



Original article

Mapping the path to decarbonised agri-food products: a hybrid geographic information system and life cycle inventory methodology for assessing sustainable agriculture

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Summary The development of a decarbonised food industry will depend on a sustainable agricultural system where embodied food product greenhouse gas emissions (GHG) can be associated with agricultural production. The method presented demonstrates how mapping agri-production can be used to calculate regional carbon footprints so GHG emission reduction is geographically strategic. Different agronomic and husbandry outcomes are mapped using Geographic Information Systems (GIS's) and carbon footprints are calculated using Life Cycle Inventory (LCI) libraries. The hybridised GIS-LCI approach reports unique insights for decarbonisation, demonstrating how farming practices can be further integrated to best deliver food security. We use the GIS-LCI method to show; (1), geography limits crop and livestock production types; (2), agri-product density data can be used to calculate a food system carbon footprint; and (3), GIS's can be used to focus food policy for sustainability.

Keywords Decarbonisation, food manufacturing, food security, food supply, sustainability.

Introduction

Defining how materials are distributed across supply chains is a starting point for developing methodologies that assess utilisation of products. When resource flows are mapped within and between supply chains, their carbon footprint for production can be established (Escobar *et al.*, 2020; Fernandez-Mena *et al.*, 2020). There are excellent legacy examples that report agricultural mass balance and carbon footprints; but these are snapshot or points-in-time scenarios, which are developed under controlled field trial conditions (Brentrup *et al.*, 2000, 2002, 2004; Küstermann *et al.*, 2010). The impact of improved access to geographic data and the remote sensing of agricultural production has spotlighted the potential for the development of real-time assessment of material flows in agriculture (Asam *et al.*, 2022; Venter *et al.*, 2022). As such, a

method that can map and segment agri-production data for carbon footprint analysis will enable future real-time responses to agri-production traceability. Reduction of systemic greenhouse gas (GHG) emissions is most probable if operators can quickly identify what natural resource impacts are most important, where products are produced, and how materials are utilised. This requires new methods of assessment because this all depends on not only the materials and processes used but also upon the geography in which production occurs.

Mapping such impacts across supply chains has become of high interest because of the need to report Scope 3 GHG emissions. These are derived from processes that are always variable and dependent on market conditions (Pelletier *et al.*, 2013; Svanes & Aronsson, 2013; Martindale *et al.*, 2020a). Decreasing the supply chain response time for changing practices that reduce GHG emissions will reduce the risk of

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overproduction and losses, essentially reducing the bullwhip effect (Martindale *et al.*, 2019). The integration of Geographic Information systems (GIS) and Life Cycle Inventories (LCI) begins the process of identifying methods that can do this more expediently and by demonstrating how sourcing products from intensive, integrated, and extensive agricultural geographies can be strategically achieved for decarbonisation.

There is much to do by utilising of geographic data for reporting traceable environmental impact and the two methods of GIS and life cycle assessment (LCA) have not yet been integrated in the food and beverage sectors for commercial or policy application. There is much to offer in doing so and the method reported here demonstrates how integration of geographic and GHG data at regional scale can help trace GHG emissions associated with agri-products. The geographic assessment of carbon footprints provides an important outcome in that it breaks the dogma of using only the functional unit for mass of a product alone in carbon footprint assessments. An example, to demonstrate this is described here for the biomass production of wheat and cattle production which cannot be compared using mass of product alone when considering the food system unless it is mapped with respect to the geography of the production system. Typical UK wheat grain biomass yield is 7.88 tonnes per hectare and cattle live-weight yield is 0.400 tonnes per hectare in the intensive production regions of England for these products. A tonne for tonne comparison does not provide a full assessment and geographic analysis is required to demonstrate the impact of extensive, integrated and intensive land use. The importance of this is twofold, it enables policy to project biomass outcomes for different production intensities with respect to GHG outputs and identifies where more intensive and extensive production systems should be encouraged. This research demonstrates a method for achieving this and provides specific insights that have not been previously accounted for.

Methods

The crop and livestock agri-products investigated in this study are the primary agri-product categories defined in the FAOStat Food Balance database that are supplied in the greatest amount of kcal.capita⁻¹.day⁻¹ in the UK. The selection of these categories from the FAOStat Food Balance Database was made from all primary agri-product categories in FAOStat. Table 1 shows the top eight categories, ranked from one to eight by the amount of kcal.capita⁻¹.day⁻¹ supplied each day in the UK. The kcal.capita⁻¹.day⁻¹ attribute was selected because it aligned with the ranking for the same agri-product categories supplying the major protein, fat and carbohydrate to UK citizens (Table 1).

Table 1 Ranked data for the UK citizen supply of kcal for food product categories defined in the FAOstat Food Balance Data 2021 ("FAOSTAT", 2024)

Rank	Agri-product group (item)	Unit	Value
1	Wheat and products	kcal/cap/d	834.31
2	Milk – excluding butter	kcal/cap/d	352.24
3	Sugar (raw equivalent)	kcal/cap/d	305.14
4	Rape and mustard oil	kcal/cap/d	166.16
5	Pigmeat	kcal/cap/d	153.5
6	Poultry meat	kcal/cap/d	131.91
7	Oilcrops oil, other	kcal/cap/d	129.5
8	Potatoes and products	kcal/cap/d	116.66

This selected the agri-product groups for further analysis in this research.

The distribution of these agri-products was mapped using the Arc-GIS Pro (ESRI) GIS software across a 5 km square grid for England. Each 5 km square cell in the grid contains the land use data used to report the agri-production density of the agri-products investigated here. Agri-production density data was derived from the Agricultural and Horticultural Census, which is conducted in June each year by the UK government departments dealing with Agriculture and Rural Affairs for Scotland, England, and Wales. The digitised data was derived from the Agricultural and Horticultural Census 2016 survey which has been fully georeferenced. Since then data has been corrected each year to account for any changes until the next full georeferenced survey. The Census surveys farmers each year via a postal questionnaire with each farmer declaring the agricultural activity on their land for 150 agri-products. The 5 km square grid is the geographical grid used by EDiNA as AgCensus for processing the Agricultural and Horticultural Census of England (see, EDiNA, 2024 <http://agcensus.edina.ac.uk>). The grid resolution for EDiNA Agcensus data is set at 5 km squares and this enables this research to report the mean agri-product density in hectares in each 5 km square for specific agri-products (each 5 km square is 50 × 50 = 2500 hectares). The Arc-GIS Pro software excludes any 5 km square cells where no agri-product production is reported so that only the amount of land in production was assessed for crops and livestock across the 5 km square grid. Agcensus data has been previously utilised to demonstrate national protein utilisation (Leinonen *et al.*, 2020) and biodiversity of bird populations (Lennon *et al.*, 2019). The method developed here provides a timely use for it that integrates land-use data with agri-product carbon footprints.

The method used here is shown schematically in Fig. 1, ESRI Arc-Gis Pro software was used to calculate the national mean density of each specific

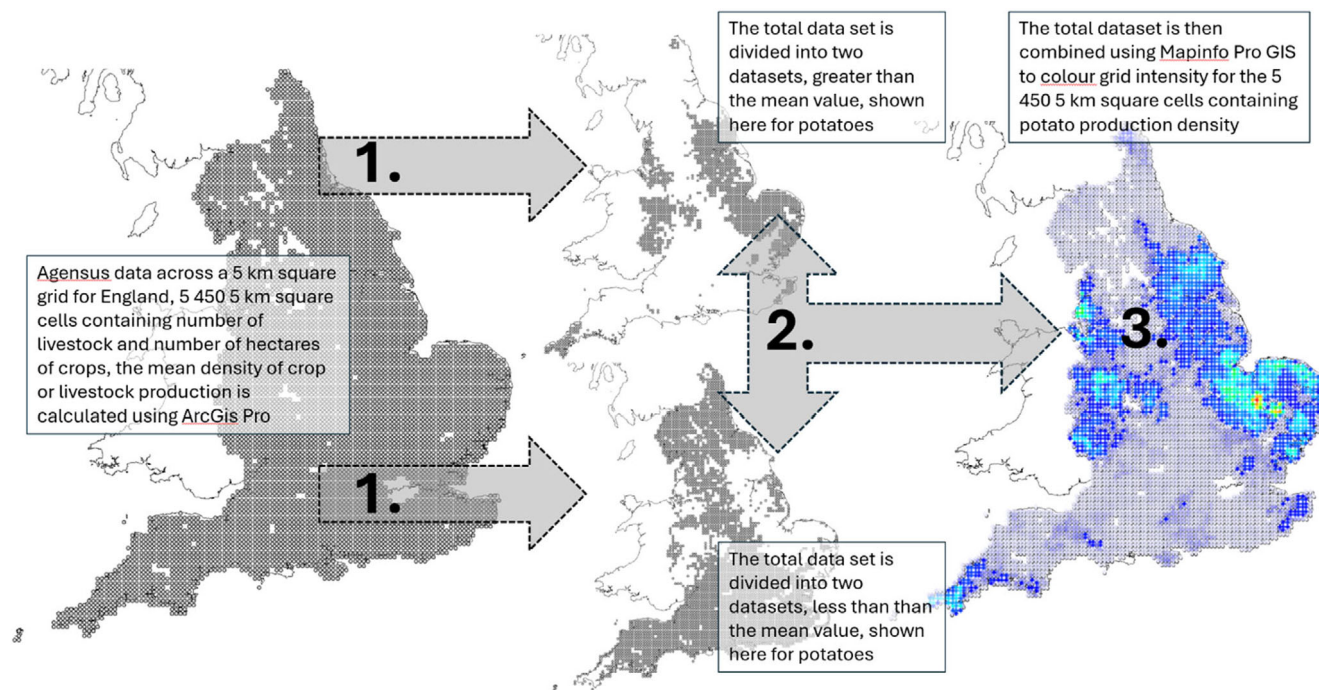


Figure 1 The method reported; (1) maps the full Agcensus 5 km square grid and calculating mean density of crops and livestock, (2) selects data for specific crop and livestock agriproducts and divides the Agcensus data into greater and less than mean value per 5 km square grid cell; and, (3) provides a colour grid of both datasets so that density of agri-products per hectare was visualised. This data was utilised to calculate the carbon footprint.

agri-product per hectare investigated. The sum of crop area (Hectares) or livestock (number of animals) in each 5 km cell was obtained so the national agri-product distribution could be divided into two datasets for agri-product densities that had greater than the mean production density per 5 km square cell and those that have less than the mean production density per 5 km square cell in the grid for the crop or livestock category under investigation. The summed amount of land or number of livestock produced was reported for those 5 km square cells that are greater and less than the mean production density of the whole production in England, 5 km square grid (Martindale *et al.*, 2020b, 2020c). The analysis includes up to 5450 of the 5 km square cells that cover the land area of England, 239 of these 5 km square cells overlap coastal boundaries containing agricultural activity but these are less than 5% of the reported land area data. Colour grid visualisations of mapped production less than and greater than mean land use or livestock number was reported using the MapInfo Pro 17.0.2 GIS software.

The method reported here was then able to obtain the total production density for specific crops or number of livestock in each 5 km square cell which

are summed to give a national figure for the items selected.

The sum of land used for less than and greater than mean categories was calculated, enabling the production of crops and livestock biomass was then obtained by multiplying the amount of land in hectares in the selected cells with the national yield of a crop in tonnes per hectare or the number of livestock and live-weights. This entailed relating crop and livestock production densities per hectare with the lifecycle of 60 days to 1 year for poultry (broiler/meat birds and laying birds) and 1–3 years for cattle and pigs. These were accounted for in LCI data when calculating carbon footprints and the stock number in each 5 km square cell was multiplied by reported national live-weight per animal to obtain biomass produced per hectare. Cattle liveweights used in this study were 500 kg per animal, poultry liveweights were 2.4 kg per bird, and pig liveweights were 120 kg per pig.

The analysis method for calculating the carbon footprint of the agri-products was the IPCC single issue method (IPCC 2021 GWP100 method) using Life Cycle Inventory (LCI) libraries principally from Agri-footprint (version 6.3 September 2022, available via www.agri-footprint.com) but also benchmarked with

Agribalyse (from ADEME and INRAE, available via <https://doc.agribalyse.fr/documentation-en/agribalyse-data/data-access>), and Ecoinvent (Converted Ecoinvent 3.8 data available via <https://ecoinvent.org/database/>). Each of these libraries has over 20 000 interlinked datasets, each of which describes a LCI at process level. SimaPro Analyst 9.4.0.3 software provides these libraries so that single issue calculations such as the carbon footprint and full LCAs can be calculated for materials and products (Silva *et al.*, 2017). The carbon footprint for the agri-products in this research were calculated using the SimaPro Analyst 9.4.0.3 software platform. The carbon footprint for poultry and pigs used the Agrifootprint library but the DEFRA category of cattle includes both beef and dairy herds and this required more detailed consideration in reporting the carbon footprint of a kg of cattle liveweight. The LCI CO_{2e} data from the Agri-Footprint Library includes dairy and beef cattle for female and male animals at 0, 1, 2, and 3-year life stages. However, cattle as a category is a catch-all by DEFRA for the different enterprises. The total cattle category used in this study uses the CO_{2e} for dairy and beef cattle by using the DEFRA Cattle Tracing System data that reports 38% of the UK total cattle herd is the beef breeding herd which Agrifootprint reports a carbon footprint by mass of 21.4 kg CO_{2e} per kg of beef cattle liveweight. The further 62% of the UK total cattle herd is the dairy breeding herd which Agrifootprint reports a carbon footprint by mass of 4.01 kg CO_{2e} per kg of dairy cow liveweight. Using these respective proportions of the breeding herds, we use a mean carbon footprints of dairy and beef as cattle at 10.62 CO_{2e} per kg of cattle, this is a necessary simplification of the beef-dairy system.

Figure 1 has demonstrated how the grid and cell geographic data was divided into greater than and less than mean production density datasets, the text

formulae below defines how the LCI libraries are used for the calculations reported that use the datasets.

- 1 Total agricultural area (from Agcensus 5 km square grid) producing crop or livestock product (from Table 1) = A.
- 2 Mean density of agri-production for crops (tonnes.ha⁻¹ each year) or livestock (stock number.ha⁻¹ each year) agri product = $\bar{X}$.
- 3 Land area (ha) less than $\bar{X}$ = ALe $\bar{X}$.
- 4 Land area (ha) greater than $\bar{X}$ = AGr $\bar{X}$.
- 5 Tonnes of crop or livestock (data from ONS/FAOstat reported yield of crops or liveweight of stock) = M.
- 6 Tonnes of crop or livestock for ALe $\bar{X}$ or AGr $\bar{X}$ = M X (ALe $\bar{X}$ or AGr $\bar{X}$).
- 7 Percent of land area in production (crop ha or livestock number) = $\frac{A}{(ALe\bar{X} \text{ or } AGr\bar{X})} \times 100$.
- 8 LCI library carbon footprint for 1 tonne of finished crop or livestock at farm = GWP100.
- 9 CO_{2e} for Le $\bar{X}$ or Gr $\bar{X}$ sample (tonnes) = GWP100 X M(ALe $\bar{X}$ or AGr $\bar{X}$).

Results

The spatial crop and livestock production in England was calculated and reported in Table 1, for crops and Table 2, for livestock. The sampled land areas show are for production density that is less than the mean (ALe $\bar{X}$) and greater than the mean (AGr $\bar{X}$) for the total amount land in production for crop and livestock are calculated. The percentage of land producing crop or livestock under consideration (ALe $\bar{X}$ or AGr $\bar{X}$) was reported. The carbon footprint (GWP100) for the crop or livestock agri-product was calculated for ALe $\bar{X}$ or AGr $\bar{X}$ using the reported yield in tonnes per hectare for crops and reported live weight of individual

Table 2 The GIS-LCI analysis of crop agri-products, each crop was segmented into land use greater and less than the mean land use value for that crop

Crop sample (Le $\bar{X}$ or Gr $\bar{X}$)	Total land area sample, (A, ha)	Crop land area in sample (ALe $\bar{X}$ or AGr $\bar{X}$, ha)	Percentage crop land area (%)	CO _{2e} for sample GWP100 (t)
Wheat > mean	5 805 000	1 324 047	22.81	3 328 285
Wheat < mean	7 752 500	359 373	4.64	903 362
Oil seed rape > mean	5 697 500	447 459	7.85	949 362
Oil seed rape < mean	7 807 500	95 253	1.22	202 096
Sugar beet > mean	2 597 500	76 061	29.28	310 839
Sugar beet < mean	10 070 000	9873	0.10	40 348
Potatoes > mean	3 907 500	87 518	2.24	356 668
Potatoes < mean	9 387 500	16 563	0.17	67 501

The total land area, crop area, and percentage are shown. The yield reported in 2016 by FAOstat is used to calculate the carbon footprint and the CO_{2e} of the crop calculated using IPCC GWP100 V1.01 methodology is shown.

livestock. The carbon footprint (CO_2e) for a tonne of crop or livestock product at the farm.

Wheat

Table 2 shows the mean hectares in the 5 km square grid of England in the agricultural census for the 2016 dataset is 310.48 ± 247.53 hectares (ha). The land area growing wheat greater than the mean value is 1 324 047 ha or 22.81% of the total land area analysed for this sample where wheat land use exceeds 310.48 ha on the 5 km square grid. The carbon footprint for UK wheat at the farm is $0.32 \text{ CO}_2\text{e}$. This means the carbon footprint associated with land that produces wheat at greater than the mean land use is 3 328 285 tonnes CO_2e for the average wheat yield of 7.88 tonnes per hectare in the UK (FAOStat data 2016). The same methodology for obtaining these results was used for land areas growing wheat less than the mean land use per 5 km square so that the carbon footprint for the two samples can be compared. Figure 2 shows the detailed data in Table 2, geographically mapped using a graduated colour grid for each 5 km square.

Oil seed rape (OSR)

Table 2 shows the mean hectares producing OSR in the 5 km square grid of England in the agricultural census for the 2016 dataset is 100.50 ± 73.09 hectares (ha). The land area growing OSR greater than the mean value is 447 459 ha or 7.85% of the total land area analysed for this sample where OSR land use exceeds 100.50 ha on the 5 km square grid. The carbon footprint for UK OSR at the farm is $0.69 \text{ CO}_2\text{e}$. This means the carbon footprint associated with land that produces OSR at greater than the mean land use

is 949 362 tonnes CO_2e for the average OSR yield of 3.07 tonnes per hectare in the UK (FAOStat data 2016).

Sugar beet

Table 2 shows the mean hectares producing sugar beet in the 5 km square grid of England in the agricultural census for the 2016 dataset is 17.00 ± 35.62 hectares (ha). The land area growing sugar beet greater than the mean value is 76 061 ha or 29.28% of the total land area analysed for this sample where sugar beet land use exceeds 17.00 ha on the 5 km square grid. The carbon footprint for UK sugar beet at the farm is $0.062 \text{ CO}_2\text{e}$. This means the carbon footprint associated with land that produces sugar beet at greater than the mean land use value is 310 839 tonnes CO_2e for the average sugar beet yield of 66.13 tonnes per hectare in the UK (FAOStat data 2016).

Potatoes

Table 2 shows the mean hectares producing potatoes in the 5 km square grid of England in the agricultural census for the 2016 dataset is 19.58 ± 31.97 hectares (ha). The land area growing potatoes greater than the mean value is 87 518 ha or 2.24% of the total land area analysed for this sample where potato land use exceeds 19.58 ha on the 5 km square grid. The carbon footprint for UK potatoes at the farm is $0.105 \text{ CO}_2\text{e}$. This means the carbon footprint associated with land that produces potatoes at greater than the mean land use value is 356 668 tonnes CO_2e for the average potato yield of 38.81 tonnes per hectare in the UK (FAOStat data 2016).

Table 3 shows the calculation for the spatial carbon footprints of total poultry, pigs, and cattle production

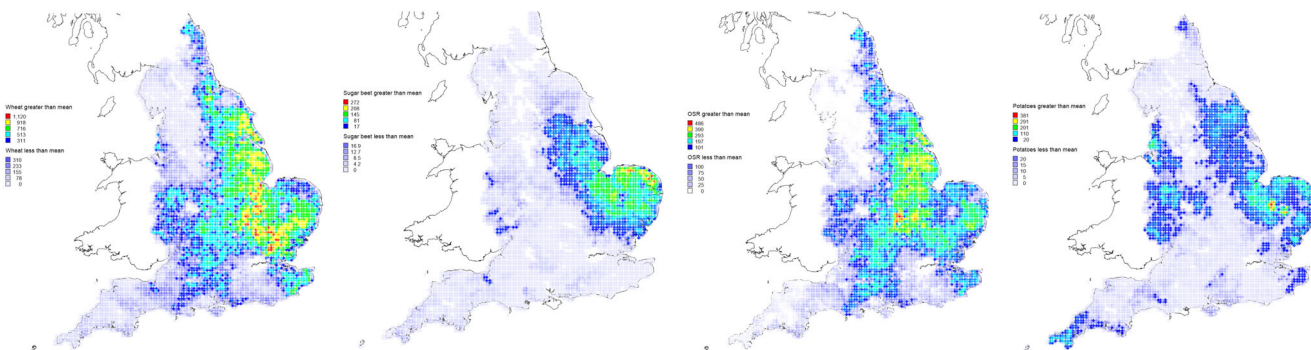


Figure 2 The land use intensity for wheat, sugar beet, oil seed rape (OSR), and potato production where the land use intensity is less than or greater than the national mean value for the land area growing those crops. Algorithms developed by EDINA convert small area data provided by the government agencies into national grid squares 5 km here (see, <https://digimap.edina.ac.uk/agcensus>). © University of Edinburgh Derived from DEFRA/DAA/RESAS agricultural census surveys. Great Britain OS basemap from agCensus Digimap Ordnance Survey data © Crown copyright and database right (2023).

Table 3 The GIS-LCI analysis of livestock agri-products, each livestock product was segmented into land use greater and less than the mean land use value for that crop

Livestock sample (Le $\bar{X}$ or Gre $\bar{X}$)	Total land area sample (A, ha)	Livestock number in sample (ALe $\bar{X}$ or AGre $\bar{X}$, ha)	Livestock number (per ha in ALe $\bar{X}$ or AGre $\bar{X}$)	CO _{2e} for sample GWP100 (t)
Poultry > mean	4 222 500	101 950 451	24	543 192
Poultry < mean	9 285 000	26 907 446	3	143 363
Pigs > mean	3 327 500	2 978 941	0.9	891 299
Pigs < mean	10 210 000	931 489	0.1	278 702
Cattle > mean	4 855 000	3 830 114	0.8	20 337 905
Cattle < mean	8 717 500	1 421 600	0.2	7 548 695

The total land area, livestock number, and number of livestock per hectare are shown. The number of stock reported by Agcensus and the weight in kilograms of a typical animal was used to calculate the carbon footprint with the CO_{2e} of the livestock calculated using IPCC GWP100 V1.01 methodology.

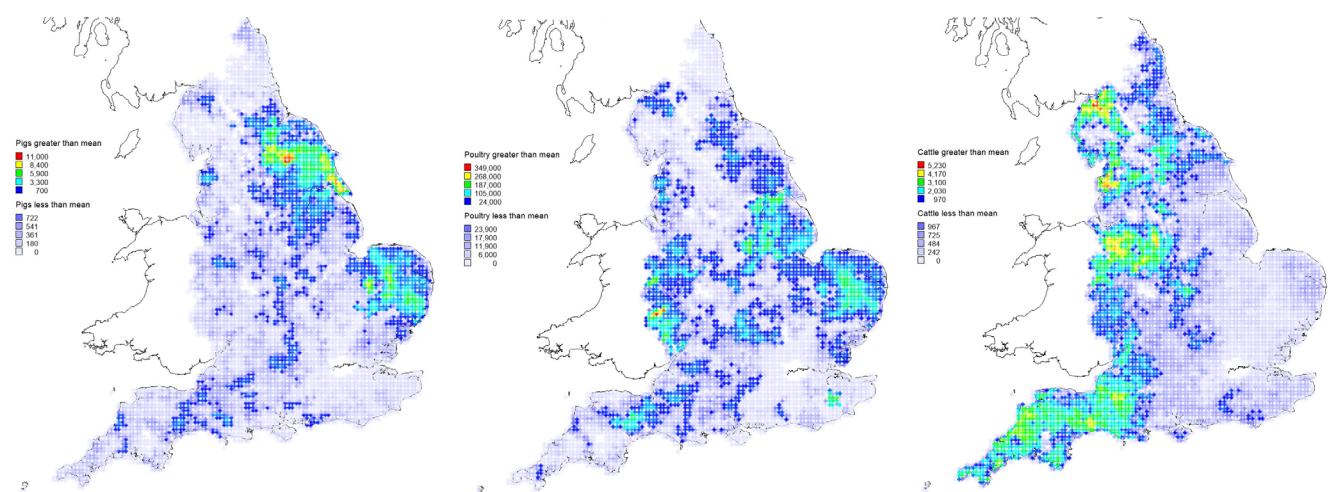


Figure 3 The land use intensity for total pig, poultry, and cattle production where the density of livestock is less than or greater than the national mean value for the land area producing those stock. Algorithms developed by EDINA convert small area data provided by the government agencies into national grid squares 5 km here (see, <https://digimap.edina.ac.uk/agcensus/>). © University of Edinburgh Derived from DEFRA/DAA/RESAS agricultural census surveys. Great Britain OS basemap from agCensus Digimap Ordnance Survey data © Crown copyright and database right (2023).

in England. The livestock number per hectare was calculated for the land area in the sample. The carbon footprint for livestock produced was calculated using the number of livestock in the sample and the carbon footprint (CO_{2e}) for each tonne of livestock at the farm.

Poultry

Table 3 shows the mean number of poultry in the 5 km square grid of England in the agricultural census for the 2016 dataset is $23\,853.74 \pm 33\,177.30$ birds. The number of birds in the land area where production is greater than the mean is 101 050 451 birds, equivalent to 24 birds per hectare in the sample. The carbon footprint for UK meat-producing chickens (broilers) at the farm is

2.22 CO_{2e}. This means the carbon footprint associated with land that produces poultry at greater than the mean bird number is 543 192 tonnes CO_{2e} for an average live bird weight of 2.4 kg (DEFRA, 2023). The same methodology for obtaining these results was used for the land area producing poultry, pigs, and cattle less than the mean land use per 5 km square. Figure 3 shows the detail of the data in Table 3, geographically mapped using a graduated colour grid for each 5 km square, demonstrating the land use intensity greater than and less than the mean.

Pigs

Table 3 shows the mean number of pigs in the 5 km square grid of England in the agricultural census for

the 2016 dataset is 722.15 ± 1146.25 pigs. The number of pigs in the land area where production is greater than the mean is 2 978 941 pigs, equivalent to 0.9 pigs per hectare in the sample. The carbon footprint for UK pigs at the farm is 2.72 CO_{2e}. This means the carbon footprint associated with land that produces pigs at greater than the mean pig number is 891 299 tonnes CO_{2e} for an average pig live weight of 110 kg (DEFRA, 2023).

Cattle

Table 3 shows the mean number of cattle in the 5 km square grid of England in the agricultural census for the 2016 dataset is 967.52 ± 922.55 cattle. The number of cattle in the land area where production is greater than the mean is 3 830 114 cattle, equivalent to 0.8 cattle per hectare in the sample. The carbon footprint for UK cattle at the farm is difficult to define and this research has used the Cattle Tracing System data from DEFRA to determine that 38% is beef herd with a carbon footprint of 21.4 and 62% dairy breeding herd with a carbon footprint of 4.01. Using these respective proportions of the herds and carbon footprints provides a carbon footprint for cattle of 10.62, which is an extrapolation of a complex beef-dairy system. This means the carbon footprint associated with land that produces cattle at greater than the mean cattle number is 20, 337, 905 tonnes CO_{2e} for an average cattle live weight of 500 kg (DEFRA, 2023).

Discussion

The carbon footprint calculated for the agriproducts in this study was 35 901 617 tonnes aligning with the GHG emission balance for the agri-food sector in the UK of 55 million tonnes which includes the whole UK and manufacturing and transport processes that account for the other 20 million tonnes (Econometrics, 2019). A critical observation in the research analysis presented here is the difference between land use intensity greater than and less than the mean value is important if sustainable intensification is to be continued and enhanced. There are areas where intensification must go ahead for food security and areas where less intensive or regenerative agriculture is favourable. Planning such a strategy requires the spatial analysis approach demonstrated here.

The total carbon footprint of the crops analysed was 6 158 461 tonnes (derived from Table 2), and the total carbon footprint of the livestock population analysed was 29 743 156 tonnes (derived from Table 3). The percentage of the total carbon footprint for each agri-product total is shown in Tables 4 and 5. Wheat production accounts for 69% of the crop group carbon footprint, wheat produced in areas greater than

Table 4 The percentage of the total carbon footprint for wheat, oil seed rape, sugar beet, and potato group analysed in Table 2 (this study), together with the total carbon footprint for the total crop and livestock agriproducts analysed in this study

Crop sample group (LeX or GreX)	% CO _{2e} in the crop group	% CO _{2e} in total agriproduct group
Wheat > mean	54.04	9.27
Wheat < mean	14.67	2.52
Oil seed rape > mean	15.42	2.64
Oil seed rape < mean	3.28	0.56
Sugar beet > mean	5.05	0.87
Sugar beet < mean	0.66	0.11
Potatoes > mean	5.79	0.99
Potatoes < mean	1.10	0.19
Total	100.00	17.15

Table 5 The percentage of the total carbon footprint for total poultry, total pigs, and total cattle group analysed in Table 3 (this study), together with the total carbon footprint for the total crop and livestock agriproducts analysed in this study

Livestock sample group	% CO _{2e} in the livestock group	% CO _{2e} in total agriproduct group
Poultry > mean	1.83	1.51
Poultry < mean	0.48	0.40
Pigs > mean	3.00	2.48
Pigs < mean	0.94	0.78
Cattle > mean	68.38	56.65
Cattle < mean	25.38	21.03
Total	100.00	82.85

mean (AGreX) production density account for 54% of the crop carbon footprint and wheat represents 12% of the carbon footprint of crop and livestock agriproducts. The crop agri-products account for 17% of the carbon footprint of total crop and livestock agri-products analysed. Cattle production accounts for 94% of the livestock group carbon footprint, and cattle produced in areas with greater than mean (AGreX) production density contribute to 68% of the group carbon footprint. Cattle represent 78% of the carbon footprint for all crop and livestock agri-products analysed. The livestock agri-products analysed in this study account for 83% of the carbon footprint of total crop and livestock agri-products. Cattle production accounts for 78% of the carbon footprint for the agri-products analysed in this study. It is important to consider the live weight of cattle is at least four times that of pigs and 200 times that of a poultry bird. These differences are crucial in presenting realistic carbon footprinting, as is the need to present the nutritional values of producing beef and milk, which

provide animal-optimised diets and nutrition. These are important future developments of the GIS-LCI modelling.

The data presented demonstrate the potential for integrating sustainable intensification and agricultural regeneration because it identifies how geographies for different production systems change the carbon footprint outcome. Produce from areas operating at less than mean production land use intensity should have greater opportunities to develop values associated with increased environmental compliance and assurance. Areas operating at greater than mean production land use intensity should focus on improving production capacity for both quantity and quality of crop products. This is not a new view of agricultural policy but digital analysis of geographic data certainly provide context here (Pretty, 2018). The method reported here includes crops in England up to the farm gate, and imports are not considered but are subject to future development of the model using input–output LCA methods, which are well-documented (Tukker *et al.*, 2009; Lin & Xie, 2016; Smetana *et al.*, 2017).

Conclusion

This research meets the objective of testing the use of GIS-LCI integration for reporting the carbon footprint of different crop and livestock production enterprises. The study identifies further work that can improve the methodology by defining livestock enterprises more precisely and account for import–export impacts. The most important impact of the study is identifying cattle production could reduce food system carbon footprint but also notes caution in trying to directly compare crop and livestock systems because one hectare of GreX⁺ cattle production yields 400 kg of biomass for food (liveweight) and one hectare of GreX⁺ wheat yields 7880 kg of biomass for food (grain). These differences can only meaningfully be compared by mapping their distribution and production densities as in the GIS-LCI reported.

Ethics approval

Ethics approval was not required for this research.

Author contributions

Wayne Martindale: Conceptualization; investigation; writing – original draft; methodology; validation; visualization; formal analysis; supervision; data curation; software; project administration; resources. **Ali Saei-dan:** Writing – review and editing; formal analysis; validation. **Farajollah Tahernezhad-Javazm:** Validation; writing – review and editing; formal analysis. **Tom**

Hollands: Conceptualization; investigation; methodology; formal analysis; data curation; writing – review and editing. **Linh Duong:** Investigation; validation; project administration; supervision; writing – review and editing. **Sandeep Jagtap:** Writing – review and editing; conceptualization; project administration; supervision; validation.

Peer review

The peer review history for this article is available at <https://www.webofscience.com/api/gateway/wos/peer-review/10.1111/ijfs.17340>.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Annotated references

1. Brentrup, F., Küsters, J., Kuhlmann, H. & Lammel, J. (2004); Brentrup, F., Küsters, J., Lammel, J. & Kuhlmann, H. (2000); Brentrup, F., Küsters, J., Lammel, J. & Kuhlmann, H. (2002). These three references have been utilized because they provide an important body of work that has established the use of energy balance and LCA in farming systems in Europe using research station/agricultural trials. The studies remain groundbreaking in their conclusions and the quality of data captured. They are from a group that established the use of LCA in agri-systems.
2. Escobar, N., Tizado, E.J., zu Ermgassen, E.K.H.J., Löfgren, P., Börner, J. & Godar, J. (2020); Fernandez-Mena, H., MacDonald, G.K., Pellerin, S. & Nesme, T. (2020). Co-benefits and trade-offs from agro-food system redesign for circularity: a case study with the FAN agent-based model. *Frontiers in Sustainable Food Systems*, **4**, 41. These two references are critical because they demonstrate how geo-spatial data can be used to assess agri-policy. Both reports are important pieces of work that demonstrate how different data approaches to assessment can be integrated. This is an important aspect of the reported research in the current paper.
3. Martindale, W., Swainson, M. & Choudhary, S. (2020b); Martindale, W., Wright, I., Korir, L., Opiyo, A.M., Karanja, B., Nyalala, S., Kumar, M., Pearson, S. & Swainson, M. (2020c). These two references are important because the work reported provides a demonstration of ranking data so that targeted investigation of specific food categories can be established. This is an important aspect of the current paper.
4. Pretty, J. (2018). Intensification for redesigned and sustainable agricultural systems. *Science*, **362**, eaav0294. This reference is utilized because Pretty essentially has laid the ground that regenerative agriculture is working on now, Pretty also established the importance of sustainably utilizing intensive agricultural solutions. Again, this is a critical aspect of this research paper, in that land use must be best utilized with respect to GHG emission intensity and agri-outcomes.



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Mapping the path to decarbonised agrifood products: a hybrid geographic information system and life cycle inventory methodology for assessing sustainable agriculture

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