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Assessing catchment scale water quality of agri-food systems and the scope for reducing unintended consequences using spatial life cycle assessment (LCA)

Graham A. McAuliffe [a], Yusheng Zhang [a,*], Adrian L. Collins [a]

[a] Net Zero and Resilient Farming, Rothamsted Research, North Wyke, Okehampton, Devon, EX20 2SB, UK

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ABSTRACT

Life cycle assessment is a multidisciplinary framework usually deployed to appraise the sustainability of various product or service supply-chains. Over recent decades, its use in the agri-food sector has risen sharply, and alongside this, a wide range of methodological advances have been generated. Spatial-life cycle assessment, defined in the current document as the interpretation of life cycle assessment results within a geographical nature, has not gone unexplored entirely, yet its rise as a sub-method of life cycle assessment has been rather slow relative to other avenues of research (e.g., including the nutritional sciences within life cycle assessment). With this relative methodological stagnation as a motivating factor, our paper combines a process-based model, the Catchment Systems Model, with various life cycle impact assessments (ReCiPe, Centre for Environmental Studies and Environmental Product Declaration) to propose a simple, yet effective, approach for visualising the technically feasible efficacy of various on-farm intervention strategies. As water quality was the primary focus of this study, interventions reducing acidification and eutrophication potentials of both arable and livestock farm types in the Southeast of England were considered. The study site is an area with a marked range of agricultural practices in terms of intensity. All impacts to acidification potential and eutrophication potential are reported using a functional unit of 1 ha. Percentage changes relative to baseline farm types, i.e., those without any interventions, arising from various mitigation strategies, are mapped using geographical information systems. This approach demonstrates visually how a spatially-orientated life cycle assessment could provide regional-specific information for farmers and policymakers to guide the restoration of certain waterbodies. A combination of multiple mitigation strategies was found to generate the greatest reductions in pollutant losses to water, but in terms of individual interventions, optimising farm-based machinery (acidification potential) and fertiliser application strategies (eutrophication potential) were found to have notable benefits.

1. Introduction

Given contemporary global interest in grand environmental challenges (e.g., Rockström et al., 2021), particularly climate change (Ripple et al., 2021), life cycle assessment (LCA) is going through what could be considered a 'Golden Age' as a framework to support exploration of pathways for realising the UN's Sustainable Development Goals. LCA has been applied to almost every product and service available as a framework to identify environmental 'hotspots' (i.e., activities within a supply chain which generate the most pollution) and to compare different supply chains to determine whether one may be more resource-efficient, usually entailing fewer losses to nature than another (Gerber et al., 2013; McAuliffe et al., 2017; Roy et al., 2009). The agri-food sector has received notable attention by the LCA community, demonstrated by a substantial increase in associated publications between 2011 (n = 190) and 2021 (n = 571; search terms = 'life cycle assessment' AND 'food' OR 'agri-food' OR 'agriculture') according to *Scopus*. Many of these agri-food related papers focus on methodological advances: for example, the food-environment nexus is gradually being elucidated in fine detail including through explicit considerations of human nutrition (McAuliffe et al., 2020) and health (Stylianou et al., 2016, 2021) within the LCA approach.

For the agri-food realm of LCA, some limited attention has been directed towards spatially-orientated assessments (Liu et al., 2018); yet,

* Corresponding author.
E-mail address: yusheng.zhang@rothamsted.ac.uk (Y. Zhang).

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there remains substantial scope to progress explicit assessment of spatial variation in LCA using suitable, complementary models, databases, and technologies such as Geographical Information Systems (GIS). As an example of efforts to enhance the capability of LCA to capture spatial variation, Roibás et al. (2018) used national economic input-output activity datasets with regional, or 'territorial', subsections to carry out normalisation of impact assessment results in the Galician region of Northwest Spain. Whilst the authors demonstrated that spatial LCA can indeed be adopted to carry out normalisation to better elucidate specific issues (e.g., water quality) at the local level, they also acknowledge that the use of normalisation in LCA is highly debated within the user community due to the typically subjective nature of the process. Indeed, normalisation is viewed as useful for decision making, but its current lack of uncertainty assessment and robustness leave many practitioners wary of applying it (Pizzol et al., 2016).

Other efforts to reconcile system-scale environmental analyses with spatial variability include work carried out by Nitschelm et al. (2016) who successfully demonstrated the possibility of combining spatial differentiation with territorial LCA to inform land use planning, a particularly pertinent exercise given the importance of optimising land use and management in the face of net zero ambitions across the globe. Tackling spatial-LCA from another angle, Antón et al. (2014) developed novel impact categories in a case study of greenhouse tomato production in Almeria, Southern Spain. The authors found that generating locally-relevant characterisation factors had a notable benefit over widely used factors such as those found in the ReCiPe (Huijbregts et al., 2017) impact method, which are designed to cover much larger areas and as a result, do not always coincide with environmental conditions in a given region. Here, for instance, water quality is a good example as it can vary considerably not only across countries, but even across individual waterbodies *within* countries. Lastly, and most recently, Lee et al. (2020) used a combination of LCA and process-based modelling to demonstrate the spatio-temporal impacts of various maize supply chains in the US Midwest States at county level. The authors were able to use their approach to highlight the pronounced nature of variation in environmental performance at the site-specific-level across a period of nine years, thereby showcasing the importance of deepening our applications and understanding of spatial-LCA.

Based on the above background and, perhaps more importantly, the recognised need to continue exploring the scope for incorporating spatial variation within LCA (Patouillard et al., 2018), the overarching goal of the current paper is to first carry out a geographically-based case exemplar using an agri-system modelling framework (CSM) to compute spatially-explicit estimates of mid-point impact categories for two farm types (arable and lowland grazing livestock). We demonstrate a data-intensive yet simple approach to conduct spatial-LCA which addresses eutrophication and acidification of freshwater. Whilst we cover a smaller geographic area than Lee et al. (2020), we do so at a finer scale, specifically, the waterbody, or catchment level. In light of pressures on farmers to reduce their impacts to nature as far as feasibly possible, a second objective is to explore how the case exemplar might account for benefits and risks of various environmental intervention strategies currently being recommended to farmers.

2. Materials and methods

2.1. Study site

Hertfordshire, a county in the Southeast of England (Fig. 1) was chosen as an appropriate study area because it is a region which is characterised by both arable- and animal-based farming systems, with the former being the dominant agricultural activity in the area. For example, The June Agriculture Survey (JAS) data in 2016 suggests that the major farming types, ranked by their relative agricultural land occupation, are cereal (80.9%), lowland grazing livestock (7.5%), general cropping (5.0%) and mixed (3.6%), with crop yields generally being higher than most other regions of the UK due to favourable growing conditions. With an area of ~1643 km^2, Hertfordshire typically receives low annual rainfall (long term values: 575.3 and 808.6 mm, for arable and livestock farm types, respectively). According to the UK's Meteorological Office (Met Office), typical daily temperatures in the region range from 9.2 to 11.2 °C and there are 84.4–119.3 ground frost days annually. The British Geological Survey indicates that soils across the region range from deep clay (Hanslope series), deep loam to clay (Batcombe, Hornbeam, Melford series) to loam over chalk (Swaffham Prior series). These intrinsic conditions have led to the dominance of intensive

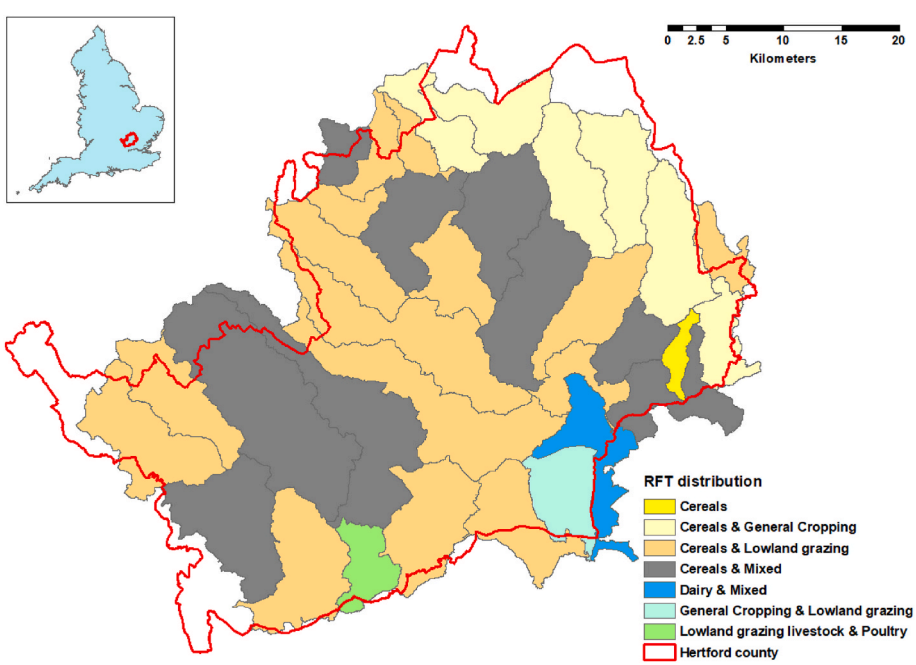

Fig. 1. Location of the study area in England and spatial distribution of robust farm types (RFTs; a classification system adopted in the United Kingdom to aid comparative analyses of predefined farm types) in the focus area.

arable agriculture (as per JAS 2016 above) with animal-based products generally being produced on extensive systems with lower stocking densities than would be found in other areas of England such as the South West where pastoral systems are more prevalent.

Unintended environmental consequences arising from current farming practices in the study area include the failure of surface waterbodies to achieve 'good ecological status.' More specifically, the 2019 assessment by the UK Environment Agency indicated that 56% of waterbodies in the study area are in 'moderate ecological status', 35% in 'poor ecological status' and 9% in 'bad ecological status'. According to the Environment Agency, poor agricultural and rural land management practices are the main reasons for failure to achieve 'good ecological status'. For instance, identified malpractices are mainly related to soil (e.g., losses of soil during heavy rainfall), nutrient (e.g., over or under application of organic or inorganic fertilisers) and livestock (e.g., sub-optimal feed conversion ratios or offering ruminants forage with low digestible energy) management. As an example, elevated phosphate levels in rivers in the study area have been confirmed as a major detrimental impact arising from current farming practices. Based on the 2019 mapped greenhouse gas (GHG) inventory at 1 km scale resolution (NAEI, 2019), agriculture contributes 64% of total ammonia emissions and 52% of total nitrous oxide emissions, both of which lead to soil and water acidification, in Hertfordshire, respectively. As a consequence of the aforementioned agri-ecological concerns, it is clear that current agricultural land management is resulting in environmental damage. Concomitantly, this points to the need for system scale analyses to assess the technically feasible scope for improving the environmental performance of South East English agriculture.

2.2. Introduction to the Catchment Systems Model (CSM)

To quantify the emission loadings to water and air, CSM (Zhang et al., 2022) was employed to generate farm-based multi-pollutant loadings in the study site under baseline (i.e., no interventions whatsoever), business-as-usual, as well as single intervention strategies and combinations thereof, to reduce the environmental impacts of both farm types (i.e., arable or livestock). CSM integrates a number of distinct models and data layers to provide a basis for examining multiple environmental outcomes of current and future potential farming systems and practices. The initial component is founded on a typology of rainfall, soil and farm type. Long-term (1981–2010) gridded (1 km^2) annual average rainfall is sourced from HADUK-Grid data (Meteorological Office, 2018). Examination of the rainfall distribution suggested that the area could be divided into three rainfall bands: <600 mm, 600–700 mm and 701–900 mm. Since the area with <600 mm rainfall only accounted for <3% of the study area, this rainfall band was not modelled. Soil type is sourced from the National Soil Map (NATMAP1000; National Soil Resources Institute, Cranfield University, UK) which details soil series and their key characteristics at 1 km^2 resolution. Hydrology of Soil Types (HOST; Boorman et al., 1995) was assigned to the soil series in the study area using established pedo-transfer functions (Zhang et al., 2017a). The soil typology suggests that 24% of the study area is represented by free draining soils, compared with 64% of soils drained for arable use solely and 12% of soils drained for both arable and grassland use.

Information on robust farm types (RFT; Defra, 2010) and the land use and livestock structures (2016) of commercial farms in the study area collected by the June Agriculture Survey (JAS) was licensed from the Department for Environment, Food and Rural Affairs (Defra, 2021a, 2021b). In total, 234 model farms were generated for the study area and these were represented by cereal and lowland grazing livestock systems. To represent farm management practices, crop-specific fertiliser application rates (averaged across 2013–2017) were sourced from the British Survey of Fertiliser Practices (BSFP, 2018). These rates are sense checked using additional bespoke surveys of the two dominant farms types in England administered by the modelling team for other research projects. Taking manure management for instance, whether manure or slurry is spread on the farm it is produced on, or transported to adjacent farms to offset their artificial fertiliser needs, utilises the scheme reported by Zhang et al. (2017a). Business as usual (BAU) uptake rates of best management practices by different farm types are extracted from a variety of data sources including agri-environment scheme data (Natural England, 2016) and Defra farm practices surveys (FPS; DEFRA, 2013). Again, uptake rates by farm type are supported by the returns from bespoke surveys administered by the modelling team.

In addition to farm type definition and agricultural management as described above, CSM uses a second module to scale out within the farming sector to capture the spatial distribution of farm types at landscape scale. Here, the EU's Water Framework Directive (WFD) surface waterbodies were used as the base spatial unit for the modelling of the study area since this hydrological unit is used for much policy support work in the UK. To ensure data/participant confidentiality, waterbodies with areas less than 25 km^2 were excluded (Fig. 1). Farm types (i.e., cereal or lowland livestock grazing) with fewer than five reported holdings in any given waterbody were also not modelled to minimise any potential risks to participant anonymity.

For comparison with baseline and BAU, six alternative management futures (scenarios AA-AF; Table S1) were modelled for cereal farms in the study area. These encompassed five bundles of measures targeting specific aspects of farm management (i.e., fertilisers, water management, machinery, zero tillage, cover cropping) and an additional 'all-in' scenario (i.e., AA; Table S1). Similarly, four bundles were modelled for lowland grazing livestock farms. These comprised fertiliser, water, machinery and livestock management and an additional 'all-in' bundle (i.e., LA; Table S2). Two global model farms were also generated for the two main farm types: one uses the average values of JAS items from all relevant farms in the study region and the other uses the median values for the same returns. These mean and median representative model farms were numbered '23' and '24' in the case of cereal farms and '38' and '39' in the case of lowland grazing livestock farms (**Data in Brief**; Tables S1 & S2, respectively). Despite the level of detail provided in supplementary material, for the purpose of the current study, which is to develop a simple, yet effective, methodology to view agri-food LCA from a geospatial perspective, soil drainage and rainfall are not examined in a multifactorial analysis. Further, given the nonparametric nature of the results, results are primarily assessed by range (i.e., minimum and maximum values are reported around the median for baseline, BAU and each alternative management scenario) rather than using mean and variance/standard deviation, with the exception of typologies '23', '24' (arable), '38', and '39' (livestock) which are indeed reported as means **(Data in Brief)**.

2.3. Inventory analysis: nutrient loss calculations

Phosphorus (P) delivery from agricultural land to rivers is computed based on the Phosphorus and Sediment Yield CHaracterisation In Catchments (PSYCHIC) model (Collins et al., 2007; Davison et al., 2008; Stromqvist et al., 2008). PSYCHIC utilises the source-mobilisation-delivery conceptualisation of the water pollutant cascade (Lemunyon and Gilbert, 1993; Haygarth and Jarvis, 1999; Haygarth et al., 2005) and calculates both dissolved and particulate P. The key P sources considered are soils, manure and fertiliser applications. Mobilisation includes solubilisation, detachment and incidental losses. These mobilisation processes are combined to generate estimates of the delivery of P to watercourses via three pathways comprising surface runoff, preferential flow through land drains and deep seepage. For particulate P, sediment mobilisation is based on the Morgan-Morgan-Finney (MMF) model (Morgan, 2001), and a parameterisation of rainfall erosivity (Davison et al., 2005). The P content of sediment is based on soil total P and particle size distribution. Delivery of P to rivers takes explicit account of distance to watercourses and field drain efficiency as important components of land-to-river connectivity (e.g., McHugh et al., 2002). PSYCHIC predictions of sediment (relevant

for particulate phosphorus estimates) and P losses to water have been evaluated across scales using various available datasets (Comber et al., 2013; Collins et al., 2016, 2021; Stromqvist et al., 2008; Zhang et al., 2017a). These evaluations have illustrated reliable predictions in the context of the known challenges of evaluating predicted water pollution emissions from a single sector (i.e., agriculture in the current context) using available water quality data which inevitably reflect contributions from all upstream sources.

Ammonia emissions from excreta and manure are estimated for livestock housing, manure storage and field spreading using the NARSES (National Ammonia Reduction Strategy Evaluation System; Webb and Misselbrook, 2004) and MANNER (Manure Nutrient Evaluation Routine; Chambers et al., 1999) models. Fertiliser driven ammonia emissions are calculated using the NT26AE model (extracted from a component report for Defra) reported by Chadwick et al. (2005). The predicted ammonia emissions using the above routines have been shown to agree with the UK GHG inventory for agriculture (Zhang et al., 2017b). Default European coefficients (Baggott et al., 2006) are used to estimate direct nitrous oxide emissions from excreta, managed manure and fertilisers (please see IPCC, 2007, IPCC, 2013; IPCC, 2006 for GHG methodology and related guidelines). Indirect nitrous oxide emissions associated from agricultural land are based on export coefficients generated using the National Environment and Agriculture Procedure-N model (NEAP-N; Anthony et al., 1996; Lord and Anthony, 2000; Wang et al., 2016). NEAP-N constitutes a meta-model of the NITCAT (Lord, 1992) and NCYCLE (Schofield et al., 1991) models, but with adjustments for both climate and soil type and is sensitive to stocking density. NITCAT computes nitrate losses from arable land, and NYCYLE computes equivalent losses from grassland. Nitrate delivery pathway apportionment between surface runoff, preferential flow and leaching towards groundwater are based on the EDEN model (Gooday et al., 2008). The nitrate losses to surface water generated by NEAP-N at national scale for England have been shown to agree well with monitored PARCOM (Paris Commission) data (1991–2010) (Zhang et al., 2017a).

2.4. Life cycle impact assessment

The impacts of the overall life cycle inventory (Sections 2.2 & 2.3) for each farm type and associated scenarios were assessed using characterisation factors from three separate methodologies (Table S3). The impact assessment known as 'ReCiPe' was first used to calculate burdens to nature for AP and EP (Huijbregts et al., 2017; RIVM, 2011). Regarding EP, given the study area's inland geographical location and its distance from coastal ecosystems (Fig. 1), marine eutrophication was not considered. It is acknowledged, however, that excluding nitrate (NO_3) effects from freshwater pollution potentials is not scientifically sound (as computed under ReCiPe's freshwater eutrophication, or FEP) as environmental conditions such as nutrient ratios (e.g., nitrogen:phosphorus) and their forms (e.g., organic or inorganic), water pH, and land management, can all affect how a watercourse is affected by nutrient pressures (e.g., Lloyd et al., 2019). Therefore, to assess the combined loads of ammonia-, nitrate-, and phosphorus-based nutrient losses, two other impact assessments were also included: Centre for Environmental Studies (CML, 2016) and Environmental Product Declaration (EPD, 2013). The impact assessments for baseline, BAU and intervention scenarios (n = 1782; see accompanying *Data-in-Brief*) were calculated in SimaPro v8.5.2 (PRé Consultants).

Unlike some other studies which adopt multiple impact assessments to cover a wider range of impact categories than would be possible using a single impact assessment (e.g., Manfredi and Vignali, 2014), we used multiple impact assessments due to losses of nitrate and ammonia to water which are not covered by ReCiPe's FEP impact category. The fate factors used in ReCiPe assume that 10% of all P on agricultural land will end up in surface freshwater (Huijbregts et al., 2017). CML, on the other hand, uses a combination of models to derive characterisation factors for AP and EP. For instance, eutrophication's PO_4^--eq is derived for air-based pollutants (e.g., ammonia) using RAINS-LCA (Huijbregts, 1999; RAINS, Regional Air Pollution Information and Simulation). Lastly, EPD assumes the same characterisation factors as the CML impact assessment baseline (EP) and non-baseline (AP), the latter of which is not used directly in the present study. It should be noted that EPD is usually used for product labelling of environmental footprints; for example, if a producer wants to demonstrate to consumers that their product has few losses to nature than their competitors. For further information on the methodologies available through the SimaPro software package, please see Pré Consultants (2020).

3. Results

The results for each farm type modelled, including baseline, BAU and single mitigation interventions, or a combination of all interventions (i.e., scenarios AA and LA), are presented in Table S4. Sections 3.1 and 3.2 address potential burdens associated with acidification and eutrophication arising from agri-food production, respectively, within the study area. It is worth noting that, upon first glance, it may appear counter-intuitively that the livestock farms generate less water pollution than the cereal-based systems; however, it is important to reiterate that Hertfordshire is not a livestock-intensive region and as such, local livestock farms within the CSM framework tend to have few animals in accordance with the JAS data underpinning the model. It is also important to note that the functional unit applied in our study is area (ha), meaning that environmental impacts are directly related to land occupation rather than product throughput as is typically the case with *most* agri-food LCA (e.g. de Vries et al., 2015; de Vries and de Boer, 2010; McAuliffe et al., 2016). Lastly, to aid the interpretation of the upcoming results, it is also worth noting that arable farms in the study area are highly intensive with much higher fertiliser inputs and lower land cover in winter compared to the livestock farm types. All of these factors lead to higher arable loadings per area (ha).

3.1. Catchment scale acidification potentials

Unsurprisingly, the baseline results have the highest AP as these systems are assumed to have no best management practices in place. BAU, on the other hand, varies from catchment to catchment (see accompanying *Data-in-Brief* article), but in terms of median values, as per Table S4, has around 9–10% lower AP than the baseline values, depending on impact assessment. Comparing interventions with BAU (as this is the current farm management in the study area), following the benefits of combining all interventions (scenario AA; ~6% lower emissions than BAU), the next most beneficial intervention for AP was scenario AD, which concerns the optimal use of farm-based machinery. More specifically, AD entails the use of correctly-inflated low ground pressure tyres on farm machinery, whilst also using slurry injection technologies as well as optimal nutrient use calibration and manufactured fertiliser placement technologies (i.e., precision agriculture); these interventions are predicted to have the technical capacity for a reduction in AP of ~4%. Out of the remaining four arable interventions considered to reduce AP from baseline, AF (uptake of cover crops) was found to be the second-most effective technology by not only establishing crops to avoid fallow soil post-harvest, but also to provide riparian and in-field grass buffer strips which combined, only reduced total AP by ~1%. All other single intervention strategies reduced AP by less than 1%.

Compared to the arable systems modelled herein, the difference between baseline and BAU is markedly lower (between 3 and 4% depending on impact assessment) for the livestock farms. For both arable and livestock farm types, however, optimising farm machinery usage (scenario LD) holds the greatest potential to reduce AP; in the case of livestock, in addition to the individual measures listed in the previous paragraph, a capacity to reduce AP by around 1%. All other interventions having negligible benefits for AP (i.e., <1% reductions).

3.2. Catchment scale eutrophication potentials

To capture the widest range of pollutants possible, this section reports differences in scenarios for the CML impact assessment (as will be seen in Section 4.1 below, the choice of impact assessment for AP as reported in Section 3.1 is not of great importance). The difference between losses to waterbodies between baseline and BAU farm types under EP were less than (7%) those for arable systems when compared to AP as reported above. Once again, scenario AA (all interventions combined) unsurprisingly reduced EP the most from BAU (5–6%). The benefits of individual interventions were slightly more pronounced under arable EP than observed under AP. For instance, scenario AF (cover crops and buffer strips) reduced arable EP by 3%, followed by ~2% under scenario AE (zero tillage; see Table S1 for more information), and ~2% under scenario AD (machinery as explained in Section 3.1). Perhaps surprisingly given the focus on water, there were no notable reductions (<1%) in arable EP when comparing scenarios AC (water management such as maintaining artificial wetlands) and AB (fertiliser management such as avoiding application at high-risk times) relative to baseline.

Regarding livestock farms, similar reductions (6%) were observed from baseline to BAU. The difference between amalgamated interventions (scenario LA) was lower for livestock than arable, however, at 3%. Once again, as above, the differences between fertiliser optimisation (scenario LB) and water management (scenario LC) were negligible (<1%). In fact, the only mitigation strategy with any influence on livestock-based EP was scenario LD (machinery and equipment; see Table S2 for more information), which reduced BAU emissions by just under 2%.

4. Discussion

4.1. Choice of impact assessment

The present study suggests that choice of impact assessment is largely unimportant for AP (Fig. 2A), with a correlation between CML and ReCiPe results of $r = 0.99$ ($p < 0.001$) for the 1782 simulated farm types. This is particularly pertinent if relative rankings (e.g., supply-chain comparisons) are the primary focus of the study rather than hotspot identification. Of course, due to slightly different characterisation factors, the absolute values vary slightly for AP, but not enough to affect interpretation by any notable degree. EP, on the other hand (Fig. 2B), requires much more consideration when choosing an appropriate impact assessment as the correlation between CML and ReCiPe was notably weaker ($r = 0.66$; $p < 0.001$). These decisions include, for instance, whether nitrogen-based pollutants are important in a given waterbody, in which case ReCiPe's FEP might be inappropriate as it does not account for nitrogen-based compounds and, further, the assessment's marine EP may be inapplicable in landlocked nations or regions. If nitrogen-based nutrients *are* limiting factors pertaining to the growth of microbial organisms, regardless of whether the waterbody is freshwater or marine, an impact assessment such as CML may be more appropriate as it captures the role of nitrate and phosphate simultaneously rather than having to interpret multiple impact categories as per ReCiPe. Another aspect which may determine methodological decisions here is data availability. Where information related to the calculation of nitrogen-based losses is missing, it may be *necessary* to use ReCiPe's FEP as nitrogen-based losses to water are not accounted for under this impact category; this is, however, thought to be of lesser importance than addressing limiting nutrients due to the availability of certain approaches to estimate nitrate losses to water via nutrient balances.

4.2. Visualising impact assessments spatially

Figs. 3A and 4A display how AP and EP differentiate spatially at the catchment scale, respectively, and are supplemented by Figs. S1 (AP, arable; CML), S2 (AP, arable; EPD), S3 (AP, livestock; CML), S4 (EP, arable; CML) and S5 (EP, livestock; CML). Figs. 3B and 4B, on the other hand, demonstrate how a combination of on-farm intervention strategies (scenarios AA and LA, respectively, in Tables S1 & S2) can reduce AP and EP, again at the catchment scale compared to baseline. Whilst LCA has long been known to be a useful tool for environmental policymakers, this level of detail (i.e., at the catchment-scale), allows decision-making to be much more spatially targeted than a typical LCA following ISO (2006) standards (although, it is worth noting that there is nothing inherent in ISO guidelines which precludes an LCA from being spatially designed or assessed). For instance, Fig. 4B demonstrates that farms adjacent to a waterbody in the north of the study area have the most potential to reduce EP (by up to 8.2%); this spatially-explicit assessment of the technically feasible benefits that might arise from on-farm water quality interventions could add an additional layer of usefulness to the LCA toolkit.

4.3. Future pathways to modelling cleaner water catchments using LCA

4.3.1. Out-scaling CSM and LCA to cover an entire country

With a framework now in place to integrate the CSM (Zhang et al., 2022) with LCA, the next steps will involve increasing the geographical coverage by out-scaling to national scale. Whilst the results reported

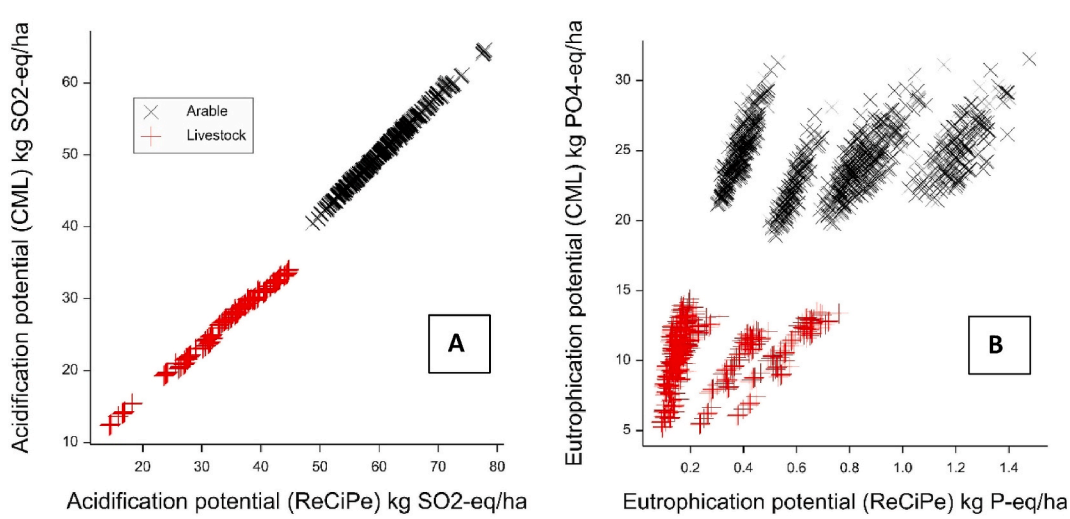

Fig. 2. Scatterplots demonstrating the relationships between CML and ReCiPe impact assessments for acidification potential (A) and eutrophication potential (B). All results are reported as impact/ha.

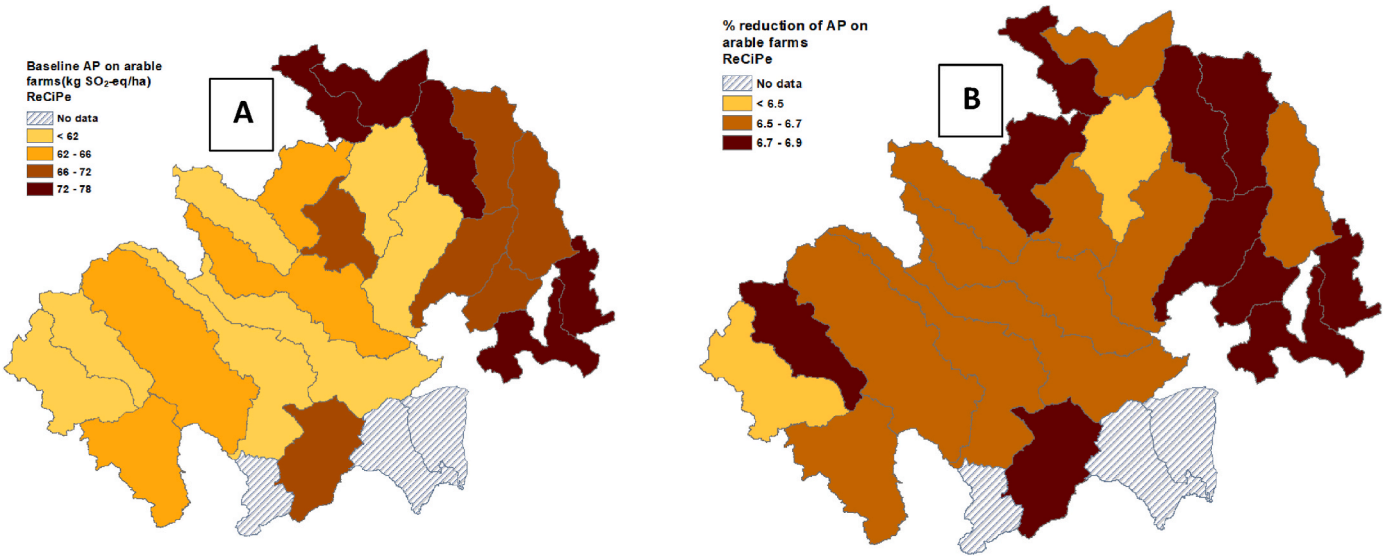

Fig. 3. Acidification potentials for each catchment in the study area reported under the ReCiPe impact assessment (A) and the percentage change (B) predicted by combining all intervention strategies (baseline vs. AA) as per Table S1.

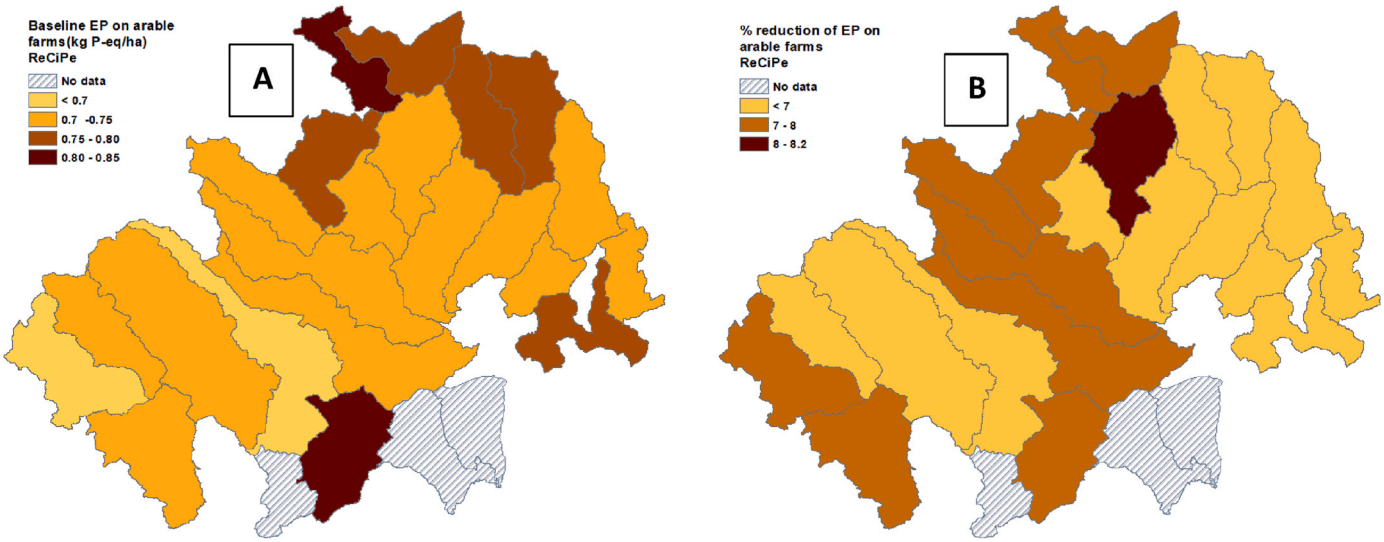

Fig. 4. Eutrophication potentials for each catchment in the study area reported under the ReCiPe impact assessment (A) and the percentage change (B) expected by combining all intervention strategies (baseline vs. AA) as per Table S1.

herein are intended for illustrative purposes primarily, they do demonstrate how a deeper analysis, for example considering microclimates and soil types in a multifactorial analysis, could take LCA into a new era of informing policy. Although LCA is known as a 'go-to' approach when it comes to sustainability assessments of agri-food systems (e.g., Roy et al., 2009), it does not tend to come to mind when geographically-specific best management interventions need to be identified. Generally speaking, this means that LCA can be a powerful tool for calculating environmental burdens which are not typically region-specific. Greenhouse gas emissions are a good example of non-region-specific pollutants as they are transient in the atmosphere and, as such, their geographic source is of less importance than *most* other impact categories. Locally important midpoint impact categories such as EP are less reliable when using pre-defined impact assessments due to the heterogeneity exhibited by the quality of rivers, lakes, estuaries, and coastal ecosystems. This indicates that, wherever possible, localised impact characterisation factors should be developed to better-determine environmental hotspots of agri-food systems under investigation in a given region, particularly at the catchment scale or even a finer resolution.

4.3.2. *Developing regional-specific impact assessments*

The development of any useful impact assessment is underpinned by a plethora of representative, high-quality data which generates a picture of water quality status in a given study region (e.g., ReCiPe has different versions which are representative of Europe or the Rest of the World). As an example of potential pathways to develop novel characterisation factors, the North Wyke Farm Platform (NWFP), a UK Research and Innovation (UKRI) National Capability (Orr et al., 2016; Takahashi et al., 2018), is a collection of grazing and arable farming systems, each being hydrologically-isolated using French drains. Each catchment on the NWFP is equipped with automated water quality monitoring stations which measure carbon, nitrogen and phosphorus losses to edge-of-field. One of the next steps in our current line of investigation is to use the NWFP to develop a localised impact assessment which will then be out-scaled using CSM (Collins et al., 2021) to cover a broader (~1843

km^2) geographic area in England. Another resource near the NWFP is the Upper Taw River Observatory (UTRO; Stone et al., 2021) which can complement work focussed on upscaling our CSM-LCA linked models when developing novel impact assessments, particularly for EP.

4.3.3. Building upon extant spatial-LCA literature

To the best of our knowledge, there is only one comprehensive assessment of literature covering spatially-orientated LCA to date (Patouillard et al., 2018). The authors of this recent review of spatial LCAs posit that a spatial dimension can be applied at any single stage, or multiple stages, of an LCA (i.e., goal and scope definition, inventory analysis, impact assessment and interpretation). Using this broad interpretation, we assert that three out of four of the LCA stages have been assessed for spatial differentiation, with the only phase being excluded from spatial exploration being the impact assessment; however, as per our analysis in Section 4.1, given uncertainties associated with impact characterisation factors, model assumptions were tested by conducting an impact assessment sensitivity analysis (Section 4.1).

Going forward, regardless of whether there is a spatial dimension or not, when carrying out LCA interpretation, particularly for EP due to the added complexities of NO_3 and PO_4^- interactions, we suggest that LCA practitioners adhere to recommended guidelines under ISO, 20060 (2006) and carry out appropriate sensitivity analyses. Whilst ISO guidelines can be open to interpretation on certain aspects of a life cycle model (e.g., allocation vs. system expansion), when *any* subjective decision may have a notable influence on a model's interpretation, the guidelines unambiguously state that these decisions should be assessed via sensitivity tests. This logic forms the basis for our recommendation of impact assessment sensitivity analysis when EP is considered (Fig. 2B demonstrates this necessity).

Patouillard et al. (2018) generated unique fit-for-purpose classification tables which categorise the sophistication of an individual spatial- or territory-specific LCA. Despite stopping short of regionalising a bespoke impact assessment, under the authors categorisation system, we surmise that this pilot study (i.e., a proof of concept to determine if CSM combined with LCA *could* be used for future policy support, particularly in light of post-Brexit land use optimisation in the UK) falls under the more sophisticated branch of spatial-LCAs. The present study, however, is the first step in the methodological journey to use LCA to guide policymakers with respect to how to improve water quality across England. With a successful proof of concept presented, one of our next steps is to combine the spatial resolutions possible herein with the spatial-analyses proposed by Lee et al. (2020), who conducted a much more sophisticated study from the point of view of methodological development. As the UK undergoes a period of political turbulence with the scheduled introduction of new agricultural policy as it navigates the urgent need to reconcile food production and environmental targets, spatially-explicit studies will be essential to optimise both land use and management across the country (CIEL, 2020).

4.4. Limitations of the current study— area vs. mass

Undoubtedly the most significant limitation of the present study relates to the area-based functional unit utilised in isolation. However, based on the current structure of CSM, specifically data availability from the farm-level predictions calculated by CSM, deriving a mass-based functional unit is impossible. This is due to a lack of direct information regarding changes to yield (i.e., tonnes/ha of arable products or live weight per total livestock heads) when interventions are assessed under the LCA framework. The aforementioned limitation may go some way to explaining the minor-to-negligible benefits reported in the case exemplar when interventions are adopted at the farm level as potential improvements to productivity are unaccounted for. Despite this limitation, it is not entirely uncommon to use area as a functional unit (e.g., Kowalczyk and Cupiał, 2020); in fact, some schools of thought are proponents of proactively calculating environmental burdens on an area-basis (Morais et al., 2018; Salou et al., 2017). This school of thought is particularly relevant when comparing intensive vs. extensive agri-food systems, as we provide in the current study. Another aspect where area-based functional units are of use is when assessing differences between organic and conventional agri-food products (e.g., Ribal et al., 2017). Whilst we believe these examples justify the use of an area-based functional unit for the purposes of the current study, it is acknowledged that the inability to calculate mass-based functional units for each product produced by each farm-type individually restricts the conclusions we can draw from the novel framework. As a result, a future ambition will be to disaggregate farm types using CSM *input* data to generate life cycle inventories whereby the denominator of the system will be throughput for each product.

4.5. Water quality at the global level

According to IPCC's Fourth Assessment Report (2007), increasing temperatures globally will have a dramatic effect on surface water quality in all corners of the planet. Specifically, the report anticipates higher levels of algal blooms due to increasing temperatures making water quality and climate change inextricably linked. As discussed earlier, in the county of Hertfordshire in England, the vast majority of surface waters fail to achieve 'good ecological status', which could become even more of an environmental challenge if recent Conference of the Parties 2021, or COP26, ambitions agreed to stabilise increasing temperatures are not realised. This, however, is not an environmental issue for England alone. Indeed, the European Union (EU, 2009) acknowledged that increasing pressures on surface waters from climate change required a change in policymaking and, as such, provided new guidance to nation states via the Water Framework Directive (WFD). Regarding agriculture, recognising that the majority of land across the entire EU is used for farming, the EU's Common Agricultural Policy (CAP) was intended to provide support for farmers to reduce their burdens to freshwater resources in line with WFD objectives. However, whilst there has been *some* notable success under the WFD and CAP, particularly with the reduction in surface water NO_3, many member states have failed to achieve their obligations to achieve at least 'good ecological status' in all fresh surface waterbodies (Soana et al., 2021).

Despite these failures, according to the Environmental Performance Index (Wendling et al., 2020), most European countries are amongst the best rated globally for water quality and sanitation according to Yale's Centre for Environmental Law and Policy world rankings. Looking further afield, the same report notes that African countries are amongst the worst rated for water quality and sanitation, with Kenya, Burundi, and Niger ranking the lowest in that order. This demonstrates a clear disparity between high- and low-income countries which is clearly reflected in health; for example, in the UK, Denmark and Germany, average life expectancy is 81 years of age (WBG, 2021). By contrast, Kenya, Burundi and Niger have average life expectancies of 67, 62, and 62 years of age, respectively. Whilst there are undoubtedly many factors which drive this disparity, clean water, and access to this vital resource, have been found to be significant contributors to life expectancy (Angelakis et al., 2021). As a consequence, it is of critical importance that tools such as the one proposed in the current study are first developed and refined, then out-scaled and upscaled, and finally made accessible to the international scientific community so that targeted interventions can be identified and deployed to improve freshwater quality across the globe.

5. Conclusion

This study has demonstrated the geographic power of merging a predictive, spatially differentiated model (CSM) with the LCA framework. Whilst the study is not the first of its kind, it is, to the best of our knowledge, one of the highest resolution LCA analyses, spatially speaking (i.e., at the catchment scale), produced to date. Unlike previous

work focussing on GHG emissions which concludes that agricultural machinery accounts for <1% of a livestock system's global warming potential (e.g., McAuliffe et al., 2018), the present study has shown that managing farm-based machinery optimally can make notable differences (~10% improvement) to water quality. These gains are noted through comparisons resulting from farms with hypothetically poor management practices versus best practice. In terms of methodology, the choice of impact assessment for AP was found to not be of particular importance for the three common assessments considered herein; however, as some EP assessments include nitrogen-based pollutants (e.g., CML) whilst others exclude it (e.g., freshwater EP, ReCiPe), the choice of eutrophication-based impact assessment is of critical importance depending on baseline water conditions prior to an intervention being assessed. Future studies will aim to: (a) out-scale the current study to cover the entirety of England; (b) devise regionalised impact assessments with bespoke characterisation factors which will elucidate the spatially variable technically feasible impacts of on-farm mitigation measures; and (c), disaggregating farm typologies to enable mass-based functional unit comparisons with the area-based functional unit reported herein. Finally, global statistics confirm the importance of good quality freshwater and its relationship with health via life expectancies. Whilst prototype environmental models such as CSM-LCA cannot fix the disparities between high- and low-income countries, pending data availability, once built, they can offer an aid for international policymakers' decision making.

Credit author statement

Graham A. McAuliffe: Conceptualisation; Formal analysis; Investigation; Methodology; Software; Validation; Writing - original draft; Writing - review & editing. Yusheng Zhang: Formal analysis; Data curation; Validation; Software; Visualisation; Writing - review & editing. Adrian L. Collins: Funding acquisition; Project administration; Resources; Supervision; Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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References

Angelakis, A.N., Vuorinen, H.S., Nikolaidis, C., Juuti, P.S., Katko, T.S., Juuti, R.P., Zhang, J., Samonis, G., 2021. Water quality and life expectancy: parallel courses in time. Water 13.

Anthony, S., Quinn, P., Lord, E., 1996. Catchment scale modelling of nitrate leaching. Aspect Appl. Biol. 46, 23–32.

Antón, A., Torrellas, M., Núñez, M., Sevigné, E., Amores, M.J., Muñoz, P., Montero, J.I., 2014. Improvement of agricultural life cycle assessment studies through spatial differentiation and new impact categories: case study on greenhouse tomato production. Environ. Sci. Technol. 48, 9454–9462.

Baggott, S., Brown, L., Cardena, L., Downs, M., Garnett, E., Hobson, M., Jackson, J., Milne, R., Mobbs, D., Passant, N., Thistlethwaite, G., Thomson, A., Watterson, J., 2006. UK Greenhouse Gas Inventory 1990 to 2004. Final report to Defra project RMP2106.

BSFP, 2018. British Survey of Fertiliser Practice – Fertiliser Use on Farm for the 2017 Crop Year. https://www.gov.uk/government/collections/fertiliser-usage.

Chadwick, D., Misselbrook, T., Ghilhespy, S., Williams, J., Bhogal, A., Sagoo, L., Nicholson, F., Webb, J., Anthony, S., Chambers, B., 2005. Ammonia emissions and crop nitrogen efficiency: ammonia emissions from nitrogen fertiliser applications to grassland and tillage land; factors affecting ammonia emissions from urea based fertilisers and ammonia emissions model. In: Final Report to Defra for Project NT2605.

Chambers, B., Lord, E., Nicholson, F., Smith, K., 1999. Predicting nitrogen availability and losses following applications of manures to arable land: MANNER. Soil Use Manag. 15, 137–143.

CIEL, 2020. NET ZERO CARBON & UK LIVESTOCK. Centre for Innovation Excellence in Livestock, York. Available: https://www.cielivestock.co.uk/wp-content/uploads/2020/09/CIEL-Net-Zero-Carbon-UK-Livestock_2020_Interactive.pdf.

CML, 2016. CML-IA Characterisation Factors. University of Leiden, Department of Industrial Ecology, Leiden. Available: https://www.universiteitleiden.nl/en/research/research-output/science/cml-ia-characterisation-factors.

Collins, A.L., Stromqvist, J., Davison, P.S., Lord, E.I., 2007. Appraisal of phosphorus and sediment transfer in three pilot areas identified for the Catchment Sensitive Farming initiative in England: application of the prototype PSYCHIC model. Soil Use Manag. 23, 117–132.

Collins, A.L., Zhang, Y.S., Winter, M., Inman, A., Jones, J.I., Johnes, P.J., Cleasby, W., Vrain, E., Lovett, A., Noble, L., 2016. Tackling agricultural diffuse pollution: what might uptake of farmer-preferred measures deliver for emissions to water and air. Sci. Total Environ. 547, 269–281.

Collins, A.L., Zhang, Y., Upadhayay, H.R., Pulley, S., Granger, S.J., Harris, P., Sint, H., Griffith, B., 2021. Current advisory interventions for grazing ruminant farming cannot close exceedance of modern background sediment loss – assessment using an instrumented farm platform and modelled scaling out. Environ. Sci. Pol. 116, 114–127.

Comber, S.D.W., Smith, S., Daldorph, P., Gardner, M.J., Constantino, C., Ellor, B., 2013. Development of a chemical source apportionment decision support framework for catchment management. Environ. Sci. Technol. 47, 9824–9832.

Davison, P., Withers, P., Lord, E., Betson, M., Strömqvist, J., 2008. PSYCHIC - a process based model of phosphorus and sediment mobilisation and delivery within agricultural catchments. Part 1: model description and parameterisation. J. Hydrol. 350, 290–302.

Davison, P.S., Hutchins, M.G., Anthony, S.G., Betson, M., Johnson, C., Lord, E.I., 2005. The relationship between potentially erosive storm energy and daily rainfall quantity in England and Wales. Sci. Total Environ. 344, 15–25.

de Vries, M., de Boer, I.J.M., 2010. Comparing environmental impacts for livestock products: A review of life cycle assessments. Livest. Sci. 128, 1–11. https://doi.org/10.1016/j.livsci.2009.11.007.

de Vries, M., van Middelaar, de Boer, 2015. Comparing environmental impacts of beef production systems: A review of life cycle assessments. Livest. Sci. 178, 279–288. https://doi.org/10.1016/j.livsci.2015.06.020.

Defra, 2010. Definitions of Terms Used in Farm Business Management, third ed. Defra, London, p. 48.

DEFRA, 2013. Farm practices survey February 2013 - greenhouse gas mitigation practices. Department for Environment, Food & Rural Affairs, London. https://www.gov.uk/government/statistics/farm-practices-survey-february-2013-greenhouse-gas-mitigation-practices.

Defra, 2021a. Farm Practices Survey. Department for Environment, Food and Rural Affairs, London. Available: https://www.gov.uk/government/collections/farm-practices-survey.

Defra, 2021b. Structure of the Agricultural Industry: Statistics about the Structure of the Agricultural Industry. Department for Environment, Food & Rural Affairs, London, UK. Available: https://www.gov.uk/government/collections/structure-of-the-agricultural-industry#2016-publications.

England, Natural, 2016. Countryside Stewardship Scheme 2016 Management Options (England). Natural England Open Data. Exeter. Available: https://naturalengland-defra.opendata.arcgis.com/datasets/countryside-stewardship-scheme-2016-management-options-england/.

EPD, 2013. Environmental Product Declaration Impact Assessment (SimaPro). In: Swedish Environmental Management Council. Available, Stockholm. https://environdec.com/about-us/global-house-of-epd.

EU, 2009. Adapting to climate change: towards a European framework for action. In: Commission of the European Communities, Belgium, Brussels. Available: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52009DC0147&from=EN.

Gerber, P.J., Steinfeld, H., Henderson, B., Mottet, A., Opio, C., Dijkman, J., Falcucci, A., Tempio, G., 2013. Tackling Climate Change through Livestock – A Global Assessment of Emissions and Mitigation Opportunities. Food and Agriculture Organization of the United Nations (FAO), Rome.

Gooday, R.D., Anthony, S.G., Fawcett, L.E., 2008. A model of soil drainage and nitrate leaching for application in nitrate vulnerable zones. Environ. Model. Software 23, 1045–1055.

Haygarth, P.M., Jarvis, S.C., 1999. Transfer of phosphorus from agricultural soils. Adv. Agron. 66, 195–249.

Haygarth, P.M., Condron, L.M., Heathwaite, A.L., Turner, B.L., Harris, G.P., 2005. The phosphorus transfer continuum: linking source to impact within an interdisciplinary and multi-scaled approach. Sci. Total Environ. 344, 5–14.

Huijbregts, M., 1999. Life-cycle impact assessment of acidifying and eutrophying air pollutants: calculations of equivalency factors with RAINS-LCA. University of Amsterdam, Amsterdam, Netherlands. Available. https://www.universiteitleiden.nl/binaries/content/assets/science/cml/publicaties_pdf/new-dutch-lca-guide/life-cycle-impact-assessment.pdf.
Huijbregts, M.A.J., Steinmann, Z.J.N., Elshout, P.M.F., Stam, G., Verones, F., Vieira, M., Zijp, M., Hollander, A., van Zelm, R., 2017. ReCiPe 2016: a harmonised life cycle impact assessment method at midpoint and endpoint level. Int. J. Life Cycle Assess. 22, 138–147.
IPCC, 2006. Guidelines for National Greenhouse Gas Inventories. In: Eggleston, H.S., Buendia, L., Miwa, K., Ngara, T., Tanabe, K. (Eds.), The Greenhouse Gas Inventories Programme, IGES. The Intergovernmental Panel on Climate Change, Japan.
IPCC, 2013. Climate change 2013: the physical science basis. Contribution of working group I to the fifth assessment report of the intergovernmental panel on climate change. In: Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
IPCC, 2007. Climate change 2007: synthesis report. Contribution of working groups I, II and III to the Fourth assessment report of the IPCC. In: Pachauri, R.K., Reisinger, A. (Eds.), Intergovernmental Panel on Climate Change, Geneva, Switzerland, p. 104.
ISO, 2006. ISO 14040: Environmental Management – Life Cycle Assessment – Principles and Framework. International Organization for Standardization, Geneva.
Kowalczyk, Z., Cupiał, M., 2020. Environmental analysis of the conventional and organic production of carrot in Poland. J. Clean. Prod. 269, 122169.
Lee, E.K., Zhang, X., Adler, P.R., Kleppel, G.S., Romeiko, X.X., 2020. Spatially and temporally explicit life cycle global warming, eutrophication, and acidification impacts from corn production in the U.S. Midwest. J. Clean. Prod. 242, 118465.
Lemunyon, J.L., Gilbert, R.G., 1993. The concept and need for a phosphorus assessment tool. J. Prod. Agric. 6, 483–486.
Liu, G., Ziv, G., Bakshi, B.R., 2018. Ecosystem services in life cycle assessment - Part 2: Adaptations to regional and serviceshed information. J. Clean. Prod. (197), 772–780. https://doi.org/10.1016/j.jclepro.2018.05.283.
Lloyd, C.E.M., Johnes, P.J., Freer, J.E., Carswell, A.M., Jones, J.I., Stirling, M.W., Hodgkinson, R.A., Richmond, C., Collins, A.L., 2019. Determining the sources of nutrient flux to water in headwater catchments: examining the speciation balance to inform the targeting of mitigation measures. Sci. Total Environ. 648, 1179–1200.
Lord, E.I., 1992. Modeling of nitrate leaching: nitrate sensitive areas. Aspect Appl. Biol. 30, 19–28.
Lord, E., Anthony, S., 2000. MAGPIE: amodelling framework for evaluating nitrate losses at national and catchment scales. Soil Use Manag. 16, 167–174.
Manfredi, M., Vignali, G., 2014. Life cycle assessment of a packaged tomato puree: a comparison of environmental impacts produced by different life cycle phases. J. Clean. Prod. (73), 275–284. https://doi.org/10.1016/j.jclepro.2013.10.010.
McAuliffe, G.A., Chapman, D.V., Sage, C.L., 2016. A thematic review of life cycle assessment (LCA) applied to pig production. Environ. Impact Assess. Rev. 56, 12–22.
McAuliffe, G.A., Takahashi, T., Mogensen, L., Hermansen, J.E., Sage, C.L., Chapman, D. V., Lee, M.R.F., 2017. Environmental trade-offs of pig production systems under varied operational efficiencies. J. Clean. Prod. 165, 1163–1173.
McAuliffe, G.A., Takahashi, T., Orr, R.J., Harris, P., Lee, M.R.F., 2018. Distributions of emissions intensity for individual beef cattle reared on pasture-based production systems. J. Clean. Prod. 171, 1672–1680.
McAuliffe, G.A., Takahashi, T., Lee, M.R.F., 2020. Applications of nutritional functional units in commodity-level life cycle assessment (LCA) of agri-food systems. Int. J. Life Cycle Assess. 25, 208–221.
McHugh, M., Wood, G., Walling, D., Morgan, R., Zhang, Y., Anthony, S., Hutchins, M., 2002. Prediction of Sediment Delivery to Watercourses from Land: Phase 2. R & D Technical Report No P2-209. Environment Agency, Bristol, UK.
Meteorological Office, 2018. HadUK-Grid Gridded Climate Observations on a 1km Grid over the UK for 1862-2017. Centre for Environmental Data Analysis. http://catalogue.ceda.ac.uk/uuid/2a62652a4fe6412693123dd6328f6dc8. (Accessed 30 March 2019). Accessed.
Morais, T.G., Teixeira, R.F.M., Rodrigues, N.R., Domingos, T., 2018. Carbon footprint of milk from pasture-based dairy farms in azores, Portugal. Sustainability 10.
Morgan, R.P.C., 2001. A simple approach to soil loss prediction: a revised Morgan-Morgan-Finney model. Catena 44, 305–322.
NAEI, 2019. Emissions Maps 2019. National Atmospheric Emissions Inventory, London, UK. Accessed Sept. 2021. Available: https://naei.beis.gov.uk/data/map-uk-das.
Nitschelm, L., Aubin, J., Corson, M.S., Viaud, V., Walter, C., 2016. Spatial differentiation in Life Cycle Assessment LCA applied to an agricultural territory: current practices and method development. J. Clean. Prod. 112, 2472–2484.
Orr, R.J., Murray, P.J., Eyles, C.J., Blackwell, M.S.A., Cardenas, L.M., Collins, A.L., Dungait, J.A.J., Goulding, K.W.T., Griffith, B.A., Gurr, S.J., Harris, P., Hawkins, J.M. B., Misselbrook, T.H., Rawlings, C., Shepherd, A., Sint, H., Takahashi, T., Tozer, K.N., Whitmore, A.P., Wu, L., Lee, M.R.F., 2016. The North Wyke Farm Platform: effect of temperate grassland farming systems on soil moisture contents, runoff and associated water quality dynamics. Eur. J. Soil Sci. 67, 374–385.
Patouillard, L., Bulle, C., Querleu, C., Maxime, D., Osset, P., Margni, M., 2018. Critical review and practical recommendations to integrate the spatial dimension into life cycle assessment. J. Clean. Prod. 177, 398–412.
Pré Consultants, 2020. SimaPro Database Manual: Methods Library. PRé Consultants, The Netherlands. Available: https://simapro.com/wp-content/uploads/2020/06/DatabaseManualMethods.pdf.
Pizzol, M., Laurent, A., Sala, S., Weidema, B., Verones, F., Koffler, C., 2016. Normalisation and weighting in life cycle assessment: quo vadis? Int. J. Life Cycle Assess. 22, 853–866. https://doi.org/10.1007/s11367-016-1199-1.
Ribal, J., Ramírez-Sanz, C., Estruch, V., Clemente, G., Sanjuán, N., 2017. Organic versus conventional citrus. Impact assessment and variability analysis in the Comunitat Valenciana (Spain). Int. J. Life Cycle Assess. 22, 571–586.
Ripple, W.J., Wolf, C., Newsome, T.M., Gregg, J.W., Lenton, T.M., Palomo, I., Eikelboom, J.A.J., Law, B.E., Huq, S., Duffy, P.B., Rockström, J., 2021. World scientists' warning of a climate emergency 2021. Bioscience 71, 894–898.
RIVM, 2011. LCIA: the ReCiPe Model. National Institute for Public Health and the Environment, The Netherlands. Available: https://www.rivm.nl/en/life-cycle-assessment-lca/recipe.
Rockström, J., Gupta, J., Lenton, T.M., Qin, D., Lade, S.J., Abrams, J.F., Jacobson, L., Rocha, J.C., Zimm, C., Bai, X., Bala, G., Bringezu, S., Broadgate, W., Bunn, S.E., DeClerck, F., Ebi, K.L., Gong, P., Gordon, C., Kanie, N., Liverman, D.M., Nakicenovic, N., Obura, D., Ramanathan, V., Verburg, P.H., van Vuuren, D.P., Winkelmann, R., 2021. Identifying a safe and just corridor for people and the planet. Earth's Future 9, e2020EF001866.
Roibás, L., Loiseau, E., Hospido, A., 2018. On the feasibility and interest of applying territorial Life Cycle Assessment to determine subnational normalisation factors. Sci. Total Environ. 626, 1086–1099.
Roy, P., Nei, D., Orikasa, T., Xu, Q., Okadome, H., Nakamura, N., Shiina, T., 2009. A review of life cycle assessment (LCA) on some food products. J. Food Eng. 90, 1–10.
Salou, T., Le Mouël, C., van der Werf, H.M.G., 2017. Environmental impacts of dairy system intensification: the functional unit matters. J. Clean. Prod. 140, 445–454.
Schofield, D., Lockyer, D.R., Tyson, K.C., Whitehead, D.C., 1991. A model to predict transformations and losses of nitrogen in UK pastures grazed by beef cattle. Plant Soil 132, 165–177.
Soana, E., Fano, E.A., Castaldelli, G., 2021. The achievement of Water Framework Directive goals through the restoration of vegetation in agricultural canals. J. Environ. Manag. 294, 113016.
Stone, M., Krishnappan, B.G., Granger, S., Upadhayay, H.R., Zhang, Y., Chivers, C.A., Decent, Q., Collins, A.L., 2021. Deposition and erosion behaviour of cohesive sediments in the upper River Taw observatory, southwest UK: implications for management and modelling. J. Hydrol. 598, 126145.
Stromqvist, J., Collins, A.L., Davison, P.S., Lord, E.I., 2008. PSYCHIC – a process-based model of phosphorus and sediment transfers within agricultural catchments. Part 2. A preliminary evaluation. J. Hydrol. 350, 303–316.
Stylianou, K.S., Heller, M.C., Fulgoni, V.L., Ernstoff, A.S., Keoleian, G.A., Jolliet, O., 2016. A life cycle assessment framework combining nutritional and environmental health impacts of diet: a case study on milk. Int. J. Life Cycle Assess. 21, 734–746.
Stylianou, K.S., Fulgoni, V.L., Jolliet, O., 2021. Small targeted dietary changes can yield substantial gains for human health and the environment. Nat. Food 2, 616–627.
Takahashi, T., Harris, P., Blackwell, M.S.A., Cardenas, L.M., Collins, A.L., Dungait, J.A.J., Hawkins, J.M.B., Misselbrook, T.H., McAuliffe, G.A., McFadzean, J.N., Murray, P.J., Orr, R.J., Rivero, M.J., Wu, L., Lee, M.R.F., 2018. Roles of instrumented farm-scale trials in trade-off assessments of pasture-based ruminant production systems. Animal 1–11.
Wang, L., Stuart, M.E., Lewis, M.A., Ward, R.S., Skirvin, D., Naden, P.S., Collins, A.L., Ascott, M.J., 2016. The changing trend in nitrate concentrations in major aquifers due to historical nitrate loading from agricultural land across England and Wales from 1925 to 2150. Sci. Total Environ. 542, 694–705.
WBG, 2021. Life Expectancy at Birth, Total (Years). World Bank Group, London, UK. Available: https://data.worldbank.org/indicator/SP.DYN.LE00.IN?most_recent_value_desc=false.
Webb, J., Misselbrook, T.H., 2004. A mass-flow model of ammonia emissions from livestock production. Atmos. Environ. 38, 2163–2176.
Wendling, Z.A., Emerson, J.W., de Sherbinin, A., Esty, D.C., 2020. Environmental Performance Index 2020. Yale University Centre for Environmental Law and Policy, New Haven, Connecticut. Available: https://epi.yale.edu/epi-indicator-report/H2O.
Zhang, Y., Collins, A.L., Jones, J.I., Johnes, P.J., Inman, A., Freer, J.E., 2017a. The potential benefits of on-farm mitigation scenarios for reducing multiple pollutant loadings in prioritised agri-environment areas across England. Environ. Sci. Pol. 73, 100–114.
Zhang, Y., Collins, A.L., Johnes, P.J., Jones, J.I., 2017b. Projected impacts of increased uptake of source control mitigation measures on agricultural diffuse pollution emission to water and air. Land Use Pol. 62, 185–201.
Zhang, Y., Griffith, B., Granger, S., Sint, H., Collins, A.L., 2022. Tackling unintended consequences of grazing livestock farming: multi-scale assessment of co-benefits and trade-offs for water pollution mitigation scenarios. J. Clean. Prod. 336, 130449.