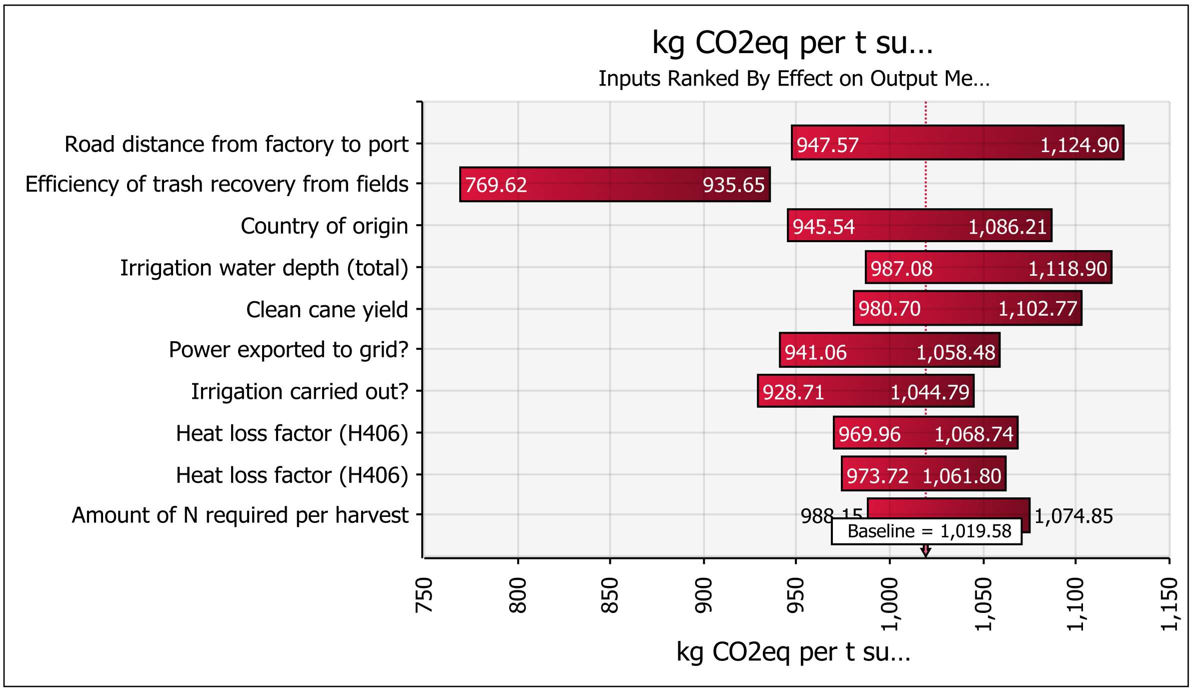

Fig. 9 – Sensitivity analysis: field-to-market refined sugar (refinery separate from factory)

Scenario 6: Low emissions refined sugar

Scenario 6 was a single static simulation in which the key drivers as identified above were manipulated to achieve low-emissions refined sugar. The inputs manipulated are listed in Table 8. The other inputs remained at their "most likely" values (i.e. without ranges) as in scenario 3.

Table 8 – Inputs manipulated: low-emissions refined sugar

Parameter	Value
Country of origin	India[22]
Cane yield (t/ha)	70.1[23]
Irrigation water usage (mm/year)	500
Electric irrigation pumps	100%
Amount of nitrogen required as fertiliser (kg/ha)	75
Amount of lime required on fields (kg/ha)	500
Filter mud returned to fields?	Yes
Distillery attached?	No
Refinery annexed to factory (i.e. not separate)?	Yes
Process steam-on-cane (approx.)	40%
% of cane burnt	0%
Surplus power exported to grid?	Yes
Boiler pressure (bar)	100
Power generation turbine overall efficiency	80%
Mill drives electrified	100%

[22] India is selected because it has a high emissions factor for average electricity production (264 g CO_2/MJ, compared to 21 g CO_2/MJ for Brazil, for example), therefore increasing the credit for power exports (see footnote 2).
[23] Average for India.

The results are shown in Appendix 1. The total carbon footprint is -262 g CO_{2eq}/kg sugar. The negative carbon footprint is due to the large credit allocated to power export (>700 g CO_{2eq}/kg sugar). Agricultural nitrogen and irrigation are the biggest contributors to emissions.

Scenario 7: Very low emissions refined sugar

Scenario 7 was the same as scenario 6, except that 100% of the land was mechanically harvested and 50% of cane trash was recovered and burnt in the boiler (constituting 20% of the total boiler fuel). The results are shown in Appendix 1. The total carbon footprint is -565 g CO_{2eq}/kg sugar. The power export credit is now over 1000 g CO_{2eq}/kg sugar (the actual power export is around 1.1 MWh/tonne sugar).

Scenario 8: Extremely low emissions refined sugar

Scenario 8 was the same as scenario 7, except that bagasse and trash were processed via biomass gasification with power produced via gas turbines. The results are shown in Appendix 1. The total carbon footprint is -1469 g CO_{2eq}/kg sugar. The power export credit is now almost 2700 g CO_{2eq}/kg sugar (the actual power export is around 2.8 MWh/tonne sugar). The emissions due to chemical manufacture and transport increase by almost 700 g CO_{2eq}/kg due to gasifier chemical usage.

Summary of results

The results from the various scenarios are summarised below. These results and conclusions are based on the assumptions listed in the paper. The nature of variable modelling carried two benefits in this regard: (a) by expressing inputs and outputs as ranges, the results are not so reliant on the accuracy of data for any single input; and (b) the sensitivity analysis highlights which assumptions are most crucial to the final results.

1. The carbon footprint of raw sugar worldwide varied in 90% of simulations between 217 and 809 g CO_{2eq}/kg sugar, with a mean of 441 g CO_{2eq}/kg.
2. The biggest drivers of variability in raw sugar carbon footprint were the country of origin, agricultural methods, power production/export and process energy efficiency.
3. Production of plantation white sugar and transport to a local market added around 100-150 g CO_{2eq}/kg to the carbon footprint, due to product transport (50%), increased chemical usage (30%), and increased energy usage (20%).
4. The global carbon footprint of refined sugar (refinery annexed to factory) varied in 90% of simulations between 329 and 1121 g CO_{2eq}/kg sugar, with a mean of 598 g CO_{2eq}/kg. The increase from raw sugar was mostly due to fossil fuel usage, and the biggest driver of variability was process energy efficiency
5. The carbon footprint associated with shipping raw sugar from port, refining at a destination refinery, and transporting to market varied in 90% of simulations between 465 and 660 g CO_{2eq}/kg sugar, with a mean of 558 g CO_{2eq}/kg. The biggest driver of variability was process energy efficiency.
6. The global carbon footprint of refined sugar (refinery separate to factory) varied in 90% of simulations between 621 and 1459 g CO_{2eq}/kg sugar, with a mean of 1022 g CO_{2eq}/kg. The key drivers were similar to the previous case, with the addition of the distance from factory to port.

7. By manipulating the key drivers, a refined sugar carbon footprint of -260 g CO_{2eq}/kg sugar can be achieved. This increases to -565 g CO_{2eq}/kg if trash recovery is carried out and -1470 g CO_{2eq}/kg if biomass gasification is adopted.

Conclusions

The potential variation in the carbon footprint of raw and refined cane sugar is large, depending on where and how it is produced. This poses a problem, particularly for refined sugar manufacturers and consumers, in that stating a specific product emissions level is difficult if not impossible. It also presents an opportunity, particularly in raw sugar manufacture and annexed refineries, in that the key drivers can be manipulated to achieve a low-emissions product. Plantation white and factory-refined sugar have a significant advantage over destination-refined white sugar. By focussing on the areas of irrigation, nitrogen and lime application, cane yields, power generation and export, process energy efficiency and cane burning, refined cane sugar can realistically achieve a negative carbon footprint, i.e. a net emissions credit of 260 g CO_{2eq}/kg sugar. This could increase to 565 g CO_{2eq}/kg if trash recovery is implemented, and to 1470 g CO_{2eq}/kg with biomass gasification. Florida Crystals have already shown in 2009 that a carbon neutral refined sugar can be produced (due to emissions credits from power generation and export).

The carbon footprint values stated in this paper are based on the Bonsucro method of analysis with assumptions, modifications and additions as stated in the paper. One critical assumption is that no non-agricultural land was converted to agricultural use after 1 January 2008. This effectively eliminates any impacts from direct or indirect land use change. It is important to understand the methodology and its boundaries when comparing these results with other published estimates.

REFERENCES

Bakker, H. (1999). Sugar Cane Cultivation and Management. Springer.

Bonsucro. (2011). Bonsucro Production Standard. Version 3.0, Appendix 3. http://bonsucro.com/standard/index.html

Defra. (2011). Guidelines to Defra / DECC's GHG Conversion Factors for Company Reporting: Methodology Paper for Emission Factors. **FAO.** Food and Agriculture Organisation of the United States, Statistics Division. http://faostat3.fao.org/home/index.html

Florida Crystals Corporation. (2008). Florida Crystals Corporation and Carbonfund.org Announce First and Only Carbon*free*® Organic and Natural Sugars. http://tinyurl.com/abdvo6s

IEA. (2011). CO_2 emissions from fuel combustion: highlights. 2011 edition. International Energy Agency. Pages 109-120.

Klenk, I., Langquist, B. and de Imana, O. R. (2012). The Product Carbon Footprint of EU beet sugar. Sugar Industry / Zuckerindustrie 137 (2012) No. 3, 169-177, and no. 4, Bartens.

Pankhurst, C. (2005). Should sugarcane trash be used as a biofuel for cogeneration or left in the field for its long-term benefits to soil health and crop productivity? A report prepared for the Sugar Yield Decline Joint Venture.

Rein, P.W. (2010). The carbon footprint of sugar. Int. Soc. Sugar Cane Technol., 27: (CD-ROM).

Rein, P.W. (2011). Sustainable production of raw and refined cane sugar. Paper presented to SIT conference, Montreal, 2011.

Rein, P.W. (2012). Sustainable sugar production. Paper presented to BSST meeting, London, 2012.

Renouf, M.A., Wegener, M.K. and Pagan, R.J. (2010). Life cycle assessment of Australian sugarcane production with a focus on sugarcane growing. Int. J. Life Cycle Assess., 15: 924-937

Smith-Baez, C. (2008). Production of bioenergy using filter cake mud in sugar cane mill factories. Sugar Processing Research Institute 2008 Conference. http://www.smithbaez.com/Download%20page%20files/FilterCakeAD.pdf.

Tate & Lyle. (2009). Tate & Lyle Reduces Its Footprint With The Carbon Trust. http://tinyurl.com/a5kovfz

Appendix 1: Results from all scenarios (mean values from 3000 simulations)

SUMMARY	Field-to-Gate Raw Sugar	Field-to-Market Plantation White	Field-to-Market White-End Refined	Raw Shipping, Port-Refining & Transport	Field-to-Market Autonomous Refined	Low Emissions Refined Sugar	Very Low Emissions Refined Sugar	Extremely Low Emissions Refined Sugar
Agriculture	585	612	619	0	594	266	276	276
Transportation of cane	45	47	48	0	46	34	45	45
Feedstocks (e.g. raw sugar)	0	0	0	0	0	0	0	0
Processing (excluding electricity)	121	192	211	459	551	72	76	734
Electricity import/export	-61	-55	-58	-8	-70	-706	-1,060	-2,696
Local transport of products	0	76	80	56	122	51	51	51
Total (ex sea transport)	690	873	900	507	1,239	-283	-612	-1,590
Allocation to bagasse	0	0	0	0	0	0	0	0
Allocation to molasses	33	43	34	2	42	-22	-47	-121
Allocation to ethanol	216	280	267	0	218	0	0	0
Allocation to sugar	**441**	**550**	**598**	**506**	**980**	**-262**	**-565**	**-1,469**
Sea transport of sugar	0	0	0	53	45	0	0	0
Total	690	873	900	560	1,285	-283	-612	-1,590
Total for sugar	**441**	**550**	**598**	**558**	**1,025**	**-262**	**-565**	**-1,469**
DETAIL								
Agricultural chems manufacture & application								
Nitrogen	88	86	89	0	93	14	14	14
K2O	15	15	16	0	14	6	6	6
P2O5	9	9	9	0	10	9	9	9
CaCO3	68	70	72	0	65	19	19	19
Herbicide	11	11	11	0	11	0	8	8
Insecticide	1	1	1	0	1	1	1	1
Total	**191**	**191**	**198**	**0**	**193**	**49**	**56**	**56**
N2O from cane/trash/filter mud/vinasse								
Cane stallk residue	6	6	6	0	6	5	5	5
Cane trash residue	32	33	34	0	30	45	23	23
Filter cake	63	67	67	0	62	56	56	56
Vinasse	29	32	32	0	26	0	0	0
Total	**131**	**138**	**138**	**0**	**125**	**107**	**84**	**84**
Agricultural fuel & energy								
Diesel fuel for transport	32	33	33	0	32	21	46	46
Diesel fuel for irrigation	123	139	138	0	130	0	0	0
Electricity used in irrigation	31	30	29	0	33	90	90	90
Total	**185**	**202**	**201**	**0**	**195**	**110**	**136**	**136**
Cane burnt								
CH4 produced in cane burning	59	61	62	0	60	0	0	0
N2O produced in cane burning	19	20	20	0	20	0	0	0
Total	**78**	**81**	**83**	**0**	**80**	**0**	**0**	**0**
Cane transport								
Diesel fuel for cane transport	45	47	48	0	46	34	45	45
Total	**45**	**47**	**48**	**0**	**46**	**34**	**45**	**45**
Bagasse burnt								
CH4 produced in bagasse burning	25	26	26	0	24	19	19	0
N2O produced in bagasse burning	1	1	1	0	1	1	1	0
Total	**26**	**26**	**27**	**0**	**25**	**19**	**19**	**0**
Fossil fuels								
Fossil fuels burnt in boiler	9	35	76	411	421	0	0	0
Gas burnt in kilns	0	0	0	8	0	0	0	0
Electricity imported/exported	-61	-55	-58	-8	-70	-706	-1,060	-2,696
Total	**-51**	**-20**	**17**	**410**	**351**	**-706**	**-1,060**	**-2,696**
Process chemicals								
Lime (CaO)	1	3	2	0	1	1	1	1
Caustic	68	71	74	14	90	33	36	386
Sulphuric acid	2	2	2	0	2	0	0	25
Miscellaneous	11	50	27	25	25	17	17	319
Total	**82**	**126**	**103**	**40**	**118**	**50**	**54**	**731**
Water/waste								
Wastewater treatment	3	3	3	0	3	2	2	2
Raw water intake	2	2	2	0	3	1	1	1
Total	**5**	**5**	**5**	**1**	**6**	**3**	**3**	**3**
Road transport of products								
Diesel fuel for granulated sugar transport	0	45	55	55	93	36	36	36
Diesel fuel for liquid sugar transport	0	0	0	0	0	0	0	0
Diesel fuel for molasses transport	0	14	13	1	17	15	15	15
Diesel fuel for ethanol transport	0	16	12	0	12	0	0	0
Total	**0**	**76**	**80**	**56**	**122**	**51**	**51**	**51**
Sea transport of products								
Raw sugar from factory to refinery	0	0	0	53	45	0	0	0
Total	**0**	**0**	**0**	**53**	**45**	**0**	**0**	**0**

Appendix 2: Results comparison (Scenarios 1-5)

No	Scenario	Min	5%	Median	Mean	95%	Max
1	Field-to-factory-gate raw sugar	-121	217	390	441	809	2251
2	Field-to-market plantation white sugar	-35	327	490	550	962	2161
3	Field-to-market refined sugar (refinery annexed to factory)	-126	329	529	598	1121	2114
4	Raw sugar port to refined market (i.e. raw shipping, refining & transport to market)	395	465	555	558	660	1227
5	Field-to-market refined sugar (refinery separate from factory)	-114	621	995	1022	1459	2885

All values are g CO_2 per kg sugar