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Quantification and valuation of ecosystem services in life cycle assessment: Application of the cascade framework to rice farming systems

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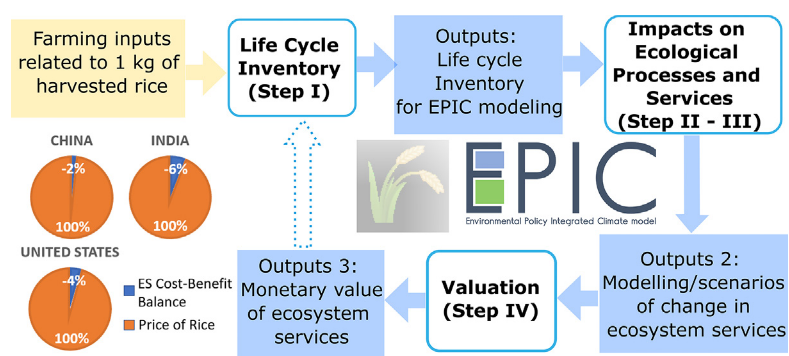
HIGHLIGHTS

- Advances are made on ecosystem services (ES) in lifecycle impact assessment (LCIA).
- This ES-LCIA framework integrates ES cascade model in LCIA cause-effect chain.
- We use spatially explicit deterministic modelling to assess four ES in rice farming.
- We derive cost-benefit balances for a unit of rice produced in China, India and USA.
- Negative cost-benefits for rice suggest that ES suffer more impacts than benefits.

GRAPHICAL ABSTRACT



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ABSTRACT

The integration of ecosystem service (ES) assessment with life cycle assessment (LCA) is important for developing decision support tools for environmental sustainability. A prequel study has proposed a 4-step methodology that integrates the ES cascade framework within the cause-effect chain of life cycle impact assessment (LCIA) to characterize the physical and monetary impacts on ES provisioning due to human interventions. We here follow the suggested steps in the abovementioned study, to demonstrate the first application of the integrated ES-LCIA methodology and the added value for LCA studies, using a case study of rice farming in the United States, China, and India. Four ES are considered, namely carbon sequestration, water provisioning, air quality regulation, and water quality regulation. The analysis found a net negative impact for rice farming systems in all three rice producing countries, meaning the detrimental impacts of rice farming on ES being greater than the induced benefits on ES. Compared to the price of rice sold in the market, the negative impacts represent around 2%, 6%, and 4% of the cost of 1 kg of rice from China, India, and the United States, respectively. From this case study, research gaps were identified in order to develop a fully operationalized ES-LCIA integration. With such a framework and guidance in place, practitioners can more comprehensively assess the impacts of life cycle activities on relevant ES

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Rice farming

provisioning, in both physical and monetary terms. This may in turn affect stakeholders' availability to receive such benefits from ecosystems in the long run.

1. Introduction

To comprehensively assess environmental impacts from products, technologies or systems, quantitative and holistic tools and methodologies such as life cycle assessment (LCA) are required. LCA is an ISO-methodology, which aims to quantify damages from human activities to ecosystems, human health and resources (ISO, 2006). An essential element of LCA is the life cycle impact assessment (LCIA) phase, which translates resource use or pollutant emissions into potential impacts using modelling of environmental cause-effect chain. Yet, major gaps still exist in the cause-effect chain, in particular in capturing damages to ecosystems services (ES), which represent the flow of benefits ecosystems provide to people (Verones et al., 2017). Many on-going research efforts nowadays attempt to address the computational challenges of integrating ES concepts into LCIA, as summarized in Rugani et al. (2019). These efforts call for a systematic and consistent methodology that accounts for the effects of human activities on ES provisioning. Therefore, a dedicated working group aiming to address this issue was established, under the United Nations (UN) Environment Program's Life Cycle Initiative flagship project on global guidance for LCIA indicators (UN Environment - Life Cycle Initiative, 2019; Verones et al., 2017).

As a response, Rugani et al. (2019) proposed a methodology, abbreviated as ES-LCIA, that integrates the ES cascade framework within the LCIA cause-effect chain to assess the impacts on ES provisioning. The proposed ES-LCIA methodology involves four steps, which are essential for addressing environmental costs and benefits resulting from human interventions. Step I in the proposed methodology is the inventory collection, the output of which is the life cycle inventory (LCI) associated with the functional unit. Step II (i.e. impacts on ecological processes) represents the interactions between the LCI and the ecological processes. In the ES cascade framework this step is where human pressures operate on ecosystems, while in LCA this step is where LCI (i.e. the inventory of human pressures) is translated to midpoint and endpoint impact indicators by applying characterization factors (CF). The outputs of Step II are the calculated impact category indicators. The alignment of ES classes, LCI flows and LCIA indicators is provided in Table 2 of Rugani et al. (2019). Step III calculates how the impacts from Step II influence the capacity of ecosystems to deliver final ES.[1] For instance, within the proposed model, the ecological processes that have been impacted can be linked to one or more stressors, such as land use changes, and in this case each type of land use can be regarded as a service provisioning unit. The output of Step III is a matrix of ES supply change. Both semi-quantitative and quantitative approaches can be applied in this step, and more details are discussed in Rugani et al. (2019), who also suggest to explore different solutions to create a robust model. It is worth mentioning that Step II and Step III are likely to overlap to some degree. For example, the global warming potential (GWP) includes the ecosystem's response due to atmospheric CO_2 fertilization (i.e. increased CO_2 removal that results from higher atmospheric CO_2 concentration). To align the existing LCIA method for GWP into the Step II and Step III dichotomy, a divorce of the ecosystem's response embedded within GWP is needed, which can be difficult to implement. Step IV eventually delivers a vector representing the benefits and costs associated with the change in ES per functional unit. The value of ES can be quantified in both physical terms and monetary units. The output from this step can be used to account for ES synergies and trade-offs. If monetary units are used, an aggregated end-point cost-benefit balance can be calculated.

For consistency and reliability, the methodology needs to be able to simulate the functioning and response of ecosystem processes, and their interactions with technological activities. The networks of technological and ecological systems are complex and nonlinear. Therefore, the linear scaling nature of conventional LCIA renders the tool insufficient for this task. Instead, ecosystem modelling tools with complex, non-linear functions may be necessary when it is clear that linear approximations result in poor assumptions. This has been suggested in Rugani et al. (2019) as a possible solution to overcome the dichotomy between Step II and Step III mentioned above. These tools consider human impacts on ecosystem structures and functions that underpin ES provisioning, as well as interactions between processes at the ecosystem level.

Many ecological models are available to quantify the capacity of various ecosystem components to provide services (Grêt-Regamey et al., 2017; Posner et al., 2016; Turner et al., 2016). One example is i-Tree, a tool for assessing and managing forests (i-Tree Canopy, 2018): the potential sequestration capacity of CO_2 and criteria air pollutants (CAP) can be quantified based on properly defined tree species, ages, and other key parameters. Another example is a wetland model that was developed to quantify the capacity of a wetland to eliminate water pollutants and excessive nutrient run-off (Kadlec, 1997). A third relevant example is the Environmental Policy Integrated Climate (EPIC) model, which is a cropping system model that can simulate the movement of carbon, nitrogen, phosphorus, and sediment - and thus the impacts on crop yield, soil loss, and water quality - with properly defined crop types, management decisions, and weather and soil conditions (Texas A&M AgriLife Research, 2015). LCI data (i.e. outputs of Step I) can be used as inputs for ES modelling, the outputs of which depict the change in ecosystem's capacity to provide ES (i.e. outputs of Step III), and can be adapted for further benefit/cost assessment (i.e. Step IV) along the life cycle. However, the full implementation of this coupling between LCI and ES models can be complex and challenging, especially when the background system also needs to be characterized.

For the proposed ES-LCIA framework to be operational, the changes in ES provisioning need to be measured. To fulfil this need, ES accounting methods, such as the Techno-Ecological Synergy in LCA (TES-LCA) developed by Liu and Bakshi (2019) can be employed. Two terminologies are introduced in TES-LCA for ES accounting, namely the *supply* and *demand* of ES. “ES supply” is the capacity of ecosystems to provide benefits to people, without harming its potential to provide these benefits in the future. On the other hand, human activities demand ES to mediate their impacts (hereinafter referred to as “ES demand”). For example, manufacturing activities may emit CAP and thus demand the air quality regulation ES provided by tree canopy to mitigate their harm to human health and ecosystems. Many, but not all, ES demand flows are represented in LCI databases as elementary flows (e.g. resource extraction flows from ground, pollutant emissions to air, etc.). In contrast, most ES supply flows (e.g. climate mitigation, water purification, particulate matter removal from air, etc.) could be seen through the LCIA lens as contributing to a reduction of impacts resulting from human activities. It is noteworthy that the demand for ES can exceed the ecosystem's capacity to supply them. But such exceedance cannot be sustained in the long run (Villamagna et al., 2013). For example, human activities have emitted more greenhouse gases (GHG) than what the natural capacity could accommodate to sequester them, which has led to increasing atmospheric CO_2 concentration, and thus negative impacts on ecosystems. In this case, we can claim that our demand for ES has

[1] Final ES are the end products of ecosystems that are directly relevant to beneficiaries; Intermediate ES are those, which underpin the outputs of final ES, but are not directly used by beneficiaries (Rugani et al., 2019).

exceeded its supply. The difference between the two components can provide an indication on whether the ecosystem has capacity to assimilate additional impacts, while sustaining its capacity to supply ES in the future. It also provides information about the reductions needed to operate within nature's carrying capacity. To provide a better idea from this perspective, they developed the sustainability metrics (v_k). For a given ES *k*, v_k is defined by subtracting its demand (d_k) from its supply (s_k) and then normalizing by its demand (Eq. (1)). v_k ranges from −1 to infinity. If v_k is equal to −1, it indicates that there is no supply of ES. If v_k is higher than 0, the ecosystem can provide mitigation for supplementary demand.

$$v_k = \frac{s_k - d_k}{d_k} \tag{1}$$

In this study, we demonstrate the first application of the integrated ES-LCIA assessment framework to a proof-of-concept case study of rice farming, introduced as part of the flagship project aiming at providing global guidance on environmental LCIA indicators under the UN Environment's Life Cycle Initiative (Frischknecht et al., 2016; UN Environment - Life Cycle Initiative, 2019). This work is also relevant to meeting the UN Sustainable Development Goals (SDG), such as SDG-14 ("life below water") or SDG 15 ("life on land"). We employ the TES-LCA methodology for ES accounting. Three rice producing regions are considered, namely, China, India and the United States (US). Four ES are assessed, namely, carbon sequestration, water provisioning, water quality regulation, and air quality regulation. Challenges and future research needs to make this approach fully operational are identified and discussed in order to advance the understanding of how to design and apply the integrated ES-LCIA framework.

2. Materials & methods

2.1. Goal and scope definition

The ES-LCIA framework proposed in Rugani et al. (2019), and briefly summarized in Section 1, was applied to a modified version of the rice case study proposed in Frischknecht et al. (2016). The original system boundary included rice farming, processing, distribution, and cooking, whereby the functional unit (FU) was represented by the consumption of 1 kilogram (kg) of cooked rice in India, China and Switzerland (the three consumer countries assumed in Frischknecht et al. (2016)). Because ES are expected to be more relevant to farming production, as compared to other life cycle stages, the present case study focuses only on the farming stage, thus redefining the FU to be the production and harvesting of 1 kg of rice in China, India and the US. It is noteworthy that the rice consumer countries and the rice producing countries are different, since in Frischknecht et al. (2016), they assumed that the rice was produced and processed in the US, and distributed and cooked in Switzerland.

The goal of this study is to evaluate and compare the change in ES provisioning where the land is managed to produce rice. Rice farming requires extensive chemical inputs, irrigation, and tillage, and therefore changes soil's properties and structure, as compared to the reference scenario where land is fallow with no rice farming activity taking place. The crop systems model EPIC is applied to model the cause-effect chain from rice farm LCI flows to the change in ES provisioning.

Several ES were identified as particularly relevant to rice farming activities, namely carbon sequestration, water provisioning, water quality regulation, and air quality regulation. These services were classified using the Common International Classification of Ecosystem Services (CICES) framework (Haines-Young and Potschin, 2018). Table 1 shows the selected ES quantified in this study according to the CICES 5.1 taxonomy. The CICES classification allows the matching between the impacts from human activities (i.e. ES demand) and the capacity of ecosystems to mediate the corresponding impacts (i.e. ES supply). The tick marks represent the correspondence between ES and the substances included in the LCI of the rice case study. The red cells represent the environmental intervention flows from human activities, generally assessed by the LCA community; and the green cells are related to ecosystem functioning and are commonly considered by the ES community. The table depicts how we translate the terminologies between these two communities in the ES-LCIA framework.

2.2. Integration of ES-LCIA modelling

Fig. 1 summarizes how the ES-LCIA integration proposed in Rugani et al. (2019) has been adapted for this study, with details for each step elaborated in each subsection below. All model and data files required to reproduce the results in this study are available free of charge at http://dx.doi.org/10.17632/m5xwds4x8r.1.

2.2.1. Data and modelling for Step I

In Step I (Fig. 1), changes in land use and management practices can be modelled as an LCI flow (e.g., changing the tillage practice may act as a stressor on the agricultural system). LCI data for irrigation water use and fertilizer application rates for rice farming are based on Frischknecht et al. (2016). We considered emissions of three GHGs, namely carbon dioxide (CO_2), nitrous oxide (N_2O), and methane (CH_4). Rather than relying on estimates from Frischknecht et al. (2016), CO_2 and N_2O emissions were modelled using the EPIC model to provide more spatial resolution for the case study. However, because the EPIC model does not provide results for CH_4 emissions, inventory values from Frischknecht et al. (2016) were used for it.

The EPIC model was selected to compile part of LCI and assess the impacts of farming activities on the change in ES because of three main reasons. First, the proficiency of EPIC model has been previously demonstrated and validated for the rice agroeconomic system (Xiong et al., 2014). Second, the EPIC model utilizes spatially explicit data for environmental characteristics, such as weather, soil, and management practices, to simulate the impacts on ES provisioning. This enables a comparison of performance between rice farms in the three countries, China, India, and the United States. Third, the EPIC model quantifies the changes in the capacity of ecosystems to provide services due to the farming activity, relative to the reference scenario.

Various data sources were used to build these farming scenarios in the EPIC model, with different degrees of assumptions. First, seeding and harvesting dates were obtained from Sacks et al. (2010). Then, specific input data to characterize the local environmental conditions were collected. Radiation and relative humidity data were obtained from the National Aeronautics and Space Administration (NASA, 2018). Wind velocity data were obtained from WindAtlas (2018). Daily minimum temperature, daily maximum temperature, and precipitation data were obtained from iAIMS Climatic Data (2018). Soil characteristics, such as texture, density, and organic matter content, were obtained from SoilGrid (2018). Finally, farm management practices, including the amount and timing of chemical application, the type and timing for field operations (i.e., tillage practices), and the use of machinery, were modelled using the built-in rice management schedule in the EPIC model and the data collected from the LCI developed in Frischknecht et al. (2016).

The procedure discussed in Xiong et al. (2014), which provides means and standard deviations of key crop parameters for rice farming in difference continents, was used to calibrate our application of the EPIC model. The calibration process adjusts influential parameters and inputs of the EPIC model for them to stay within their reasonable ranges, so that the model results are realistic. After the calibration, the EPIC model can be executed to provide results for rice farms in the three countries on farming energy use, GHG emissions, and nutrient runoff (i.e., nitrogen, phosphorus). Because the EPIC model does not have pesticide profiles corresponding to those provided in the LCI of Frischknecht et al. (2016), the pesticide impact factors were assumed

Table 1
Selected ecosystem service (ES) implemented in this study and grouped according to the Common International Classification of Ecosystem Services (CICES) 5.1 taxonomy.

	Flows from Ecosystem Sphere Terminology: ES supply or life cycle impact mitigation				
	Section	Regulation & maintenance (biotic)			Provisioning (abiotic)
	Division	Regulation of physical, chemical, biological conditions	Transformation of biochemical or physical inputs to ecosystems	Regulation of physical, chemical, biological conditions	Water
	Group	Atmospheric composition and conditions	Mediation of wastes or toxic substances of anthropogenic origin by living processes	Water conditions	Surface water used for nutrition, materials or energy
	Class	Regulation of chemical composition of atmosphere and oceans	Filtration/sequestration/storage/accumulation by micro-organisms, algae, plants, and animals	Regulation of the chemical condition of freshwaters by living processes	Surface water used as a material (non-drinking purposes)
	Corresponding terminology used in this paper	*Carbon sequestration*	*Air quality regulation*	*Water quality regulation*	*Water provisioning*
Flows from Technology Sphere Terminology: Life Cycle Inventory or ES demand	CO (to air)		√		
	NO_x (to air)		√		
	PM_{10} (to air)		√		
	SO_x (to air)		√		
	CH_4 (to air)	√	√		
	N_2O (to air)	√			
	CO_2 (to air)	√			
	Nitrogen (to water)			√	
	Phosphorus (to water)			√	
	Water (from ground)				√

to be 1 in this study, meaning that rice yield was not subject to pest damages.

For the emissions of CAP, including carbon monoxide (CO), nitrogen oxides (NO_x), sulphur oxides (SO_x), and particulate matter (PM_{10}), it is assumed that they were primarily emitted due to the combustion of diesel in farming machinery, therefore the corresponding emission factors were obtained from the GREET model (Energy Systems. Argonne National Laboratory, 2018) to convert diesel consumption to CAP emissions. Each LCI profile per FU contains resource, land, and emission flows.

2.2.2. Data and modelling for Steps II & III

As indicated in Fig. 1, Steps II and III are combined in this study because the EPIC model provides results for Steps II and III simultaneously and it was not technically possible to decouple the ecosystem's response from the impacts. However, merging Steps II and III is still in line with the scope of the cascade framework proposed in Rugani et al. (2019), since there is no loss of information regarding the changes in the ecosystem's capacity to supply ES due to the impacts on the production system: this information is still considered within the supply-demand approach.

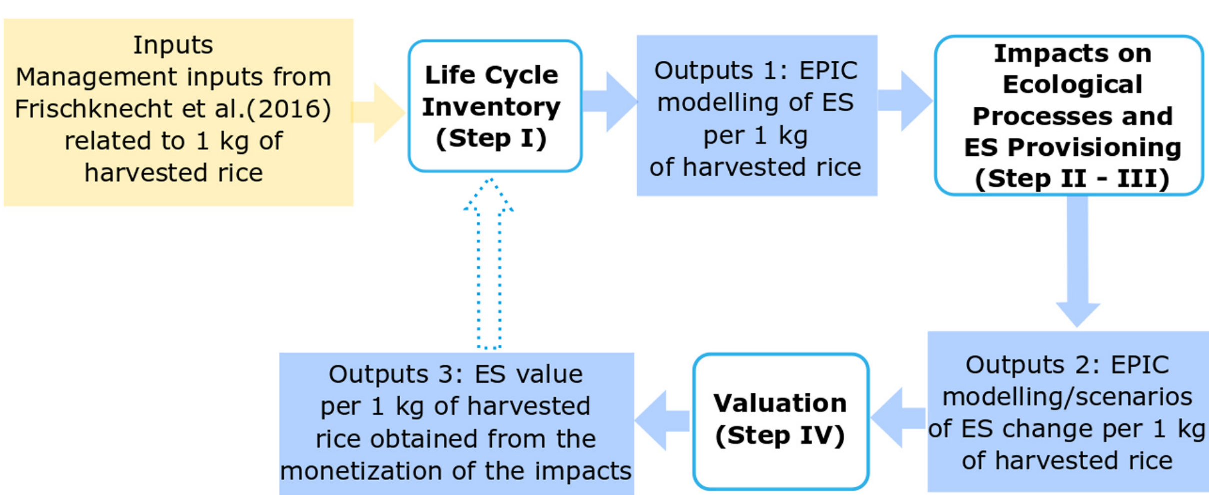

Fig. 1. Application of the ES-LCIA framework to the rice case study. Note that Step II and Step III, as outlined in Fig. 1 of Rugani et al. (2019), are now combined and feedback loops are not considered (as indicated by the dotted arrow).

Step II characterizes the impacts on ecosystem structure and outputs impact category indicators. In the context of this case study, rice farming may change soil's properties and structure, and thus have environmental implications in various impact categories. The calculation of midpoint indicators was not carried out explicitly in this study, but CFs were used when trying to combine flows contributing to the same impact category. For example, to calculate net climate regulation, CO_2, CH_4, and N_2O flows were converted to unit of mass of CO_2 equivalent. Step III translates the change in land use (i.e., from fallow lands to rice farms), to the change in the flow of final ES over time (i.e. the net ES that are still available to the final beneficiary), which can be monetized in Step IV.

On one hand, for carbon sequestration and water provisioning ES, both their demand and supply are directly related to the rice farming activity (i.e. the EPIC model can be utilized to quantify both the demand and supply components). For example, which tillage practice to be implemented affects the amount of fuel used (i.e., conventional tillage incurs more fuel consumption compared to no tillage). The different level of CO_2 emission due to fuel combustion represents varied quantities of ES demand. The tillage practice would also affect the percentage of plant residues left on the field, thus changing the agro-ecosystem's capacity to supply carbon sequestration service in the form of soil organic carbon.

On the other hand, for services of air quality regulation (the remediation of local ecosystem for CAP) and water quality regulation (self-cleaning capacity of local water body for fertilizer runoff), only their demands change with rice farming activities. For instance, different fuel consumption rates result in different levels of air pollutants emissions; while various amount of fertilizer application rates lead to various quantities of nutrient runoff. However, the EPIC model does not provide an estimate of the agro-ecosystem's capacity to provide these services (i.e., their supplies). This might be due to a gap in modelling the cause-effect relationship between midpoints impacts and ES provisioning or simply because the supply of these services from rice farming activities are negligible. In both cases, we have assumed that the air and water pollutants cannot be mitigated by the rice farming activity itself, resulting in an onsite ES supply of 0. We refer to this as the "0% Supply" scenario hereinafter.

Nonetheless, in this study, we want to demonstrate how the final ES available from the land would change, as compared to the reference land use scenario. To do so, and to cope with the lack of more site-specific data, we have adopted a sensitivity analysis approach for the assessment of air and water quality regulation ES, by constructing plausible land use scenarios where the supply of these services are made available from the piece of land being managed to produce rice.

The supply of air quality regulation ES would have been available if part of the land was used for reforestation. It was assumed that 5%, 10%, and 15% of the land area was used for forests to show how the results progress with different constructed scenarios. The removal rates of CO_2, CO, NO_x, SO_2, and PM_{10} by trees were available from the i-Tree Canopy tool, with a county-level resolution (i-Tree Canopy, 2018). Because i-Tree data pertain to locations in the United States only, climate zones were identified and matched to similar regions in the United States for rice farming systems in China and India. The sequestration rates from the counties within the corresponding United States climate zone were averaged to approximate those from China and India rice farms.

Similarly, water quality regulation ES would have been provided if part of the land was used for wetland construction, because wetlands have a self-cleaning capacity. It was assumed that 0.5%, 1%, and 1.5% of land area was used for wetland development. A wetland model was used to determine nutrient removal capacity with a steady-state, first-order approximation (Kadlec, 1997). Wetland inlet nutrient concentrations were estimated based on the amount of nutrient and water runoff from the EPIC model simulations. Outlet nutrient concentrations after treatment depended on water surface temperature, hydraulic loading rate, and wetland characteristics (i.e. area, bed porosity, and depth). The provisioning of water quality regulation ES was calculated from the difference between the inlet and outlet nutrient concentrations and the amount of water runoff. The demand for water quality regulation equalled the amount of nutrient runoff. Background concentrations of nitrogen and phosphorus were 1 mg/L and 0.02 mg/L, respectively, which set the limit for treatment. In this case, the supply of water quality regulation never exceeded demand (i.e., v_k was never larger than 0, while close to 0 indicated sustainable performance), because the assumption is that the concentration of nitrogen and phosphorus at the wetland outlet cannot be negative or less than the treatment limit.

Nonetheless, in the conceived scenarios, where part of land is used for reforestation or wetland construction, the total amount of rice produced from the land would decrease. This might cause expansion of rice farming elsewhere to satisfy the overall rice demand, which is beyond the scope of this study. It is noteworthy that trade-offs exist between ES (i.e., the ability of land to maintain rice yield versus other types of ES, as mentioned above). The level of such a trade-off varies according to the ES considered. Vide infra, a small wetland can mitigate most of the nutrient runoff, with only little sacrifice in yield; while the trade-off between air quality regulation and yield provisioning ES might be more significant.

2.2.3. Data and modelling for Step IV

Finally, results from modelling ES changes from Step III were translated into monetary terms to derive a cost-benefit balance for the FU. Monetary profit from rice farming was calculated from the difference in ES provisioning and the cost of mitigating ecosystem impacts for each service (Table 2). The rationale underpinning final ES valuation is that if the demand of an ES does not exceed the carrying capacity of the corresponding ecosystems to supply it, then there would be a net "benefit", which can be potentially applied to mitigate impacts from other sources. Otherwise, a net "cost" is recorded.

2.3. Results for steps I

Average rice yield data were provided in Frischknecht et al. (2016) as 7452, 6450, and 3500 kg/ha, respectively, for the United States, China, and India farms. However, in the current study, all rice yields were calculated endogenously within the EPIC model. The resulting location-specific rice yields were 6226, 6202, and 3363 kg/ha, and thus did not match exactly with those from Frischknecht et al. (2016), especially for the United States farm. The differences could be resulted from the use of localized information that includes spatial heterogeneity when running the EPIC model, while the prior case study used regional, average yield data.

2.4. Results for steps II-III

The results for the four ES under consideration, namely carbon sequestration, water provisioning, air quality regulation, and water quality regulation, based on 1 FU (i.e., 1 kg of rice harvested), are summarized in Fig. 2.

For carbon sequestration, the CO_2, CH_4, and N_2O emissions from soil and farming operations are regarded as "demand"; and the carbon content of plant residual incorporated into the soil as "supply" (Liu and Bakshi, 2019) (Fig. 2a). Note that emissions of CH_4 and N_2O are combined with CO_2 by applying their corresponding CF to calculate global warming potential in terms of kg CO_2 equivalent. For all farms, the amount of GHG emitted from rice paddy was lower than that can be sequestered, resulting in positive v_k metrics. These results are consistent with Fan et al. (2015), which suggests that with proper management, soil organic carbon accrual is feasible for rice farms, leading to net carbon gains. CH_4 emissions also contributed to the global warming potential of rice farms, ranging from 23% for a farm in India to 58% for a farm in the United States. However, in this study, the inventory for CH_4

Table 2
Monetary data collected for the valuation step of the cause-effect chain based on the cascade model proposed by Rugani et al. (2019).

Type of monetary data/rationale	Original value	Unit	Reference flow	Region	Source	Conversion factor[a]	Final monetary value	
Mean willingness to pay for off-farm surface water used for irrigation.	0.0270	2016 US $/m^3	Surface water	Arkansas (United States)	(Knapp et al., 2018)	1.07	0.0289	$/m^3
Value of environmental externalities based on the average carbon tax rate (among Sweden, Norway, Finland and Denmark = 14.25 €/t CO_2-eq.	0.0783	2006 US $/kg CO_2-eq.	GHGs emissions: CH_4, CO_2, N_2O	Jiangsu (China)	(Lv et al., 2010)	1.29	0.1010	$/kg CO_2-eq.
External benefit of carbon sequestrated by the farming system (using the same carbon tax rate)	0.0782	2006 US $/kg C seq.	Carbon sequestration	Jiangsu (China)	(Lv et al., 2010)	1.29	0.1009	$/kg C seq.
A Social Cost of Atmospheric Release (SCAR) model is used to provide a valuation of air emissions in terms of damages per ton of pollutant (cost of injury/replacement; scenario: median total; declining rate).	0.73	2007 US $/kg	CO	Global average	(Shindell, 2015)	1.25	0.9125	$/kg CO
A Social Cost of Atmospheric Release (SCAR) model is used to provide a valuation of air emissions in terms of damages per ton of pollutant (cost of injury/replacement; scenario: median total; declining rate)	47	2007 US $/kg	NO_x	Global average	(Shindell, 2015)	1.25	58.7500	$/kg NO_x
Value of air pollution removed by trees in the Greenbelt (rationale: potential costs of human impact if natural capital is depleted).	5.01	2005 CAD$/kg	PM_{10}	Ontario (Canada)	(Wilson, 2008)	0.97	4.8597	$/kg PM_{10}
A Social Cost of Atmospheric Release (SCAR) model is used to provide a valuation of air emissions in terms of damages per ton of pollutant (cost of injury/replacement; scenario: median total; declining rate).	42.00	2007 US $/kg	SO_2	Global average	(Shindell, 2015)	1.25	52.5000	$/kg SO_2
Value of environmental externalities based on the external cost of nitrogen fertilizer.	1.21	2006 US $/kg N	Nitrogen (leaching & runoff)	Jiangsu (China)	(Lv et al., 2010)	1.29	1.5609	$/kg N
Phosphorous abatement costs; lowest estimation.	1.50	Euro/kg P	Phosphorous (leaching & runoff)	European average	(Prokofieva et al., 2011)	1.17	1.7550	$/kg P

[a] Equivalent actual value adjusted with Consumer Price Index (CPI-inflation), in 2018 US$ (source of calculation: http://fxtop.com/en/currency-converter-past.php) Results.

emission was based on regional average values obtained from Frischknecht et al. (2016), because the EPIC model does not simulate CH_4 emissions.

The demand for water provisioning is characterized by irrigation water use and the evapotranspiration rate of rice crop, while its supply is determined by precipitation (Chan et al., 2006; Liu and Bakshi, 2019). The rice farm in India has the greatest water demand; however, if demand is compared to supply using the v_k metric, then the United States farm performs the worst, with a v_k of −0.25 (Fig. 2b). Comparing China and United States farms, the supply of water is similar, but because the farm in China uses less irrigation water, its environmental performance is better (i.e., the v_k value for the Chinese farm is close to zero, greater than the United States farm).

Results for air quality regulation for multiple air pollutants, i.e. CO, NO_x, PM_{10}, and SO_2, are illustrated in Fig. 2c–f. Demands are determined by their corresponding emissions from the combustion of diesel in farming machinery. At the farm scale, the supply of air quality regulation ES is approximately zero. Some deposition of air pollutants on rice crops may occur; however, rice has a relatively small leaf area index (Fagade and De Datta, 1971), therefore, its capability to provide air quality regulation is limited and thus ignored. In the constructed land use scenarios, we assume that part of farmland is converted to forest land to mitigate impacts of air pollutants and overall rice yields are reduced proportionally. In these reforestation scenarios, supplies of the air quality regulation ES are quantified by the CAP removal rates of forests that surround the farmland. In Fig. 2c–f, only one demand value is shown, since this value is consistent across all supply scenarios due to the use of normalized results per kg of harvested rice. PM_{10} and SO_2 emissions are completely assimilated by onsite forest under the 5% reforestation scenario (i.e. "5% Supply" scenario), leading to positive v_k values. However, the emissions of CO and NO_x cannot be taken up completely by onsite forests, even under the 15% reforestation scenario (i.e. "15% Supply" scenario). For NO_x, the 15% reforestation scenario assimilates 25%–35% of emissions, resulting in v_k values ranging from −0.75 to −0.65.

Results are similar for water quality regulation (Fig. 2g–h). At the farm scale, fertilizer runoff creates demand for water quality regulation ES. However, these nutrients cannot be mitigated onsite, and therefore the local ES supply is zero. Nutrient runoff into local watersheds may be assimilated by receiving waters, but instream and lake processes cannot be modelled within EPIC. Watershed and water quality models may be used, but this is beyond the scope of the current study. Moreover, local watershed information is not available for farms in China and India; therefore, we construct scenarios in which 0.5%, 1%, and 1.5% of land is used for wetland construction. We observe that the wetlands have substantial impacts on reducing eutrophication (Fig. 2g–h). With a 150 m^2 wetland per hectare (i.e. 10,000 m^2) of land, nitrogen runoff is decreased to background concentration for all three rice farms. For farms in India and the United States, a 150 m^2 wetland is also able to reduce phosphorus runoff to background concentration; while for the farm in China, the phosphorus concentration is reduced from 1 mg/L to 0.037 mg/L. Even with a 50 m^2 wetland, nitrogen runoff concentrations are reduced to background level for farms in India and the United States; while nitrogen runoff from the farm in China is reduced by 67%. With regards to phosphorus, a 50 m^2 wetland reduces runoff concentrations by 67%, 77%, and 81% for China, India and the United States farms, respectively.

2.5. Results for steps IV

Monetary valuation can be included as the last step of the cascade modelling analysis, when the benefits and costs to human beings can be expressed in terms of monetary values (Fig. 3). To estimate these economic impacts, the difference between the supply and demand of ES associated with 1 FU (Fig. 2) is multiplied by an average monetary price related to each ES over the three countries (Table 2). Lower demand for carbon sequestration compared to its supply (Figs. 2a and 3a) is reflected by a positive externality; while the three countries (except for China for a marginal benefit associated with water provisioning) have negative externalities across the other ES classes. Negative values are related to the cost of detrimental impacts associated with higher demand (than supply) of those ES. When summed into a final ES cost-benefit balance and compared to the price of rice sold in the market (Fig. 3b) in order to understand the magnitude of such economic

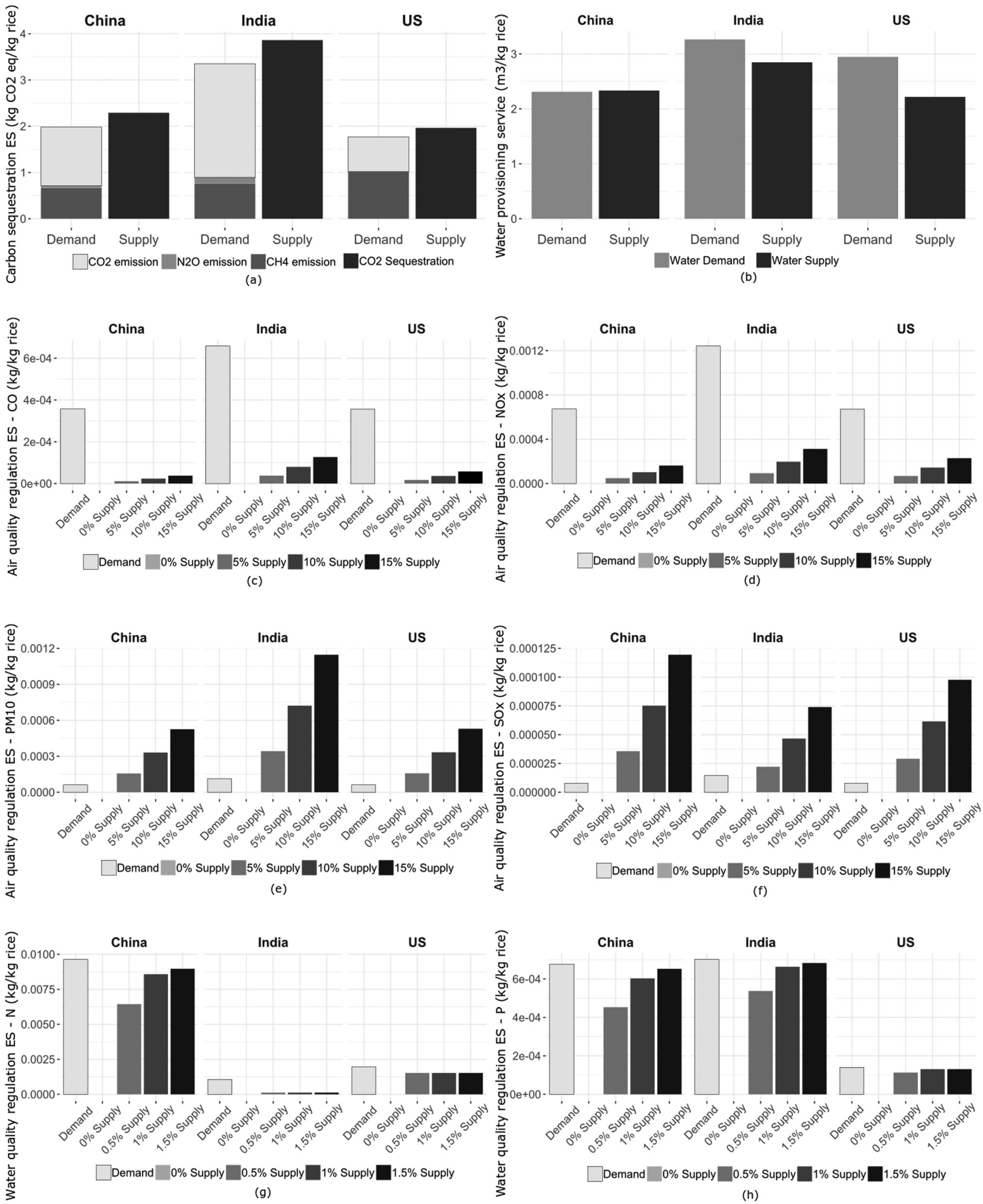

Fig. 2. Results from steps II and III in Fig. 1 for: (a) Carbon Sequestration Service; (b) Water Provisioning Service; (c) Air Quality Regulation Service - CO; (d) Air Quality Regulation Service - NOx; (e) Air Quality Regulation Service - PM_{10}; (f) Air Quality Regulation Service - SOx; (g) Water Quality Regulation Service - Nitrogen; (h) Water Quality Regulation Service - Phosphorus.

impact, those externalities reveal a "negative" net value associated with the FU (the monetary "demand" for ES is, on average, higher than the monetary "supply" of ES across the different scenarios analysed in Fig. 2). This value represents around 2%, 6%, and 4% of the cost of 1 kg of rice from China, India, and the United States, respectively. From the stakeholders' perspective, this would mean a "hidden" economic impact that should instead be incorporated into the price of rice to compensate for the lack of ES supply.

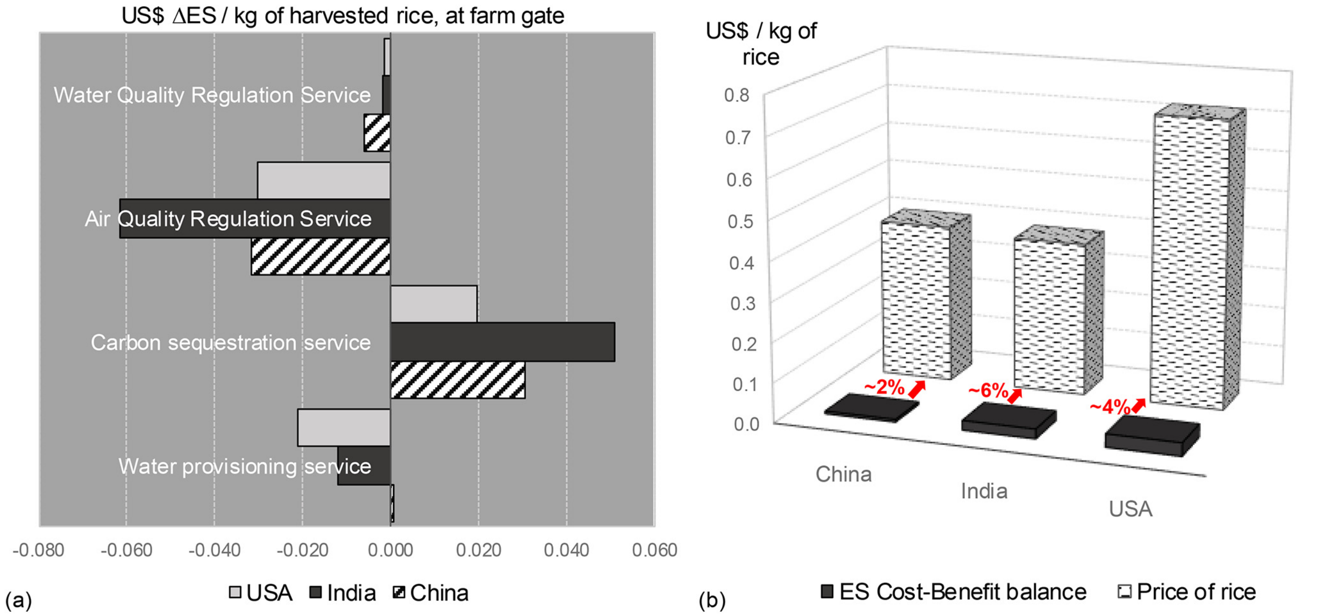

Fig. 3. Results of valuation (step IV in Fig. 1): (a) monetary costs (value <0) and benefits (value >0); For air and water quality regulations, the mean value among supply-demand difference scenarios is considered; (b) comparison between the price of 1 kg of harvested rice and the sum of the ES values shown in (a), in the form of ES cost-benefit balance, which provides an indication of the potentially missing amount of externalities in the price of rice sold in the market.

3. Overall discussion: advantages, drawbacks and practical challenges

In this study, we have incorporated spatially explicit data to quantify the demand and supply of ES using the EPIC model, instead of using generic/regional averaged data as in conventional LCA. As demonstrated in the case study, performance varies within and across different farm regions. This suggests that accounting for spatial heterogeneity in ES provisioning is essential, because the same type and amount of interventions may have different implications for ES provisioning depending on the landscape context. Moreover, the perception and prioritization of different ES also vary according to the human needs on that landscape context. For instance, water provision may be an essential issue on a water scarce area, but not so much of an issue on an area where water is abundant. The EPIC and similar ecological models capture the complex interactions between human activities and local ecosystems. Therefore, they can evaluate how and to what extent human interventions would change ES provisioning. Conventional LCA, intended as a tool standardized according to the ISO 14044:2006 (ISO, 2006), is inadequate for such tasks due to its linear scaling nature. The valuation step (Step IV) in our application is seemingly close to the idea of "payments for ecosystem services" (PES) (Farley and Costanza, 2010) and "cap-and-trade" (Schmalensee and Stavins, 2017). PES is a framework to incentivize the provision of ES by managing ecosystems, in which monetary value is assigned to ES (in particular with regard to non-marketed ES) to help decision-makers understand the environmental externalities associated with the ES loss (Bellver-Domingo et al., 2016). However, the PES approach does not aim to model a cause-effect relationship to link the interventions from human activities to the changes in ES provisioning. Our proposed ES-LCIA approach, on the other hand, attempts to integrate the LCIA cause-effect chain with ES cascade modelling.

In addition, even though demonstrated through an application to rice farming systems, the ES-LCIA methodology is generic enough to be applied to other sectors and products, where human activities are impacting the ES provisioning and where ES synergies and trade-offs exist. For example, this framework can be extended to assess the food-energy-water nexus, and the relevant ES may include biomass grown for nutritional purpose and as a source of energy, water provisioning and quality regulation. Ecological models, such as the Soil & Water Assessment Tool (SWAT, 2012), can be applied to model ES flows and derive the cost-benefit balance. This framework may also be adapted to solve sustainable supply chain design problems while accounting for ES (Ghosh and Bakshi, 2019).

However, applying rigorously the ES-LCIA framework requires complex procedures and many data and knowledge gaps have not been filled yet. Therefore, we have made simplified assumptions, leading to several limitations. First, the proposed methodology in Rugani et al. (2019) has a feedback loop, where the changes in ES provisioning can potentially feedback into the initial results from Step I and II. A consequential approach may be required to quantitatively define the feedback amount, which is beyond the scope of this analysis. Second, as has already been discussed in Section 2.2.2, Steps II and III are combined in this study because the EPIC model provides results for Steps II and III simultaneously. Even though there is "no loss of information", the combination leads to limited model functionalities (i.e. not able to obtain separate results from Step II and III).

Through the application, practical challenges have been identified and future research work is required to make the framework fully operational. First, as demonstrated in the case study, the utilization of ecological models requires an extensive amount of spatial data, the collection and quality of which can present difficulties and increase uncertainties of the modelling results. There are also uncertainties associated with the EPIC model parameters, e.g. the harvest index and the planting density (Xiong et al., 2014). Uncertainties also exist in the valuation step when the monetisation of various environmental externalities are summed up. For these reasons, the results obtained in this analysis need to be interpreted with caution. Sensitivity analyses could be performed to understand how these uncertainties would affect the final results. However, this was beyond the scope of this study. The time varying aspect of ES provisioning is also not accounted for.

Second, the consideration of ecosystems and their ES into the assessed system boundaries renders the approach incompatible with the current structure of LCA tools. Even though there have been research efforts to develop computational structures for incorporating the role of ES in LCA, they have not yet been implemented in commonly used LCA tools (Liu et al., 2018a, 2018b; Weidema et al., 2018). Besides this issue of practical implementation, other potential challenges include how the aggregation needs to be performed since there would be an increasing number of indicators that should be leveraged in the final decision-making. In this analysis, we have utilized monetary aggregation. Another possible aggregation scheme may be through normalization and weighting, as with conventional LCA when converting midpoint to endpoint indicators (ISO, 2006). In such cases, new normalization and weighting schemes need to be devised.

Third, the current case study has considered only four ES, which the authors deem to be most relevant to rice farming, and demand and supply of which are quantifiable to some extent. However, in order to better understand the synergies and trade-offs, the integrated ES-LCIA framework should take the advantage of ES classification schemes, such as CICES, to come up with a list of comprehensive, mutually exclusive, yet relevant ES (Haines-Young and Potschin, 2018). Of course, consistent methods need to be developed in order to quantify the demand and supply of each ES under concern. Information about ES demand is generally available from LCI; while, information on supply can be obtained from detailed ecological models or remote sensing. The proposed framework would benefit from the application of additional models or modelling systems that quantify a broad range of ES change per ecological process (and affected land cover). A review of such methods, data, and models is available from Turner et al. (2016) and Grêt-Regamey et al. (2017). A comprehensive and consensus-based matching should also be performed between every elementary flow in LCI to the range of ES classified in CICES. For example, the emission of CO_2 can be matched with carbon sequestration service; while nitrogen fertilizer runoff is associated with water quality regulation ES. In this way, when ecological models are developed for each land cover type in terms of their ability to provide a variety of ES, the ES demand and supply components can be quantified.

Finally, an additional challenge lies in defining the beneficiaries of ES and the associated spatial extent of the assessment. Our study considered local beneficiaries. However, the assessment of ES should ideally also be conducted at the serviceshed scale (Liu and Bakshi, 2019). Larger boundaries increase complexity because other beneficiaries may compete for the same ES. For example, allocation may be needed to determine the share of ES supply to each beneficiary. The sustainability metric and monetary benefits can be quantified based on the beneficiary's demand and the “allocated supply”. Alternatively, we can calculate the supply and demand of ES in the entire serviceshed and consider that if the serviceshed is operating within its carrying capacity, all activities in it can also be considered to have this property. In such case, it should be noted that different ES operate at different serviceshed extents; for example, carbon sequestration has a global serviceshed while air quality regulation has a regional serviceshed. More details on this can be found in Liu and Bakshi (2019).

4. Conclusions and outlook

We implement a tailored cascade model to a case study on rice farming using the EPIC model to simulate changes in ES provisioning and demonstrate the value of the integrated ES-LCIA assessment framework. Even though the case study is developed using limited cascade model functionalities (e.g., feedback loops were not included) and narrowed to a few ES, the steps in our case study manifest the feasibility and relevance of adopting an ES cascade modelling approach in the assessment of cause-effect relationships between human interventions and their impacts on intermediate and final ES provisioning. The operability and flexibility of our framework are also illustrated.

In addition, we demonstrate how the ES cascade model complements LCIA by including externalities associated with the supply and demand of ES. The result of the cost-benefit balance for rice farming is negative, suggesting that for the rice farming systems, as scoped and modelled in this study, the impacts to ES are greater than the associated benefits. Compared to the price of rice sold in the market, the net impact on ES represents around 2%, 6%, and 4% of the cost of 1 kg of rice from China, India, and the United States, respectively. This indicates the extent of environmental externalities from ignoring the selected ES.

With such a framework and guidance in place, practitioners can more comprehensively assess the impacts of life cycle activities on relevant ES provisioning, in both physical and monetary terms. This may in turn affect stakeholders' availability to receive such benefits from ecosystems in the long run. In a wider context, the work conducted herein can therefore contribute to better assess the environmental consequences and interactions of human activities and thus contribute to meeting the UN SDGs, such as SDG-14 (“life below water”) or SDG 15 (“life on land”).

CRediT authorship contribution statement

Xinyu Liu: Methodology, Software, Investigation, Writing - original draft. **Bhavik R. Bakshi:** Conceptualization, Methodology, Writing - review & editing, Supervision, Project administration. **Benedetto Rugani:** Conceptualization, Methodology, Writing - review & editing, Project administration. **Danielle Maia de Souza:** Writing - review & editing. **Jane Bare:** Writing - review & editing. **John M. Johnston:** Writing - review & editing. **Alexis Laurent:** Writing - review & editing. **Francesca Verones:** Writing - review & editing.

Declaration of competing interest

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

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