Integrating Life Cycle Assessment Into Landscape Studies: A Postcard From Hulunbuir

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Abstract

Context

Conventional life cycle assessment (LCA) has been increasingly criticized for lacking spatial information, especially for agricultural systems where high spatial sensitivity is present.

Objectives

The objective of this research is twofold: first, to assess the potential environmental impacts and the production efficiency of pastoralism farming, and, second, to identify the influence of the spatial distribution of farms on the environmental impacts, if any.

Methods

A cradle-to-gate spatialized agricultural LCA was conducted for 45 farms surveyed from the Hulunbuir Grassland by splitting direct onsite processes from upstream processes, adopting the spatialized characterization factors (SCFs) of IMPACT World+.

Results

Contrasting results were observed for different impact categories regarding whether upstream or onsite processes served as the environmental hotspot. While direct onsite animal emissions did not show spatial dependence at the inventory stage, its resulting impact scores demonstrated the most contrasting spatial patterns among various impact categories, depending on whether and how spatial resolution and location were introduced during the LCIA stage.

Conclusions

A cradle-to-gate spatialized agricultural LCA was proposed and applied to assess the environmental impacts of pastoralism farming in Hulunbuir Grassland. The overall spatial dependence of the LCA results was weak, if present, it depended on the interactions between spatial variation within the life cycle inventory and the spatial resolution and location of the SCFs. Environmental burden shifting occurred between different impact categories, and it remains a policy challenge as how to increase the production efficiency in the pastoralism system.

1. Introduction

Increasing demand for dairy and meat products in many countries calls for urgent action to balance consumption and environmental impacts. A robust and scientific assessment is needed to understand and balance the consumption and impacts of dairy and meat production, as the dairy production system is an integral part of the larger social-ecological system (Chen et al. 2018; Chen et al. 2020; Qi et al. 2017). Life cycle assessment (LCA) is among the most promising approaches to address this knowledge

need because it is considered a holistic assessment of multiple environmental impacts. Unfortunately, a standard LCA (i.e. following ISO 14040) considers aggregated elementary flows (regardless of their geographic origins) that are then multiplied by default characterization factors instead of site-specific impact characterization. It typically addresses a problem from the perspective of a product system (e.g., unit process flowchart) without incorporating any spatial factors and context of landscape structure, which are fundamental assumptions for various ecological models (Gaucherel et al. 2010, Yu et al. 2017, Kobler et al. 2019).

The “unit world” assumption (Reinhard et al. 2017) in conventional LCAs has been criticized and challenged, especially for the agricultural system, where high spatial sensitivity is present (Antón et al. 2014, Reinhard et al. 2017). Site-dependent impact categories like acidification and eutrophication are especially susceptible to (misleading) results obtained from spatially indifferent standard LCA (Mutel and Hellweg 2009). Empirical evidence has demonstrated that integration of spatial information in LCAs can lead to very high variation by location (Pelton 2019, Yang et al. 2020) and sometimes result in different or even opposite outcomes to those of standard LCAs (Chaplin-Kramer et al. 2017, Frischknecht et al. 2019).

Recently, Patouillard et al. (2018) standardized nomenclature and definitions related to the spatial dimension in LCA. For example, *inventory regionalization* is differentiated from *inventory spatialization,* where the former improves the geographic representativeness of a product system and the latter attributes geographic information to an elementary flow for characterization with regionalized characterization factors. In this study we refer to spatialized LCA as matching spatialized elementary flows (SEFs) with spatialized characterization factors (SCFs) at a chosen spatial resolution that is referred to as “regionalized characterization factors” in Patouillard et al. (2018).

Discrepancies between SEFs and SCFs are a major factor restraining the implementation of spatialized LCA (Frischknecht et al. 2019), among many other factors such as engaging new computational structure of LCA (Patouillard et al. 2018). With the recent development of regionalized life cycle impact assessment (LCIA), impact pathways taking into account the background depositions, emissions transportation and fate, and ecosystem sensitivity have been well modeled at a desirable spatial resolution (Helmes et al. 2012, Roy et al. 2012a, 2012b, 2014). SCFs for impact categories that are important to agricultural systems (e.g., water scarcity, biodiversity, land use change, acidification, eutrophication) are being constantly developed (Geyer et al. 2010, Helmes et al. 2012, Roy et al. 2014, Clarke et al. 2019, Boulay and Lenoir 2020). While SCFs are developed at different resolutions (i.e. the optimal spatial scale determined by LCIA method developers), harmonization is possible with the development of consistent regionalized LCIA such as IMPACT World+ (Bulle et al. 2019) and LC-IMPACT (Verones et al. 2016).

Contrasting SCFs, geo-information at a coerce spatial scale of elementary flows (e.g., country-level data supplied by various LCI database) makes it difficult to perform a consistent spatialized LCA (Frischknecht et al. 2019). Emissions with spatial information can be modeled by taking into account spatially dependent factors. For example, spatially explicit simulation models for agricultural nitrogen emissions are available at different complexity, e.g., the complex TNT2 model (Beaujouan et al. 2002) or simpler

models (EMEP/EEA 2013). Various solutions have been proposed, with some constructed as GIS-based inventory and emission models (Geyer et al. 2010, Kim et al. 2015). Mutel et al. (2012) matched inventory with SCFs by calculating spatial autocorrelation to choose the most appropriate spatial scale of impact assessment. Reinhard et al. (2017) developed a calculation framework to transform spatial raster data into unit process datasets structure in Ecoinvent, which allows an automated site-specific generation and assessment of regionalized unit process datasets.

While comprehensive spatialized LCA can be performed by adopting the above-mentioned frameworks, substantially more effort is needed to clean up the inventory to match SEFs with SCFs. In most LCA studies, background data such as unit processes supplied by Ecoinvent is used, each situating at a different geographic location which is further linked to various intermediate unit processes. Here for a farm-gate agricultural LCA, a simplified version of spatialized LCA is proposed by splitting the calculations into impacts due to direct onsite processes from everything else (i.e. upstream processes), following a similar practice of Mutel (2018) in a rice LCA. Similarly, Lee et al. (2020) estimated spatially and temporally explicit life cycle impacts of corn production in the U.S. Midwest by separating direct on-farm emissions from all other supply chain activities.

The splitting approach highlights the variations in the inventory due to changes in microspatial environmental parameters on the agricultural field (Dresen and Jandewerth 2012) while putting minimal effort into differentiating spatial information for background processes that are not under the management control of farmers. We take this approach and develop a cradle-to-gate spatialized LCA to identify the environmental impact of the pastoral farming system on the Hulunbuir Grassland landscape in Inner Mongolia, China. The specific objective of our study is, for the first time, to develop spatialized LCA for the pastoral farming system in the study area by splitting onsite processes from all upstream processes, to assess their potential environmental impacts and to identify the influence of the spatial distribution of farms on environmental impacts.

2. Methods

2.1 Study site

Hulunbuir Grassland is one of the major pastoral farming regions in China. The farms included in this case study (48°23'N 118°31"E / 49°38'N 120°36'E) are located in three pastoral areas near Hailar city: 1) the pastoral area to the northeast of Hailar city (E1 – E19); 2) the pastoral area west of Hailar city (W1 – W9); and 3) the pastoral area south of Hailar city (S1 – S17), scattered along the Yimin He (Figure 1). All the farms employ a pastoralism farming system, relying on natural grasslands with minimal manmade resources input. Arable land is restricted in this area to protect natural grasslands. Self-produced hay is the major feedstock used during the non-grazing season in addition to purchased feeds. Due to low milk prices and competition from domestic intensive dairy farms, local farm households mainly rely on meat production (e.g., beef, lamb) as their major income sources. The traditional pastoralism system results in low productivity and leads to grassland ecosystem degradation in many cases.

2.2 Spatialized LCA

2.2.1 Goal and scope

Farm-gate spatialized LCAs were conducted for 45 farms from the study area. The functions of agricultural activities are often multiple, including but not limited to producing food, managing agricultural resources, and providing ecosystem services (e.g., eco-tourism). Several measures of functional unit (FU) have been proposed based on a single product (Baldini et al. 2017), multiple products (Parajuli et al. 2018), nutrient content (Kristensen et al. 2011), land (O'Brien et al. 2012, Raschio et al. 2018), or income (van der Werf et al. 2014). The goal of our LCA is to assess impacts and production/economic efficiency associated with pastoral farming and identify the influence of their spatial locations. Each farm has multiple outputs; we defined the FU as one unit of gross income (in Chinese yuan RMB) earned by each farm in the year 2018, regardless of what agricultural products were produced and sold.

We split the LCA into two modules: 1) direct emissions and resource consumption from onsite processes, including emissions from diesel combustion for hay production and transportation; emissions from coal-burning for onsite heating; emissions from animals (e.g., livestock raising, housing, and grazing), and direct resource consumption (e.g., water intake); and 2) associated emissions and resource consumption from upstream processes for everything else, including the production of energy carriers (e.g., electricity, coal, and diesel) and materials (e.g., purchased feed). While the system boundary is set at individual farm level, shared resources (e.g., water and pasture) are used by multiple farms. Due to a lack of data, we did not include land occupation in the onsite processes. The grazing and haying locations are slightly different but not far from the farm locations (i.e. where household and livestock housing are located), and their spatial differentiation is considered during LCI. Allocation was not performed because FU is income-based instead of product-based. Manufacturing of capital goods (e.g., agro-machinery) and infrastructure are not included in the system boundary. Farm-site and livestock housing construction/maintenance are not included. Bedding materials are excluded, as most farms apply waste product (e.g., solid manure), and the amount of materials is not measurable. Transportation of purchased feeds is excluded due to a lack of data, as they are typically transported by suppliers to the farm site.

Due to the nature of the pastoral farming system, the overall quality of the field-surveyed data is relatively low in regards to precision, completeness, and representativeness. Unlike industrial processes, where precise measurements are often possible, these farmers did not keep detailed records of their production activities. The survey data supplied by farmers is mainly based on experience and roughly estimated from annual total energy costs. Consequently, we prefer not to conduct a quantitative uncertainty analysis, as such analysis will only provide useful information when inventory data are precisely measured and their probability distribution is properly defined and established.

For impact assessment, midpoint impact categories on climate change, fossil fuel consumption, freshwater eutrophication, terrestrial acidification, and water scarcity were selected because they are considered important to agricultural activities and relevant to the study site. Geo-spatial analysis is

applied to LCA results to statistically identify emission clusters (if any) and their relationship with location factors.

2.2.2 Life cycle inventory

Following the principles laid out in the goal and scope of the study, we included LCI from two separated subsystems: 1) resource consumption and direct emissions from direct onsite processes, and 2) resource consumption and associated emissions from upstream processes for all other activities required to support onsite activities. Primary agricultural activity data were collected for the onsite processes, including 1) daily climate data and farm features (e.g., livestock and feed structure, manure characteristics, soil structure etc.) that were used as inputs for onsite emission modeling; 2) onsite energy consumption (diesel, coal, and electricity); 3) feed input (self-produced hay onsite and purchased feed); and 4) natural resources input (water resources). There are no agrochemicals used in the pastoralism farming system. Secondary data, including emissions associated with onsite processes as well as all other upstream activities and their associated emissions, were simulated using the DairyGEM model (v3.3) (DairyGEM 2020) and collected using the Ecoinvent database (v3.6 cut-off) (Wernet et al. 2016). Primary agricultural activity data were obtained from our field surveys conducted with farm owners during the summer of 2018. Spatial information were collected for onsite processes, while upstream processes were not spatially differentiated in our study.

2.2.2.1 Onsite processes

Emissions associated with livestock raising from housing, grazing, and manure management were modeled by DairyGEM, which is a farm-level model estimating emissions of dairy production systems as influenced by climate and farm management (DairyGEM 2020). Onsite emissions from diesel combustion and coal burning were obtained from Ecoinvent database. Natural water resources are a major input for livestock raising in the pastoralism farming system. While the water intake for animals and pasture growth can not be measured or estimated directly, we used the DiaryGEM model to simulate the onsite water use, which was further determined through climate data (DairyGEM 2020). Water embodied in purchased feed was considered in the upstream processes by using the Ecoinvent database.

Spatial information for onsite processes included collecting location data as well as daily climate information for each farm in 2018. Daily climate data on solar radiation (MJ/m^2), average temperature (^oC), maximum temperature (^oC), minimum temperature (^oC), total precipitation (mm), mean daily wind velocity (m/s) at 2 m above the ground were downloaded from NASA POWER Data Access Viewer, which was used as the weather input for the DairyGEM model.

The farm location is associated with the emissions from housing animals (e.g., onsite enteric fermentation and manure management) and emissions from coal-burning. The grazing location is associated with the natural resource consumption (i.e. animal water intake) and emissions during grazing (e.g., animal excrement). The haying site as well as the route from the farm to the haying site is associated with the emissions from diesel-burning for tractors and agro-machinery such as hay mower.

For simplicity, we assume that haying and grazing locations are also point-data and are the same as the farm location, because these sites are generally not far from each other for individual farm households. This assumption is based on the fact that for even the most spatially-sensitive impact category (i.e. freshwater eutrophication), its characterization factor is differentiated at a spatial resolution of 0.5° × 0.5° (i.e. around 50 km for the latitudes of our study site). Moreover, direct emissions from grazing locations such as ammonia and nitrous oxide are not relevant to the assessment of freshwater eutrophication, which assumes phosphorus as the limiting factor. Other impact categories have SCFs at a much coarser spatial resolution, so detailed spatial differentiation for the farm/haying/grazing locations for the same farm household at the inventory stage is not necessary, as it does not influence the impact assessment and the final spatialized LCA results.

2.2.2.2 Upstream processes

The activity data for the energy and material input were obtained from field surveys while their associated emissions and resource consumption were obtained from Ecoinvent database.

Table 1. Life cycle inventory data – primary and secondary data for onsite and upstream processes used in the LCA modeling

1. Primary agricultural activity data (surveyed and/or expert estimated)	
Item	Reference / description
1.1 Farm features	
Breed	Small Holstein, Guernsey (cow breed in the DiaryGEM model that is most close to the local cow breed raised onsite)
Grazing period (time on pasture)	Full days during grazing seasons (6 months per year)
Number of lactating animals	23 on average, with a minimum of 4 and a maximum of 105
Young stock under one year old	16 on average, with a minimum of 3 and a maximum of 80
First lactation animals (%)	3.25% on average, with a minimum of 0% and a maximum of 15%
Pasture areas	125 ha shared usage for each farm, ranging 10-400 ha
Cow/heifer housing	Free stalls and open lots
Bedding	Solid manure or no bedding
Soil type and acidity	Loamy soil, sandy loam, or sandy soil, with average pH of 6.8
Climate condition	According to its latitude and longitude, each farm has its own climate data obtained from NASA POWER Data Access (https://power.larc.nasa.gov/data-access-viewer/), used as input in the DiaryGEM model
1.2 Self-produced hay onsite	
Crude protein (%DM)	9.6
Degradable protein (%CP)	35
Acid detergent insoluble protein (%CP)	5
Net energy of lactation (Mcal/kg DM)	1.11
Neutral detergent	35

fiber (%DM)	
1.3 Purchased feed	Types and amount of purchased energy and protein feed are obtained for each farm, with upstream production obtained from Ecoinvent database
1.4 Energy consumption	Amount of diesel, electricity, and coal (lignite) are obtained via survey for each farm
1.5 Manure management	
Collection method	Hand scraping
Storage method	Stockpiling and dry stack
Manure type	Dry (70% DM) and solid (20% DM)
2. Secondary data source	
2.1 Onsite emissions from livestock and resource input	
Onsite emissions from livestock raising, housing, and grazing	Simulated using DairyGEM v3.3
Water use for livestock raising and hay production onsite	Simulated using DairyGEM v3.3
2.2 Onsite emissions from coal and diesel combustion and upstream production of energy sources and purchased feed	
Diesel production (upstream processes) and onsite emissions during combustion	Ecoinvent v3.6 cut-off: unit process 'diesel, burned in agricultural machinery' – with input attributed to upstream production while the output/emissions to onsite processes
Coal production (upstream processes) and onsite emissions during burning	Ecoinvent v3.6 cut-off: unit process 'heat production, lignite briquette, at stove 5-15kW' – with input attributed to upstream production while the output/emissions to onsite processes

Electricity consumption (upstream processes)	Ecoinvent v3.6 cut-off: unit process 'market for electricity, low voltage, SGCC (State Grid Corporation of China)'
Purchased feed production (upstream processes)	Ecoinvent v3.6 cut-off: with following unit processes used as input for different farms: 'market for protein feed, 100% crude', 'soybean meal to generic market for protein feed', 'cottonseed meal to generic market for protein feed', 'distiller's dried grains with solubles to generic market for protein feed', 'rape meal to generic market for protein feed', 'wheat bran to generic market for energy feed', 'maize chop to generic market for energy feed', 'market for maize grain', 'market for maize silage', 'market for hay'

2.2.3 Life cycle impact assessment

For the three impact categories that are spatially dependent (i.e. water scarcity, freshwater eutrophication, and terrestrial acidification), we adopted the characterization methods of IMPACT World+ (Bulle et al., 2019) with SCFs developed for each impact category at different levels of spatial resolution. For the two impact categories that are not spatially dependent (e.g., climate change and fossil fuel consumption), the same CF is used throughout the calculation for different farm locations. Climate change uses the impact method of IPCC 2013 – global warming potential (GWP) 100a, and the fossil fuel consumption uses the impact method of 'cumulative energy demand – non-renewable energy resources, fossil'.

The study areas are generally not sensitive to eutrophication or acidification problems, nevertheless, they are included in the assessment, as manure management and animal excrete are extensively involved. Only freshwater eutrophication is selected as we focus on onsite processes, and marine eutrophication is irrelevant due to the study location. The eutrophication model adopted by the IMPACT World+ is the one developed by Helmes et al. (2012) with characterization factors at a spatial resolution of 0.5° × 0.5° globally. Terrestrial acidification is included with an SCFs at a spatial resolution of 2° × 2.5° following Roy et al. (2012a, 2012b). Water scarcity has a relatively coarse spatial resolution following the AWARE model (Boulay et al. 2018, Boulay and Lenoir 2020) at the watershed level. For the study area, a total of three, four, and one set(s) of SCFs are identified for onsite eutrophication, acidification, and water scarcity, respectively.

Freshwater eutrophication is as unique at approximately half of the farms are located in grid cells with null values of CFs. And three sets of applicable CFs are identified for the remaining half of the farms, which are all located around Hailar city. In contrast, no corresponding eutrophication CFs are applicable for those farms located below 49°00'N in the study area, which means those farms will have zero potential eutrophication impact in the LCA results. This is explained by Helmes et al. (2012) during the model development, as one-fifth of all grid cells have a discharge of zero; these are arid, and evaporation exceeds precipitation on a yearly basis at global scale.

We differentiated calculation procedures for the site-dependent impact categories from the two impact categories that are not (i.e. climate change and fossil fuel consumption). For the latter, the same default

CFs was applied to both onsite and upstream processes. For the site-dependent impact categories, we separated LCI obtained from onsite processes for each farm from LCI of upstream processes, which were obtained through modeling with Brightway2 framework (Mutel 2017). The onsite SEFs were then multiplied with the corresponding SCFs associated with individual farm locations. The site-dependent impact categories were downloaded directly from the IMPACT World+ (IMPACT World+ 2020); we used R to locate SCFs for each farm and do the impact assessment calculation (supplementary information). For all other activities (i.e. upstream processes), the default global CFs were applied to calculate the impact. Together with the site-dependent impact results, they were combined as the final farm-gate LCA results.

2.2.4 Geospatial Analysis

To understand the influence of the spatial distribution of farms on the outcome (i.e. environmental impacts), LCA results are shown on the map spatially. In addition, we performed the Moran I test under randomization to see if there is any spatial autocorrelation in the LCA results to understand the degree to which an LCA result of a farm is similar to its nearby farms.

3. Results

Contrasting results are observed for different impact categories regarding which process (upstream vs. onsite) is the environmental hotspot (Figure 3). For both GWP and AP, onsite processes are the major hotspots, where direct animal emissions contribute most to the final impact scores, followed by the emissions from coal burning while emissions from diesel consumption are relatively negligible. In contrast, for EP and WS, the major (and almost the only) contributor is from upstream processes. This is due to differences in elementary flows contributing to different impact categories as well as the distinct SCFs applied to upstream vs. onsite processes during the LCIA stage for the same impact.

The spatial dependence of the LCA results is generally weak and becomes evident only when the spatial heterogeneity is introduced during the LCIA for selected impact categories. At the inventory stage, upstream energy consumption shows relatively stronger spatial dependence than all other processes. Direct onsite animal emissions do not show spatial dependence at the inventory stage, and its resulting impact scores demonstrate the most contrasting spatial patterns among various impact categories, depending on whether and how spatial resolution and heterogeneity are introduced during the LCIA stage.

3.1 Climate change – global warming potential (GWP)

The GWP for all farms is mainly from onsite processes, which is on average about two to three times higher than that of the upstream process. Large variations on the final GWP exist among the farms for both upstream and onsite processes, with outlier farms exhibiting extremely low economic efficiency. For upstream processes, the contribution is mainly from electricity and coal production, while purchased feeds and diesel production contribute to a lesser extent, typically below 30%. For onsite processes, a

detailed breakdown indicates that emissions from animals are the major contributor, followed by coal burning.

Spatial dependence was not observed for the total GWP, while the upstream process is weakly related to the location factor (p-value <0.01). This can be ultimately attributed to some weak spatial dependence shown in the inventory data of coal and electricity consumption, as well as the input of the purchased feed per farm by income level (p-value <0.05). GWP from all onsite processes does not exhibit any spatial dependence. A detailed breakdown indicates that only the GWP from onsite coal burning shows weak spatial dependence (p-value <0.05), similar to the spatial dependence shown on its raw consumption. The major GWP contributor for onsite processes – GWP from animal emissions – does not show any spatial dependence, nor its emissions at the inventory stage, as the LCIA stage does not involve SCFs for GWP.

3.2 Acidification potential (AP)

Overall results for AP resemble that of the GWP without considering its spatial pattern. The major contributor for AP is from onsite processes, in particular, onsite animal emissions, due to the large amount of ammonia emissions during animal grazing. Large variations were observed among all farms, and the CoV for onsite processes is 26% higher for AP than for GWP. This is due to the spatial variability introduced through using SCFs for onsite processes; consequently, the final AP results represent higher degrees of variability than the GWP results (Figure 3).

Strong spatial dependence (p-value <0.0001) was observed for the total AP of each farm, due to the application of SCFs for onsite processes – a major contributor for AP. The upstream process results in a spatial pattern that is similar to the GWP upstream process, which does not apply SCFs. For onsite processes, while the animal emissions during the inventory stage did not show any spatial dependence, the resulting AP demonstrates the strongest spatial dependence among all impacts, indicating that the SCFs applied is the sole reason that leads to its spatial autocorrelation.

3.3 Eutrophication potential (EP)

The LCIA results for EP represent a different picture compared to GWP and AP; the major (and almost the only) contributor for EP is from upstream processes. This is because the freshwater EP is P-limited, and only onsite coal-burning generating phosphorus emissions make even a minor contribution. N-emissions from animals and diesel burning are not contributing processes to EP. A contribution analysis reveals that while different types of energy sources and feed production all contribute to GWP and AP, the upstream EP are dominantly contributed from coal production and purchased feed production. For many farms that mainly rely on self-produced feed, coal production alone can account for over half of the EP.

The overall spatial dependence observed for the total EP is moderate (p-value < 0.01). For onsite processes, unlike the complete four sets of SCFs values applied for acidification, for the SCFs of EP, NA value is encountered for 51% (23 out of 45) of farms in our study region according to the IMPACT World+ (Bulle et al. 2019). The spatial autocorrelation for onsite process becomes higher after we remove these

NA values (p-value < 0.001), indicating that the spatial variation in the SCFs applied in the LCIA stage for EP has strengthened that of the inventory data of coal consumption.

3.4 Water scarcity (WS)

Overall patterns for WS resemble that of the EP, with the major contribution from the upstream process, which is typically over 20 times higher than that from the onsite process. One of the reasons for the gap between the upstream and onsite processes is due to the SCFs applied. For onsite processes, the study region obtained a low SCF of 2.24 (m^3 world-eq. per m^3 consumed) from the AWARE model, whereas the default CF of 42 – about 20 times higher than the onsite SCF – is used for all upstream processes.

Spatial dependence of WS is generally weak (p-value < 0.05) – slightly stronger than that of the GWP, and weaker than the AP and EP. As the study region only receives one SCF for onsite processes, spatial patterns observed in the final LCIA results for both upstream and onsite processes originate from the inventory stage. Specifically, the spatial dependence of onsite processes for WS (p-value < 0.05) stems from the spatial dependence of self-produced feeds onsite and, consequently, their water intake. The inventory data on water consumption for animals, including drinking/cooling/parlor cleaning, which is on average less than one-tenth of the water intake for feed production, on the other hand, demonstrates spatial randomness, similar to the spatial irrelevance shown in the onsite animal emissions.

3.5 Cumulative energy demand

Only total cumulative energy demand is recorded, as all consumption is attributed to upstream processes to match the SCFs although the energy is used onsite. Overall performance of the cumulative energy demand resembles that of the GWP of the upstream processes with slightly stronger spatial dependence (p-value < 0.005). As with the GWP, the similar source of spatial variation from inventory data (e.g., purchased feed, coal, and electricity consumption) explains the spatial dependence shown in the cumulative energy demand.

Table 2. Cradle-to-gate LCA results per FU (i.e. annual income) for the studied farms on global warming potential (GWP), acidification potential (AP), eutrophication potential (EP), water scarcity (WS), and cumulative energy demand (fossil). The final results consist of upstream and onsite processes, with onsite processes further breakdown with three sub-processes for GWP and AP.

Impact Category	Median, Mean	CoV
GWP_total *(kg CO_2-eq.)*	1.17, 1.43	0.56
GWP_upstream	0.32, 0.39	0.79
GWP_onsite	0.90, 1.04	0.54
GWP_onsite_diesel	0.02, 0.03	1.14
GWP_onsite_coal	0.31, 0.43	0.81
GWP_onsite_animal	0.53, 0.59	0.55
AP_total (kg SO2 eq.)	1.53e-05, 1.76e-05	0.59
AP_upstream	3.91e-06, 4.74e-06	0.84
AP_onsite	1.11e-05, 1.28e-05	0.68
AP_onsite_diesel	3.53e-07, 5.88e-07	1.13
AP_onsite_coal	1.72e-06, 2.28e-06	0.82
AP_onsite_animal	7.55e-06, 9.97e-06	0.78
Fossil_total *(MJ* eq.*)*	4.58, 6.08	0.78
EP_total *(kg PO4 P-lim eq.)*	5.58e-04, 7.99e-04	0.85
EP_upstream	5.58e-04, 8.00e-04	0.85
EP_onsite	0.00, 1.87e-07	1.51
WS_total *(m3 world-eq./m3 consumed)*	33.40, 41.02	0.72
WS_upstream	31.49, 38.90	0.75
WS_onsite	1.29, 2.13	1.19

4. Discussion

Since the integration of spatial technologies with LCA was first proposed by Bengtsson et al. (1998), numerous efforts have been made to advance the integration of spatial dimension into LCA. The coupling has yielded various new topics such as regionalized LCA (Frischknecht et al. 2019), territorial LCA (Loiseau et al. 2018), spatial LCA (Hiloidhari et al. 2017), and spatialized territorial LCA (Nitschelm et al. 2016). Nevertheless, no standardized definitions, methodological development, applications, and/or best practices are available, and there is a lack of empirical studies applying these new topics. We conducted a cradle-to-gate spatialized LCA by combining the SEFs with SCFs at the same spatial scale for onsite processes while making minimal effort to differentiate spatial information regarding upstream processes.

At the inventory stage, for onsite processes, direct animal emissions due to the housing and grazing activities do not show spatial dependence, possibly due to the low variance in geophysical factors, as the farms surveyed cover a relatively small spatial scale with similar climate and soil conditions. This imply that the within-farm variability of the LCA results is mainly due to the farming practices (e.g., cow breed, feed structure) that are not spatially dependent. Because both spatially related site-specific climate information and farming practices are used as input during the inventory modeling in the DiaryGEM model. This finding supports the conclusion that farming practices can be much more important in determining impacts from animals (i.e. animal housing and grazing) than other spatially related factors, which in our case included a relatively small spatial-scale and similar climate and soil conditions.

Unlike direct animal emissions, onsite feed production and its water intake demonstrate spatial dependence. In contrast, diesel consumption used for farming machines shows the least spatial dependence among all resource and energy input. Comparatively, coal and electricity consumption, which are used as auxiliary inputs for the production system, shows stronger spatial dependence than diesel. This (spatial) mismatch between energy consumption and production/economic output deserves further invetigations, as consumption does not necessarily convert to productivity in our case. It remains a question for policymakers how to covert material and energy consumption to production efficiency in pastoralism systems.

We performed comparisons of the carbon intensity for the studied pastoralism households with an average Chinese household. Compared to the CO_2 emissions of 0.639 kg per 2017 PPP $ of GDP, or 7.5 metric tons per capita in 2014 in China (WorldBank 2020), the median CO_2 emissions for farmers in our study is about 7.6 kg per 2017 USD (assuming an exchange rate of 6.5 RMB per USD) or 49.75 metric tons per capita (assuming 3 persons per household on average). While we cannot convert the farmers' annual income to the same benchmark unit (2017 PPP $ of GDP), the result roughly indicates that the carbon intensity for a farmer at our study site is about ten or seven times than that of an average Chinese consumer, when measured by income or per capita, respectively. This finding contributes to the debate over who should hold responsibility for the carbon inequality in the global value chains (Hubacek et al. 2017).

Among the three pastoral areas studied, farms located farther away from Hailar city (the west pastoral area and south area along the Yimin He) generally receive lower impact scores than farms located in the pastoral area close to and northeast of Hailar city. This raises the possibility of the existence of a high vs. a low emission cluster for farms located close to Hailar compared to those located further south/west of the city. Nevertheless, due to the small number of farms surveyed in the study site, this hypothesis remains untested.

The final spatial pattern of LCA results varies due to both LCI and SCFs as well as their interactions, and no single factor can solely determine the final pattern without further scrutiny. The spatial pattern of raw LCI data will ultimately determine the LCIA results for non-spatially dependent impact categories. In contrast, the spatial resolution and heterogeneity of the SCFs, as well as its interactions with the LCI data,

contribute to the final results and spatial layout for spatial impact categories. While animal emissions did not show any spatial dependence at the inventory stage, its AP, in contrast, shows the strongest spatial dependence due to the application of SCFs. Compared with AP, the higher spatial resolution of SCFs for EP (0.5° × 0.5°) does not necessarily lead to a stronger spatial dependence for EP results. The insignificant contribution of onsite processes to EP is mainly because N-compounds are irrelevant to the impact model used in our study, and only onsite coal-burning that generates phosphorus emissions contributes to EP in our study, resulting in a seemingly strange pattern. This finding, on one hand, brings uncertainty in formulating policy, while on the other hand, it reiterates the importance of considering spatial heterogeneity in both LCI and LCIA stage for agricultural LCA.

The LCA results suggest that mitigation strategies for GWP and AP should target emission reduction from onsite processes; however, the opposite holds for EP and WS because the upstream processes dominate almost all impacts for EP and WS. Overall, to avoid environmental burden shifting among the two life cycle stages, we suggest that emphasis should be placed on reducing onsite emissions from animals by refining agricultural management practices – methane management in particular – while improving production efficiency at the same time.

The overall robustness and reliability of the results may be limited by the data quality issue from surveyed farms. We were only able to keep two-thirds of farms surveyed in the final analysis, due to lack of data and low data quality, as most data were recalled by farmers instead of recorded accurately. In addition, a detailed breakdown of ingredients in purchased feeds was not obtainable from suppliers. This prevents us from selecting the unit process that is mostly similar to the supplied feed from Ecoinvent database based on the best guess of experts. Onsite emissions and water consumption data could only be estimated from models instead of accurately measured, and some important environmental issues, such as land occupation and degradation and biodiversity losses are not considered in our impact assessment, due to the lack of an appropriate methodological choice (van der Werf et al. 2020).

5. Conclusions

We proposed a cradle-to-gate spatialized agricultural LCA by splitting all onsite processes from upstream processes, which eased the data handling requirement of collecting and matching SEFs with SCFs while at the same incorporating the spatial sensitivity in the agricultural system. Through surveying 45 farms in Hulunbuir Grassland in Inner Mongolia, contrasting results were observed for different impact categories, as the upstream processes acted as the environmental hotspot for GWP and AP, while the onsite processes dominated EP and WS. Onsite animal emissions did not show spatial dependence at the inventory stage, indicating that farming practices are the determining factor for impacts from livestock. The resulting impact scores from animal emissions, on the other hand, demonstrated the most contrasting spatial patterns among various impact categories, depending on whether and how spatial resolution and heterogeneity are introduced during the LCIA stage. A spatial mismatch between household energy consumption patterns and productivity (as demonstrated by the FU) is observed among the farms, and it remains a challenge to policymakers (i.e. to covert the material and energy

consumption to production efficiency in the pastoralism system). While the overall spatial dependence of the LCA results of studied farms is generally weak, where it exists, the final spatial pattern is determined by both the spatial information incorporated within the LCI and the spatial heterogeneity introduced during the LCIA, as well as their interaction.

Declarations

Funding

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Conflicts of interest/Competing interests (include appropriate disclosures)

Not applicable.

Ethics approval

Not applicable.

Consent to participate

The research team has communicated with the local government before taking the onsite farm survey.

Consent for publication

Not applicable.

Availability of data and material

Data are uploaded to https://github.com/susierwu/IM2020_farm_SpLCA. The processed raw survey data, the DairyGEM model, as well as the calculated LCA results, are presented in the “data” folder. The LCA calculation are presented in the “LCA_calc” folder.

Code availability

Codes are uploaded to https://github.com/susierwu/IM2020_farm_SpLCA. Python and R codes used for LCA calculations are presented in the “LCA_calc” folder. R codes used for the spatial analysis, to compile the result figures, and to develop the online interactive maps are presented under the master folder. The map is deployed at https://susdatability.shinyapps.io/IM_SpLCA/.

Authors' contributions

Susie Ruqun Wu: conceptualized the work, performed the calculations/coding, wrote the manuscript.

Xinchao Liu: conducted the site visit and field survey, assisted in data processing, analysis, and mapping.

Lulu Wang: conducted the site visit and field survey, assisted in data processing and analysis.

Peiling Zhou: performed the spatial analysis.

Jiquan Chen: conceptualized the work, contributed to the manuscript writing.

Changliang Shao: helped with the proposal writing and funding.

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Figures

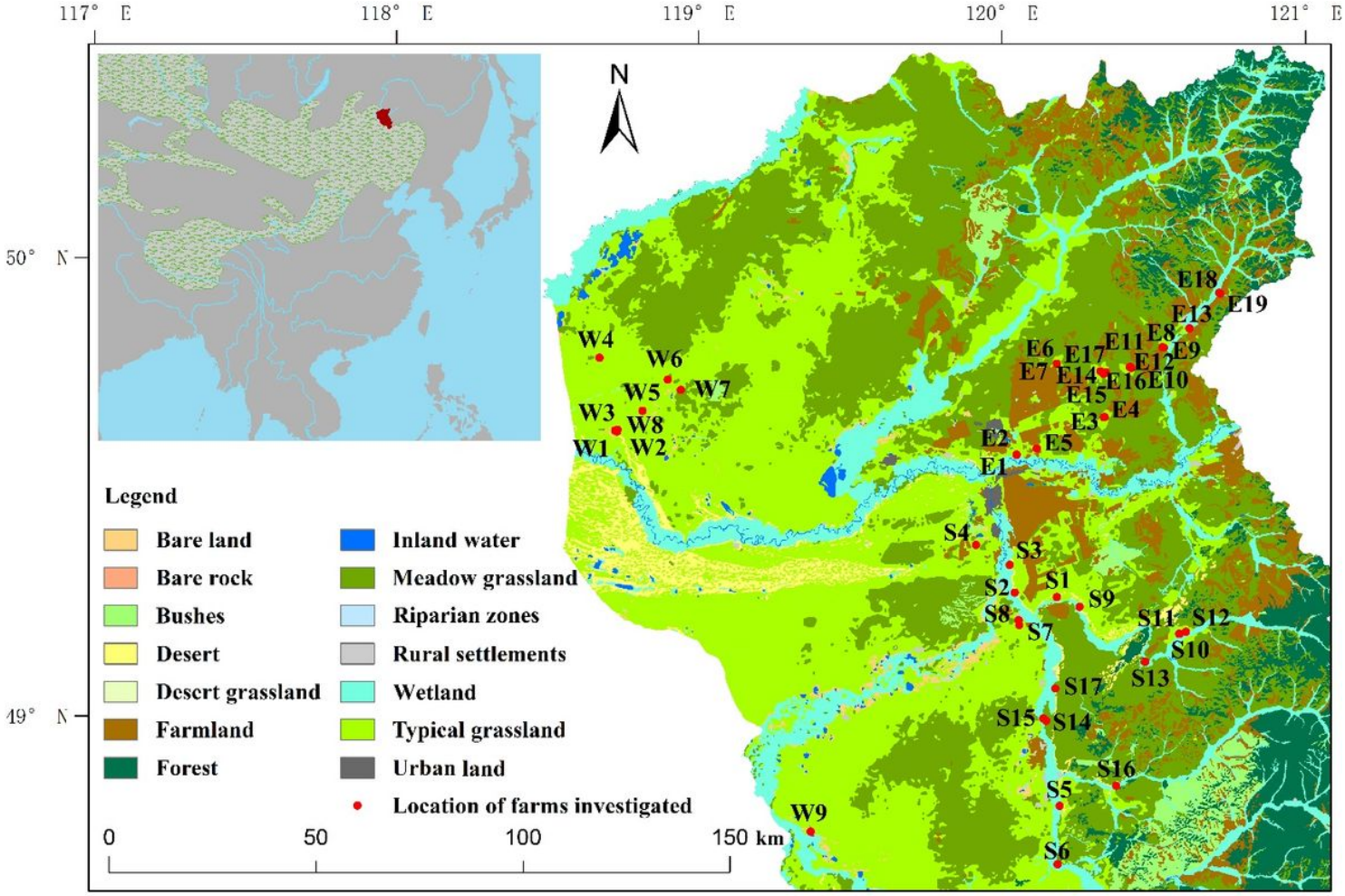

Figure 1

Study site and the spatial distribution of farms investigated. Nineteen farms (E1 – E19) are located northeast of Hailar city, nine farms (W1 – W9) are west of Hailar city, and seventeen farms (S1 – S17) are south of Hailar city, along the Yimin He. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

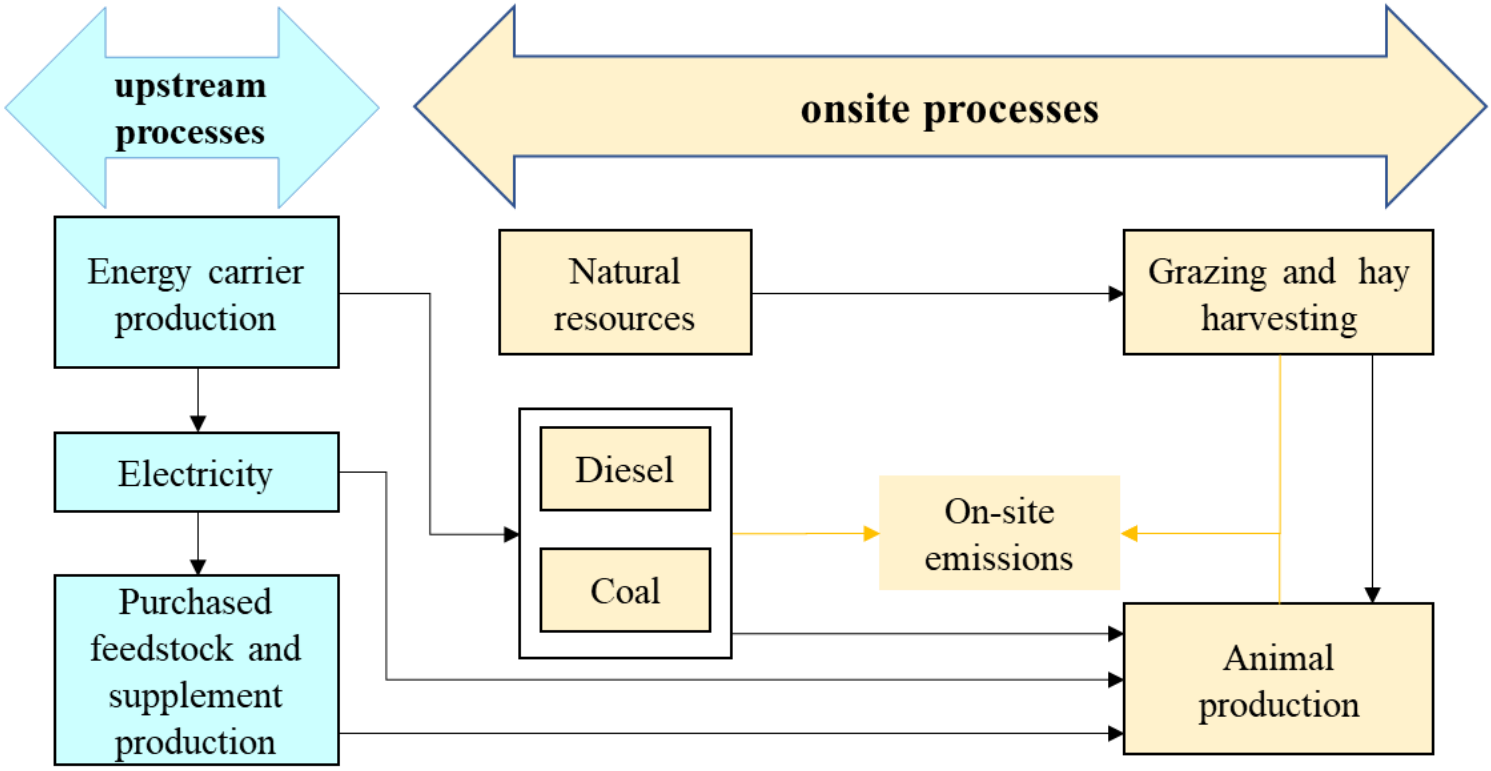

Figure 2

System boundary for the cradle-to-gate LCA for each farm (black and yellow arrows are inputs and emissions, respectively). The spatialized LCA is realized through splitting the calculations into impacts due to: 1) direct onsite processes (e.g., the natural resources input, the onsite emissions from diesel/coal combustion, and from animal raising), and 2) indirect upstream processes (e.g., all resource input and emission from the production of energy sources and other material input).

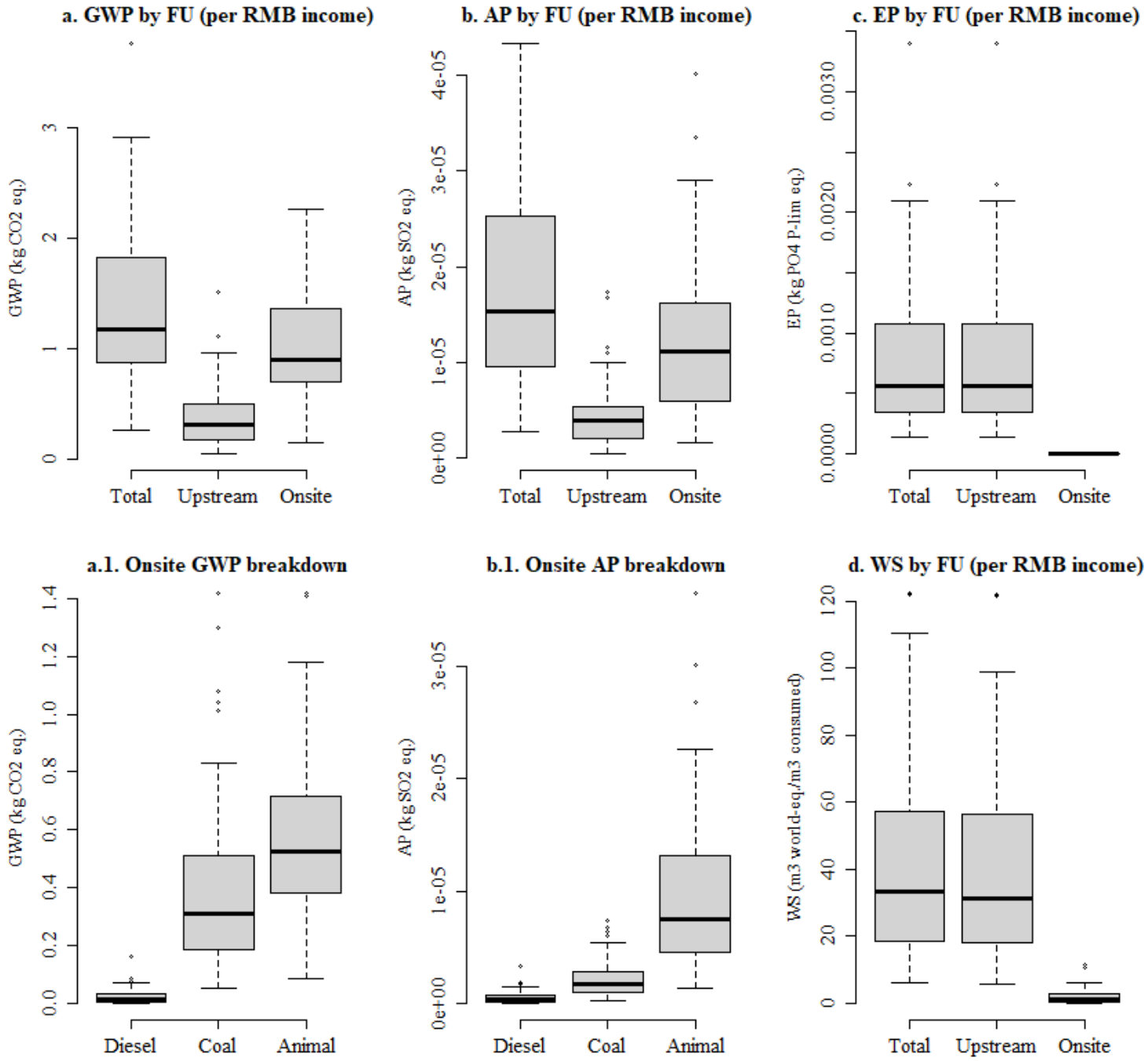

Figure 3

Total LCA results of the studied farms for GWP (a), AP (b), EP (c), and WS (d) by splitting upstream from onsite processes. The onsite processes for GWP and AP are further broken down by separating contributions from direct air emissions from diesel and coal burning and livestock raising.

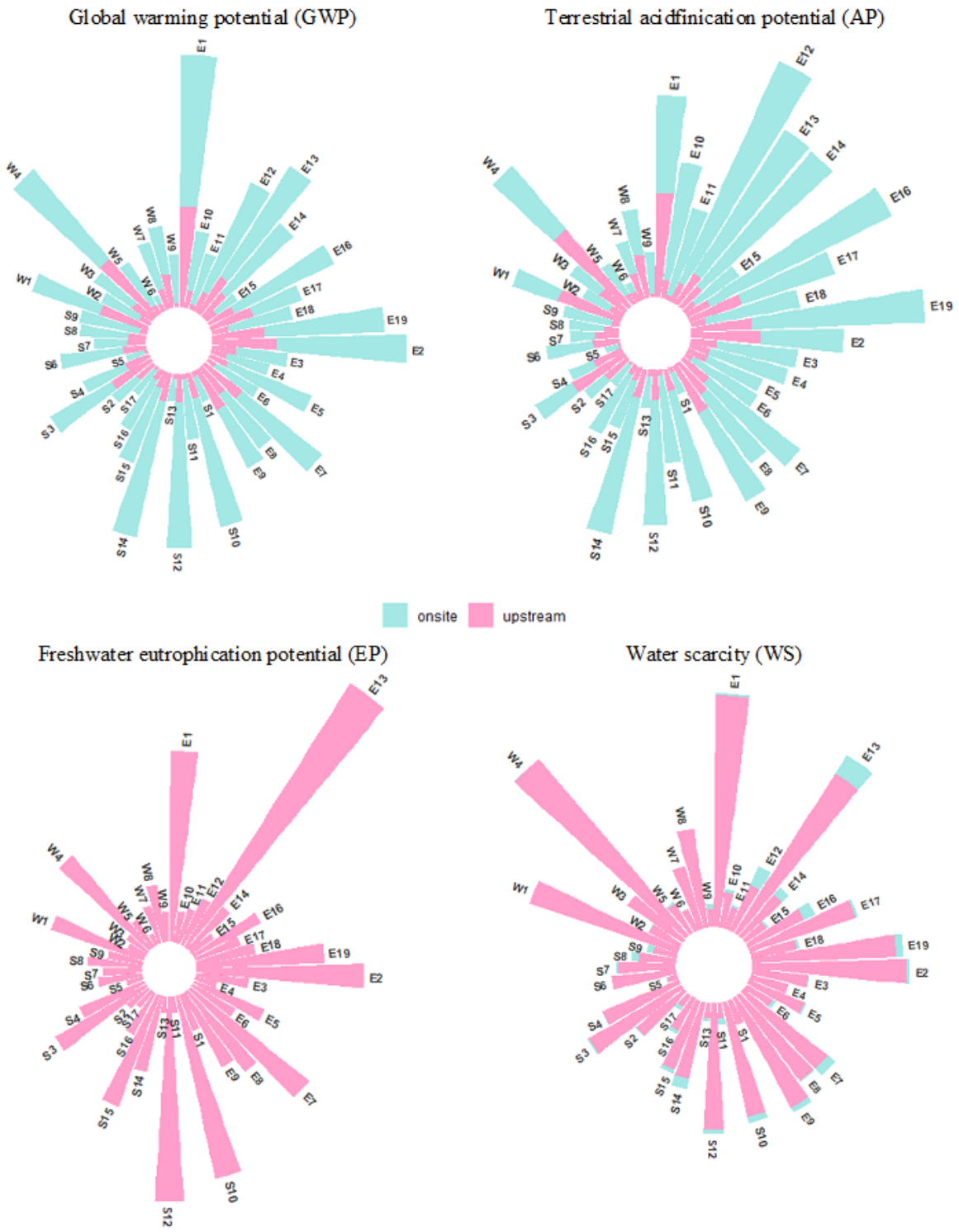

Figure 4

Upstream and onsite LCA results of the 45 studied farms for GWP, AP, EP, and WS, indicating the large variance between farms. The onsite processes dominate the GWP and AP while the opposite holds for the EP and WS.

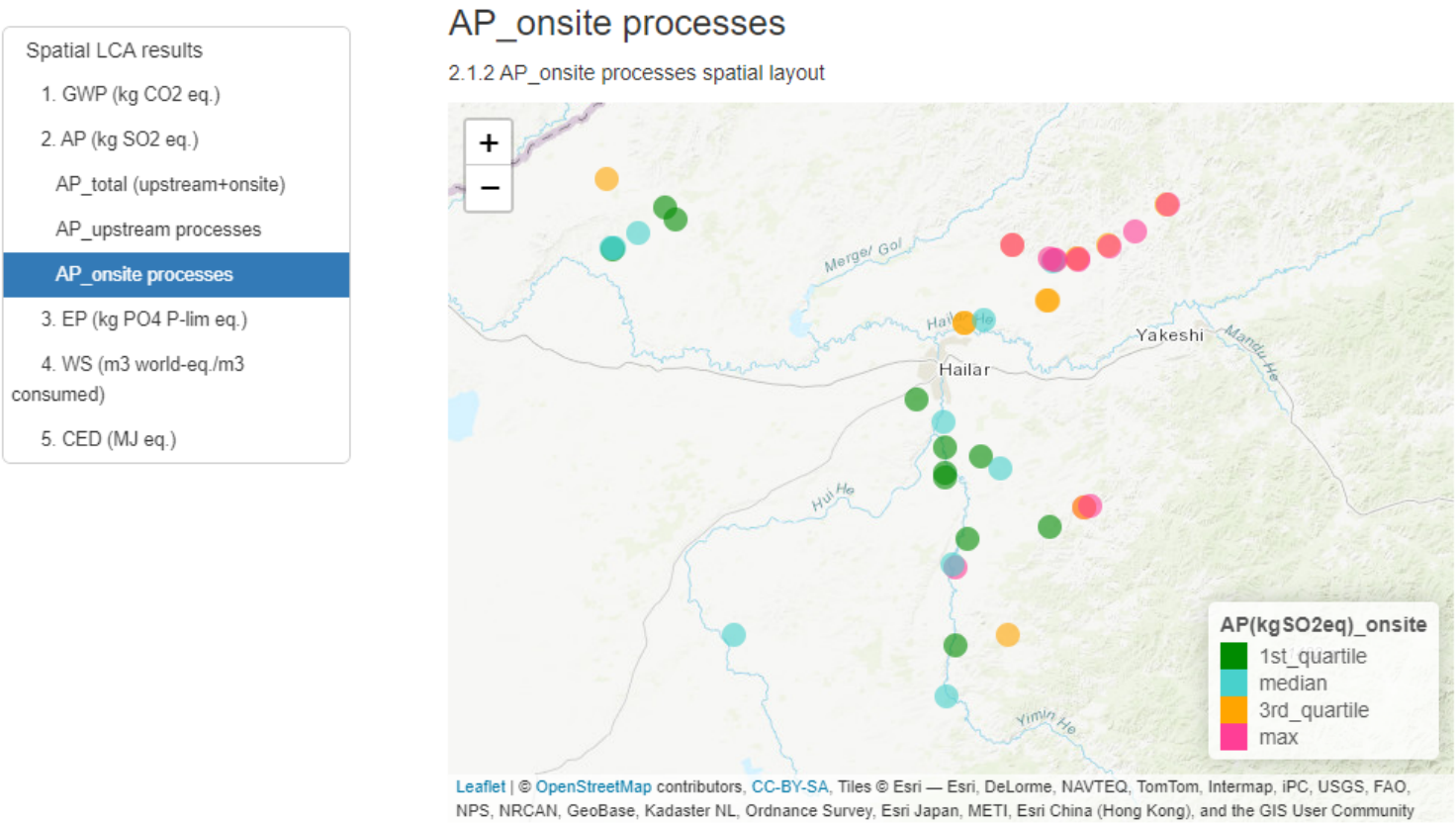

Figure 5

A screenshot of the LCA results shown on the map. The spatialized LCA results for the five impact categories are shown on a total of 13 interactive maps and accessible online https://susdatability.shinyapps.io/IM_SpLCA/. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.