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 variation and 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 dependency 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 life cycle impact assessment (LCIA) stage. Statistical evidence supported a high emission cluster for farms located close to Hailar city compared to a low cluster for those located further south/west of the city.

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 dependency of the LCA results was weak at the individual farm level, if present; it depended on the interactions between the 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 the policy challenge of how to increase production efficiency in the pastoralism system remains.
Introduction

Increasing demand for dairy and meat products in many countries calls for urgent actions to balance consumption and environmental impacts. A robust and scientific assessment is needed to understand and balance these impacts, as the dairy and meat production system is an integral part of the larger social-ecological system (Qi et al. 2017; Chen et al. 2018; Chen et al. 2020). 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, the 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 spatially explicit information and the 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 agricultural systems, where high spatial variation and sensitivity is present (Antón et al. 2014; Reinhard et al. 2017). Site-dependent impact categories, such as 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).

Patouillard et al. (2018) standardized nomenclature and definitions related to the spatial dimension in LCA. Inventory regionalization is differentiated from inventory spatialization, where the former improves the geographic representativeness of a product system and the latter attributes geographic information of an elementary flow. 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, b, 2014; Pfister et al. 2020). 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 spatial 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 coarse spatial scale of elementary flows (e.g., country-level data supplied by various LCI databases) makes it difficult to perform a 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 dataset 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 organize 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 splits the impacts due to direct onsite processes from everything else (i.e., upstream processes), following a practice similar to 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 of the 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.

Methods

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 east 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 (Fig. 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 for the non-grazing season, in addition to purchased feeds. Due to low milk prices and competition from domestic intensive dairy farms, local farm households rely mainly 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.

Spatialized LCA

Goal and scope

Farm-gate spatialized LCAs were conducted for 45 farms from the study area. Many of these farms engaged in multiple agricultural activities, 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 use 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 regard 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 estimated roughly from annual total energy costs. Consequently, we opted 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 (Fig. 2).
Life cycle inventory (LCI)

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). The DairyGEM model is a software developed by the United States Department of Agriculture (USDA) to estimate gas emissions such as greenhouse gas (GHG), ammonia, and hydrogen sulfide from dairy production systems. Input parameters for the model are provided in the supporting files (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) (refer to the “Availability of data and material” statement). Primary agricultural activity data were obtained from our field surveys conducted with farm owners during the summer of 2018. Spatial information was collected for onsite processes, while upstream processes were not spatially differentiated in this study.

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 the Ecoinvent database. Natural water resources are a major input for livestock 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). Embodied water 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/m²), average temperature (°C),
maximum temperature (°C), minimum temperature
(°C), total precipitation (mm), and mean daily wind
velocity (m/s) at 2 m above the ground were down-
loaded from NASA POWER Data Access Viewer,
which was used as the climatic input for the Dairy-
GEM model.

The farm location is associated with the emissions
from housing animals (e.g., onsite enteric fermenta-
tion 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 routes from
the farm to the haying site is associated with the
emissions from diesel-burning by tractors and agro-
machinery such as hay mowers. 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 individ-
ual farm households. This assumption is based on the
fact that for even the most spatially sensitive impact
category (i.e., freshwater eutrophication), its charac-
terization 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.

*Upstream processes* The activity data for the energy
and material input were obtained from field surveys,
and their associated emissions and resource
consumption were obtained from the Ecoinvent
database (Table 1).

*Life cycle impact assessment (LCIA)*

For the three impact categories that are spatially
dependent (i.e., water scarcity, freshwater eutrophica-
tion, and terrestrial acidification), we adopted the
characterization methods of IMPACT World+ (Bulle
et al., 2019) with SCFs developed for each impact
category at different 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 consump-
tion 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 excretion are extensively
involved. Only freshwater eutrophication is selected
as we focus on onsite processes, and marine eutroph-
ication is irrelevant due to the study location. The
eutrophication model of the IMPACT World+ is the
one developed by Helmes et al. (2012) with charac-
terization 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, b). 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 landscapes, a total of
three, four, and one set(s) of SCFs are identified for
onsite eutrophication, acidification, and water scar-
city, respectively.

Freshwater eutrophication is unique at approxi-
mately half of the farms, which are located in grid cells
with null values of CFs. Three different applicable
SCFs are identified for the other farms, which are all
located around Hailar city. In contrast, no correspond-
ing eutrophication CFs are applicable for those farms
located below 49° 00’ N in the study area, which
means those farms will have zero potential eutroph-
ication 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 (i.e., climate change and fossil fuel con-
sumption). 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. Brightway2 is
Table 1 Life cycle inventory (LCI) data—primary and secondary data for onsite and upstream processes used in the LCA modeling

| Item | Reference/description |
|------|-----------------------|
| **1. Primary agricultural activity data (surveyed and/or expert estimated)** | |
| **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 fiber (%DM) | 35 |
| **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** | Simulated using DairyGEM v3.3 |
| Onsite emissions from livestock raising, housing, and grazing | | |
| 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** | 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 |
| Diesel production (upstream processes) and onsite emissions during combustion | | |
| Coal production (upstream processes) and onsite emissions during burning | Ecoinvent v3.6 cut-off: unit process ‘heat production, lignite briquette, at stove 5-15 kW’—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’ |
an open-source python-based framework for LCA and offers unique advantages as compared to other conventional LCA software such as increasing the data and model transparency. 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 performed the impact assessment calculation. For all other activities (i.e., upstream processes), the default global CFs were applied to calculate impacts. Together with the site-dependent impact results, these were combined as the final farm-gate LCA results. Finally, the coefficient of variation was recorded among LCA results of different farms.

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 show the degree to which an LCA result of a farm is similar to its nearby farms.

Results

Contrasting results are observed for different impact categories regarding which process (upstream vs. onsite) is the environmental hotspot (Fig. 3). For both GWP and terrestrial acidification potential (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 freshwater eutrophication potential (EP) and water scarcity (WS), the major (and almost the only) contributors are 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 dependency of the LCA results is generally weak but becomes evident only when the spatial heterogeneity is introduced during the LCIA stage for selected impact categories. At the inventory stage, upstream energy consumption shows relatively stronger spatial dependency than all other processes. Direct onsite animal emissions do not show spatial dependency 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.

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. Larger 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 < 30%. For onsite processes, a detailed breakdown indicates that emissions from animals are the major contributor, followed by coal burning.

Spatial dependency 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 dependency 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 dependency. A detailed breakdown indicates that only the GWP from onsite coal burning shows weak spatial dependency (p-value < 0.05), similar to the spatial dependency shown on its raw consumption. The major GWP contributor for onsite processes—GWP from animal emissions—does not show any spatial dependency, nor do emissions at the inventory stage, as the LCIA stage does not involve SCFs for GWP.

Terrestrial acidification potential (AP)

Overall results for AP resemble those of GWP regarding the placing of the environmental hotspots. The major contributor for AP is from onsite processes, in particular, onsite animal emissions, due to the large amount of ammonia emissions associated with animal
Large variations were observed among all farms, and the coefficient of variation 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 (Fig. 3).

Strong spatial dependency (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 dependency, the resulting AP demonstrates the strongest spatial dependency among all impacts, indicating that the SCFs applied is the sole factor contributing to its spatial autocorrelation.

Freshwater eutrophication potential (EP)

In contrast with the 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 makes even a minor contribution. N-emissions from animals and diesel burning do not contribute significantly to EP.
not contribute 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 is dominantly contributed from coal production and purchased feed production. For the many farms that mainly rely on self-produced feed, coal production alone accounted for over half of the EP.

The overall spatial dependency 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, null 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 null value (p-value < 0.001), indicating that the spatial variation in the SCFs applied in the LCIA stage for EP has extensive effects on the final spatial patterns of the LCA results.

Water scarcity (WS)

Overall patterns for WS resemble those of EP, with the major contribution coming from the upstream process, which is typically over 20 times higher than that of the onsite process. One of the reasons for this 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 (m³ world-eq. per m³ 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 dependency 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 receives only 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 dependency of onsite processes for WS (p-value < 0.05) stems from the spatial dependency 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, demonstrates spatial randomness, similar to the spatial irrelevance shown in the onsite animal emissions.

Cumulative energy demand (fossil)

Only the 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 dependency (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 dependency shown in the cumulative energy demand (Figs. 4, 5; Table 2).

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 in landscape studies. We conducted a cradle-to-gate spatialized LCA by combining the SEFs with SCFs at

| Impact category | Median, mean | Coefficient of variation (CoV) |
|-----------------|-------------|-------------------------------|
| GWP_total (kg CO₂eq.) | 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.) | 1.53 × 10⁻⁵, 1.76 × 10⁻⁵ | 0.59 |
| AP_upstream | 3.91 × 10⁻⁶, 4.74 × 10⁻⁶ | 0.84 |
| AP_onsite | 1.11 × 10⁻⁵, 1.28 × 10⁻⁵ | 0.68 |
| AP_onsite_diesel | 3.53 × 10⁻⁷, 5.88 × 10⁻⁷ | 1.13 |
| AP_onsite_coal | 1.72 × 10⁻⁶, 2.28 × 10⁻⁶ | 0.82 |
| AP_onsite_animal | 7.55 × 10⁻⁶, 9.97 × 10⁻⁶ | 0.78 |
| Fossil_total (MJ eq.) | 4.58, 6.08 | 0.78 |
| EP_total (kg PO₄ P-lim eq.) | 5.58 × 10⁻⁴, 7.99 × 10⁻⁴ | 0.85 |
| EP_upstream | 5.58 × 10⁻⁴, 8.00 × 10⁻⁴ | 0.85 |
| EP_onsite | 0.00, 1.87 × 10⁻⁷ | 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 |

The final results consist of upstream and onsite processes, with onsite processes further breakdown into three sub-processes for GWP and AP.
the same spatial scale for onsite processes while making minimal effort to differentiate spatial information of the upstream processes.

At the inventory stage, for onsite processes, direct animal emissions associated with housing and grazing activities do not show spatial dependency, possibly due to the low variance in geophysical factors, as the farms surveyed cover a relatively small spatial extent with similar climate and soil conditions. This implies that the within-farm variability in the LCA results is mainly due to 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 inputs during inventory modeling in the DiaryGEM model, this finding supports the assumption 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 consumption demonstrate spatial dependency. In contrast, diesel consumption used for farming machines shows the least spatial dependency among all resource and energy inputs. Comparatively, consumption of coal and electricity, which are used as auxiliary inputs for the production system, show stronger spatial dependency than diesel. This (spatial) mismatch between energy consumption and production/economic output deserves further investigation, as consumption does not necessarily convert to productivity in our case. It remains a question for policymakers how to convert material and energy consumption to production efficiency in pastoralism systems.

We compared the carbon intensity of the studied pastoralism households with the average Chinese household. Compared to the CO₂ 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 CO₂ emissions for farmers in our study landscape 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), these results infer that the

Fig. 6 Boxplots of LCA results on farms with three spatial groups (farms located on east (E1-E19) vs. west (W1-W9) vs. south (S1-S17) as shown in Fig. 1), and two spatial groups (farms located close to Hailar city (E1-E19) vs. farms located further south and west of Hailar city (S1-S17 and W1-W9 combined)). P-values of the Kruskal–Wallis (K-W) and Mann–Whitney U (M-W) tests are labeled for each LCA impact category, with red color (p-value < 0.01) indicating strong evidence for rejecting the null hypothesis (same median from different spatial groups).
carbon intensity for a farmer at our study area 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 be assigned responsibility for the carbon inequality in the global value chains (Hubacek et al. 2017).

Among the three pastoral areas, farms located farthest away from Hailar city (the west pastoral area and the south area along the Yimin He) generally receive lower impact scores than farms located in the pastoral area close to and east of Hailar city. This raises the possibility of the existence of a high vs. low emission cluster for farms located close to Hailar compared to those located further south/west of the city. Correspondingly, a Mann–Whitney U test was conducted on two farm clusters (east vs. south & west farms). In addition, Kruskal–Wallis test was conducted on the original three farm clusters (farms located on east (E1–E19) vs. west (W1–W9) vs. south (S1–S17), Fig. 1). The results of the Mann–Whitney U test generally supported a high vs. low emission cluster for farms located close to Hailar compared to those located further south/west of the city. These evidences showed differences among the five impact categories, as AP showed the strongest statistical significance, followed by GWP, EP, and fossil, while no evidence of a high vs. low impact was observed for WS. The results of the Kruskal–Wallis test, on the other hand, did not support a significant shift in the impact scores among the three farm clusters due to the similar low impacts on farms located in the south and west (Fig. 6).

The final spatial pattern of LCA results varies due to both LCI and SCFs as well as their interactions, with no single factor solely responsible for 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 their 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 dependency at the inventory stage, its AP, in contrast, shows the strongest spatial dependency due to the application of SCFs. Compared with AP, a higher spatial resolution of SCFs for EP (0.5° × 0.5°) does not necessarily lead to a stronger spatial dependency 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

![Fig. 7 Sensitivity analysis (SA) on two hypothetical scenarios to replace the current coal burning utilising low-quality lignite with two alternative heating fuels: 1) a higher-quality anthracite and 2) natural gas. The SA was conducted for global warming potential (GWP) per functional unit (FU) for farm1, with the detailed process contributions separated (upstream vs. onsite). The “natural gas” case projected extensive reduction on the final GWP](image)

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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, albeit 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 conclude 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.

In addition, onsite coal burning was identified as an environmental hotspot for both GWP and AP, and a mitigation strategy for restructuring the local energy supply is desirable. Correspondingly, we conducted a sensitivity analysis on a hypothetical scenario to replace the current coal burning using low-quality lignite with two alternative heating fuels: (1) using a higher-quality anthracite without altering the current capital equipment (e.g., stove) and (2) switching to natural gas as the fuel source with more extensive capital investment. By assuming the same annual heating requirements, replacing the anthracite would only reduce the total GWP for the selected farm by 0.3%. In contrast, replacing the traditional onsite coal burning with cleaner fuel source (e.g., natural gas) would extensively reduce the total impacts of GWP by 20%. This sensitivity analysis did not incorporate more detailed and precise parameters (e.g., the impacts of establishing energy infrastructure to deliver natural gas). However, the results infer that policymakers should consider the possibility of entirely replacing open-air coal burning with other heating methods, which is likely to reduce environmental impacts as well as risks of adverse health effects for farmers (Fig. 7).

One of the limitations of our study, which is also a concern for agricultural LCAs, is related to the selection of appropriate FUs. Ideally, a single monetary-based FU supplemented by other physical-based FUs (e.g., hectare (ha), kg product, or MJ digestible energy) will improve understanding of the evaluated system. Yet this is challenging in a field survey of small-scale farm households from a practical perspective. The most accurate data that the farmers could provide was monetary-related, such as annual income, energy costs, and feedstock costs. The farmers did not have the capacity to record data such as the nutritional composition of feedstock, the content of milk fat, and protein produced. The estimation of their grassland area and self-produced forage was also very rough without a detailed data recording system. More importantly, as stated in the methods, as multi-purpose livestock production systems, these farms usually engaged in production of milk, beef cattle (including calves and culled dairy cows for fattening and feeding, which were slaughtered after fattening), and other livestock (such as sheep, horses, donkeys and camels). Such complex production systems prevented us from adopting a physical FU without precise data and a common measurement for product conversion, as no standards of production currently exist for the study areas.

This lack of data and data quality issue also impact the overall robustness and reliability of results. We were only able to keep two-thirds of farms surveyed in the final analysis, again 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 the suppliers. This prevented us from selecting the unit process that is most 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, rather than 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 a lack of an appropriate methodological choice (van der Werf et al. 2020).

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 spatial sensitivity in the agricultural system. Through surveying 45 farms in
Hulunbuir Grassland in Inner Mongolia, contrasting results were received for different impact categories, as the upstream processes acted as environmental hotspot for GWP and AP, while the onsite processes dominated EP and WS. Direct animal emissions did not show spatial dependency at the inventory stage, indicating that farming practices are the dominating factor for impacts from livestock. On the other hand, the impact scores from these emissions 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 production efficiency was observed among the farms, and this remains a challenge to policymakers (i.e., to convert material and energy consumption to production efficiency in the pastoralism system). As an environmental hotspot for both GWP and AP, it is suggested that policymakers consider the possibility of restructuring the current energy supply, such as by replacing open-air coal burning with other heating methods. While the overall spatial dependency of the LCA results of studied farms was generally weak at the individual farm level, statistical evidence supported a high vs. low emission cluster for farms located close to Hailar city compared to those located further south/west of the city. And when the spatial dependency existed, the final spatial pattern was determined by both the spatial information incorporated within the LCI and the spatial heterogeneity introduced during the LCIA, as well as their interactions.

Author contributions SRW: conceptualized the work, performed the calculations/coding, wrote the manuscript. XL: conducted the site visit and field survey, assisted in data processing, analysis, and mapping. LW: conducted the site visit and field survey, assisted in data processing and analysis. PZ: performed the spatial analysis. JC: conceptualized the work, contributed to the manuscript writing. CS: helped with the proposal writing and funding.

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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/.

Declarations

Conflict of interest Not applicable.

Ethical 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.

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