Introducing a Localised Spatio-temporal LCI Method with wheat production as exploratory case study

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Abstract

The use of dynamical information, which is temporally and spatially explicit, to quantify environmental impacts is gaining importance in recent years. Life Cycle Assessment has been applied to identify environmental impacts of, for example, wheat production. However, conventional Life Cycle Assessment is typically limited by its static nature and cannot explicitly consider temporal and spatial variability in its matrix-based mathematical structure. To address this limitation, a novel dynamical Life Cycle Assessment framework that applies spatio-temporal mathematical models in Life Cycle Inventory is introduced. This framework employs the existing Enhanced Structural Path Analysis (ESPA) method paired with a spatial dispersion model to determine the localised emissions over time within the Life Cycle Inventory. The spatially explicit calculations consider emissions to the surrounding area of an origin. A case study was undertaken to demonstrate the developed framework using the production of wheat at the Helford area in Cornwall, UK. Results show the spatio-temporal dispersion for four example emissions atmosphere, soil, flowing and groundwater. These outcomes show that it is possible to implement both spatial and temporal information in matrix-based LCI. We believe this framework could potentially transform the way LCA is currently performed, i.e., in a static and spatially-generic way and will offer significantly improved understanding of life cycle environmental impacts and better inform management of

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processes such as agricultural production that have high spatial and temporal heterogeneity.

1. Introduction

The relation between agriculture and climate change has become an important issue (Edwards-Jones et al., 2009). The food sector is one of the largest industries in the world and hence uses a large amount of energy and resources
⁵ and contributes to global warming and total CO_2 emissions (Roy et al., 2009). The demand on food will drastically increase in the coming decades. Therefore, the pressure on food production and cultivation of land will rise, as well. At the same time, climate change will cause more challenges in the agricultural sector (van der Werf et al., 2014): Agriculture is supposed to meet the principles
¹⁰ of sustainability, therefore, it is expected to produce a large amount of food to feed growing populations and at the same time ensure food security (Brentrup et al., 2004). Furthermore, one of the main concerns is the impacts of increasing input levels during the production of grain. These impacts include land use change and emissions through a higher demand for soil tillage, fertilisers, pes-
¹⁵ ticides and irrigation. All these influence the level of greenhouse gases (GHG) released during agricultural production (Goglio et al., 2012). Hence, enhancing global food security while reducing emissions and environmental impact — two seemingly conflicting goals — requires a rigorous analysis of food production practices and technologies to develop more sustainable agriculture.

²⁰ Accounting for approximately 30% of the global grain cultivation, wheat is one of the most important contributors to global food production (Röder et al., 2014). According to the FAO Food Prospects and Food situation report 70% of the wheat produced is for food production and the rest is used for other purposes such as animal feed. In 2014/15, a global wheat yield of 716 million tonnes is
²⁵ expected (FAO, 2014). Linquist at al. (2001) calculated in their meta-analysis

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of GHG Global Warming Potential (GWP) values of CH_4 and N_2O of 662kg $CO_2e/1t$ of wheat. Furthermore, they found 1.21% of N applied was emitted as N_2O (Linquist et al., 2012).

Life Cycle Assessment (LCA) is commonly used to evaluate the environ-

mental impacts of different products, processes and activities. Assessments can consider the entire life cyle or a determined time interval of the life cycle (Edwards-Jones et al., 2009; Roy et al., 2009). A LCA can be performed to identify ways to reduce pollution, excessive use of resources and may stop the mitigation of environmental impacts between different production stages (Mc-

Manus, 2010). Within a LCA environmental impacts such as climate change, stratospheric ozone depletion, smog eutrophication and acidification and influences on human health and ecosystems are analysed (Rebitzer et al., 2004). LCA can be seen as a comprehensive assessment which is standardised in ISO 14040 and includes all attributes of natural environment, human health and

resources (Technical Committee ISO/TC 207, 2010). A life cycle approach is useful to avoid problems in the process from shifting from one stage, country or environmental problem to another (McManus, 2010). In recent years LCA has become an important decision support tool for policy makers as well as product developers and designers to assess the cradle to grave impacts of prod-

ucts. Three forces support the current position of LCA: Due to a movement from government regulations closer to "life-cycle accountability" point of view, manufacturers are responsible for direct product impacts, but also for impacts in life cycle stages after a product's purchase. Some businesses also take part in sustainable actions or schemes which demands "for continuous improvements

through better environmental management systems" (Srinivas, 2014). And last for consumer markets and government procurement guidelines environmental performance of products has a high level of importance (Srinivas, 2014).

On the other hand, LCA is "primarily a steady-state-tool" that does not consider temporal or spatial information (Udo de Haes, 2006). These limitations

impact on results from conventional LCA and many, in particular, environmental issues cannot be determined explicitly (Levasseur et al., 2010; Owens,

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1997; Dyckhoff and Kasah, 2014). In recent years more studies include either temporally or spatially explicit information, and new methodologies for time-dependent LCA (Levasseur et al., 2010; Dyckhoff and Kasah, 2014; Commission, 2010) and spatial LCA (Geyer et al., 2010; Mutel and Hellweg, 2009) have been developed. To the best knowledge of the authors, however, no studies have been performed that include time- as well as space-dependent information in conventional matrix-based LCA. Hence the aim of the present study is to: integrate both, temporal and spatial information in a novel dynamical LCA framework that is capable of producing more detailed results and hence offering more insights for sustainability assessment. We apply this new approach to evaluate the environmental burdens of wheat production as an illustration. The Dynamical Life Cycle Assessment (DLCA) sections summarises previous studies and current implementation of time and space in LCA. The calculation approach used in our study is outlined in the Method section. The Case Study section introduces the used data, followed by the results. Conclusions for the study and also recommendations for implementing time and space information in future studies are drawn in the Conclusion section.

2. Dynamical Life Cycle Assessment

ISO 14042 mentions the absence of time in LCA, but at the same time does not provide a guideline for an inclusion of time in LCA (Technical Committee ISO/TC 207, 2010) and previous studies explore different ways in doing so. Broadly, it differs between time included in the Life Cycle Inventory (LCI) and in the Life Cycle Impact Assessment (LCIA) stage of a LCA. According to Collet et al. (2011) the temporal information of emissions is lost by aggregation and the ensuing concentrations of emissions in the air are unknown. On the other hand, time in LCIA is only considered as timescales to gain information about the emissions that influence the environmental impacts (Collet et al., 2011). Dyckhoff and Kasah (2014)) define DLCA as an useful tool to "assesses the impacts of a system at a determined point in time.

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Pehnt (2006); Zhai and Williams (2010) and Viebahn et al. (2011) perform dynamical studies in the renewable energy sector and assessed future greenhouse gas (GHG) emissions by past and potential developments of material and operation methods to improve efficiency of production. Zhai and Williams (2010) perform a LCA of photovoltaic (PV) systems and consider technology-dependent dynamics of embodied energy and GHG emissions. The study focusses on energy-related flows, but with some improvement of the model other impact categories could be included. Zhai and Williams (2010) conclude that the environmental processes have a significant effect on reducing emissions of PV systems.

Pehnt (2006) introduces in his paper a dynamic approach towards LCA of renewable energy systems. For his dynamical approach, he develops a background system with the state of the best available technology and uses extrapolation of future developments to calculate the emissions for energy resource consumption, emissions of GHGs, acidification and eutrophication. Within his DLCA he includes only parameters, that are environmentally significant and at the same time exhibit an important time-dependency.

Viebahn et al. (2011) perform a study about concentrated solar power (CSP) by using a dynamical LCI approach. Within the LCI the environmental impacts between 2007-2050 were calculated considering six development steps such as increase of lifetime, up-scaling, increase of storage time, higher efficiency, reduction of material use and adapting background processes. The development scenarios were assumed to follow a pessimistic, an optimistic-realistic and a very optimistic trend. The study shows that CSP can be deployed in the long-term, depending on the development of energy policy. Furthermore, the emissions from CSP plants are relatively low in comparison with fossil fuel-based systems, and further reductions of emissions are possible and likely to happen in the future.

In a more recent study, Beloin-Saint-Pierre et al. (2014) develop a calculation tool that uses temporal information to describe a system by differentiating elementary and process flows. The authors modify the traditional LCI calculation

method to be able to consider time dependent information. This new method is called Enhanced Structural Path Analysis (ESPA) Beloin-Saint-Pierre et al. (2014). Beloin-Saint-Pierre et al. (2014) compare different LCA studies and found that results obtained, considering evolving process flows over time, differ from those obtained by more traditional approaches in LCA. Also including time variance indicated an effect of industrial dynamics on DLCA results. In their comparison of different DLCA studies they also found that most approaches used in these studies did not clearly "differentiate at a temporal level".

Porsö and Hansson (2014) describe time-dependent absolute and instantaneous indicators to calculate the global mean surface temperature.

In 2005, Spatari et al. (2005) used a dynamical model with an annual time series for production steps, an empirical model to calculate waste flows and a residence-time model to determine post-costumer flows of the copper production in North America.

A different approach has been proposed by Levasseur et al. (2010), see also Kendall et al. (2009); Kendall (2012) and Yang and Chen (2014) with time dependent characterisation of global warming factors and the timing of fixed time horizons, which applies in the LCIA. Levasseur et al. (2010), improve the results of LCA "by addressing the inconsistency of temporal assessment" (Levasseur et al., 2010) and by including time dependent characterisation factor in the LCI stage. The results of the study show that a chosen time horizon creates inconsistency with time range, which the LCA covers. Nevertheless, using this method for a case study of biofuels revealed differences in the results of a statical approach and a DLCA that are significant enough to change the conclusion of the entire study.

In another recent study by Dyckhoff and Kasah (2014), the time-dependent global warming impact using radiative forcing and a new method to define time horizons was developed. They indicate that the accuracy of DLCA studies depends on chosen time horizons. Therefore, they develop instantaneous and cumulative time dominance criteria. This study was based on the work of Levasseur at al. (2010), which has been, according to Dyckhoff and Kasah

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(2014), the most elaborated work within the DLCA field so far. But the same time they criticise time horizons as "highly subjective assumptions" without scientific foundations and in addition an "implicit weighting of emissions" takes place. To improve these factors the authors introduced their concept of time dominance regarding the study of (Levasseur et al., 2010) (Dyckhoff and Kasah, 2014).

Bright et al. (2012) performed a study on climate impacts of bioenergy. They consider "two dynamic issues, first the temporary changes to the terrestrial carbon changes and second temporary changes to land surface albedo" Bright et al. (2012) in the context of active land use management for bioenergy. Hellweg et al. (2003) see LCA as a tool that treats past, presence and future emissions, divided into equal sections and integrated over time, but Bright et al. (2012) criticise the limitation of this method applied on biomass systems. They use the neglect of CO_2 emissions from biomass conversion or combustion due to "the carbon and climate neutrality principle". According to the authors, this principle is acceptable for fast growing biomass, but is less feasible for slow growing biomass (Bright et al., 2012). As the study of (Levasseur et al., 2010), Bright et al. (2012) calculate GWP indices. In contrast to Levasseur's approach,Bright et al. (2012) apply the carbon radiative forcing within the LCIA stage. Furthermore, they use Impulse Response Functions combined with the time distributed emissions and removals of CO_2 from biomass to calculate the change in atmospheric CO_2 concentrations. As (Levasseur et al., 2010), (Bright et al., 2012) and Arbault et al. (2014) calculate Characterisation Factors (CFs) using Impact Assessment Models. The CFs used in their study are related to Human Health, Natural Resources and Natural Environment. The authors point out that CFs and LCIA indicators evolve "with regard to the usefulness of natural resources for human purposes" Arbault et al. (2014). The incomplete involvement of ecosystem services (ES) in the current LCIA application represents a notable limitation of LCA to several sectors, which are influenced by the ES. This study uses integrated earth systems dynamic modelling to solve this issue. Furthermore, a Global Unified Metamodel of the biosphere is selected and CFs

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are calculated. Although the model indicates the possibility to retrieve CFs, a
simple conversion into LCIA calculations is not functional so far Arbault et al.
(2014).

Another study calculating CFs in LCIA was undertaken by Seppälä et al.
(2006). The study developes new site-dependent characterisation factors for
emissions occuring during acidification and eutrophication in Europe. The cal-
culation of the CFs has been based on accumulated exceedance (AE). The cal-
culation method was introduced by the United Nations Economic Commission
for Europe Convention on Longrange Transboundary Air pollution (UNECE,
2014). Seppälä et al. (2006) found that the CFs were independent of the reduc-
tion percentage that was normally used to calculate CFs. Because the errors
calculated for each CF turned out to be 0, the CFs were unable to describe ef-
fects of small changes of most emissions included in LCA. Also their study shows
significant differences in CFs calculated for many countries in the EU Seppälä
et al. (2006).

Another important issue with Life Cycle Assessments is lack of spatial in-
formation. Spatial LCA can be applied in every stage of the life cycle. If it
is applied in LCI usually GIS and spatial databases are used, while in LCI a
CF is developed (Nitschelma et al., 2015). Typically, to receive localised LCA
results, this is often performed at country scale, with little information where
emissions arise within the country. Also, localised CFs are used. The use of
those CFs is described in two methods, that were developed in the past two
decades. The TRACI model was proposed by the U.S. Environmental Pro-
tection Agency, and includes acidification CFs for each U.S. state and for the
country as a whole (Bare et al., 2003). The other method developed is called
GLOBOX and includes around 250 countries and seas (Wegener Sleeswijk and
Heijungs, 2010). But so far no method was developed that regionalises LCI. Ear-
lier attempts are based on using regional output percentages (ROP) to allocate
life cycle emissions to different regions (Hill et al., 2009; Tessum et al., 2014). In
his study Hill analyses the impacts of PM2.5 emissions of corn ethanol, gasoline
and cellulosic ethanol for human health. Depending on the source of land he

found out that cellulosic ethanol can offer health benefits from PM2.5 reduction. Tessum et al. (2014) uses temporally, spatially and chemically life cycle emission inventories. They found out that using "corn ethanol, coal based or 'grid average' electricity increases [...] environmental health impacts by 80O".

Kim et al. (2015) develop Regional Emission Information (REI) and linked with the characterisation results in LCIA. They compare their results with studies without REI and found out that not using regionalised information underestimated environmental impacts (Kim et al., 2015). They use exiting LCA calculation methods such as ReCiPe and CFs and then include outside emissions such as air emissions by using REI. Outside emissions are defined as emissions that occur outside of the actual system boundary, but that still influence the environmental impact, such as emissions from a busy road next to a field of wheat that is studied (Kim et al., 2015).

Gasol et al. (2011) combined LCA with Geographic Information System (GIS) to present a method to determine an energy crop implementation strategy. Therewith, a reduction of energy and CO_2 is possible. They concluded that the combination of LCA and GIS is beneficial to obtain "environmental results from energy and material flows based on territorial organisation" (Gasol et al., 2011).

Engelbrecht et al. (2013) study GHG mitigation in grain production in Australia. They used Integrated Spatial Technologies (IST). Therefore, LCA, Remote Sensing (RS) and GIS are interlinked with each other. IST consists of two stages using RS data from satellite images and aerial photographs as inputs into GIS and the application of a stream linked LCA. LCI results are integrated into a RS and GIS database to analyse the spatial distribution of agricultural systems (Engelbrecht et al., 2013). The results show that using IST may result in choosing another mitigation option than with using the a traditional LCA approach, but so far only includes carbon footprint modelling.

Humenöder et al. (2013) use a model called AEZ-BLS to calculate the effects on land use change on the carbon balance of 1st generation biofuels. The agro-ecological zonde model (AEZ) includes spatial information, while the general equilibrium model of world food economy (BLS) works on a regional

basis. The AEZ-BLS is the combined with the LCA approach of the EU Renewable Energy Directive. The results show a GHG emission saving from 1st generation biofuels compared with fossil fuels of -2-13% in the most realistic scenario (Humpenöder et al., 2013).

A spatialised territorial LCA (STLCA) method for agricultural territories was developed by Nitschelma et al. (2015). This method considers the spatial variability of emissions and impacts within a territory and represents an extension to conventional LCA studies. In comparison with other studies mentioned above, this studies aims to include the spatial approach in all life cycle stages (Nitschelma et al., 2015).

Roy et al. (2014) analyse terrestrial acidification at the global scale. They used characterisation factors for atmospheric fate, sensitivity factor and effect factors. Spatial variability was added by calculating $2°x2.5°$ emission grids worldwide for each pollutant (Roy et al., 2014).

3. Method

The proposed DLCA framework consists of two main parts. In the first part time-dependent LCI is calculated. These results provide the basis for the second part spatial LCI calculation. Both approaches are explained in detail below after describing the static LCI matrix calculation. LCI data flows are extracted from Ecoinvent 3 database (Weidema et al., 2013). All calculations are performed using Matlab (Version 2015b) algorithms (Matlab, 2015).

During the LCI stage of a LCA all energy, material and economic in- and output flows are identified and quantified. For the calculation these flows are split into single processes. Each of these processes considers inputs from other processes, which creates an interlinked system of all process flows. The processes are linear functions of their inputs and therefore, the system can be written in matrix form (1) (see Table 1) (Heijungs, 1994; Suh and Huppes, 2005).

$$g = B \times s = B \times (I - A)^{-1} \times f, \tag{1}$$

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Table 1: LCI matrix calculation parameter

Symbol	Name	Dimension	Definition
f	final demand vector	m	vector of economic flows
A	technology matrix	$m \times m$	exchange between processes
B	intervention matrix	$n \times m$	exchange between environment
s	scaling vector	m	vector of scaling factors
g	inventory results	n	vector of environmental flows
I	identity matrix	$m \times m$	square matrix with ones on the main diagonal, rest 0

where I is the identify matrix, A is the technology matrix and B is the environmental intervention matrix. All process flows are defined in the columns of matrix A, with each element in the columns representing inflows and outflows of commodities necessary for the process to happen. Every row in B defines an elementary flow, describing the amounts released to or extracted from the environment by the corresponding processes in the columns (Saurat and Ritthoff, 2013). g, s and f are the inventory, the scaling and final demand vectors, respectively (see Table 1).

3.1. Time-dependent LCI Model

The dynamic method integrated in the proposed framework in this study is the Enhanced Structural Path Analysis developed by Beloin-Saint-Pierre (Beloin-Saint-Pierre et al., 2013). This method uses relative temporal distributions (see Figure 1a) to specify elementary and process flows of a system and the system network they create. With the specific information format the calculation of temporally descriptive LCI are possible (Beloin-Saint-Pierre et al., 2013). Beloin-Saint-Pierre et al. (2014)) extends equation (1) to obtain a time-dependent expression for the vector g of the temporally explicit LCI.

In a static LCI matrix equation (1), it is straightforward to obtain the inventory vector g by matrix-matrix and matrix-vector products of environment

matrix B, matrix $(I-A)^{-1}$ of process flows and scenario vector f. However, matrix product do not simply allow for temporal information of the process-related distributions included in a dynamical LCI calculation. To retain temporal information, convolutions of the time-dependent process and environmental data are calculated. A convolution induces an "overlay" of two time-distributions to produce a third distribution, see Figure 1b. Within the ESPA method discrete time convolution is used and in this case the two distributions, one distribution for A and one for B, are summed up to receive a third one Pinsonnault et al. (2014).

It is not possible to obtain a matrix inverse $(I-A)^{-1}$ without losing the temporal information in technology matrix A. A power series expansion is therefore applied to obtain

$$(I - A)^{-1} = \sum_{k=0}^{\infty} A^k. \qquad (2)$$

Equation (2) is only applicable if A has eigenvalues with absolute values less than 1. For the application to data from realistic processes this may require a scaling of A. Assuming a time-varying technology matrix, the power series (2) is altered as a series of convolutions of A with itself:

$$(I - A)^{-1} = I + A + A * A + A * A * A + \dots . \qquad (3)$$

Here, the $*$-symbol indicates the convolution operation which is considered as component wise convolution, while the matrix-matrix multiplication rules apply to the time-distribution entries of the matrices. Applying (3) to the inventory equation (1) gives

$$g = B * (I + A + A * A + A * A * A + \dots) * f$$
$$= B * f + B * A * f + B * A * A * f + B * A * A * A * f + \dots . \qquad (4)$$

In computational implementations, the power series has to be truncated after a maximum number $k \in \mathbb{N}$ of convolutions of A. Typically this can be done by setting k or via threshold as the maximum of the $\underbrace{A * \dots * A}_{k \text{ times}}$ is decreasing exponentially with k.
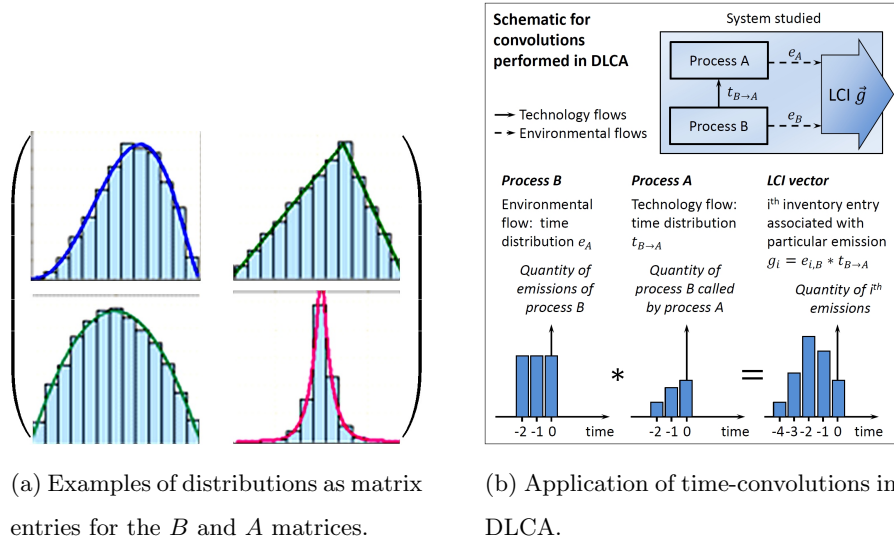
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(a) Examples of distributions as matrix entries for the B and A matrices.

(b) Application of time-convolutions in DLCA.

Figure 1: Examples distribution and use of convolutions.

3.2. Spatial Propagation Model

The result from the time-dependent LCI equation serves as input to the spatial propagation model. For the spatial propagation model a study site of a particular size is designated as a raster $\mathcal{R}$ of grid cells. As initial condition a time-dependent and localised inventory vector is chosen and the inventory entries are propagated through time. Localised in this case means only emissions are considered in the spatial propagation model that are attributed to the study site. This requires an intermediate step of mapping temporal varying LCI entries to a location. The propagation model is based on two operators generated from (a) geographical or atmospherical data, and (b) dynamical dispersion models. Both operators may be individualised to the emission type, category or possibly individual emissions and inventory impacts.

Hence, topographic details, land use information, soil properties, as well as data about water flows, characteristics of currents, ground water occurrence or regional atmospheric flows are used to generate an impact parameter map M_G (see Figure 2). For a location (x, y) and an inventory entry/emission g_i, the application of the operators $M_{G,i}(x, y)$ quantifies the proportion of interaction

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of the emission i (of a particular type or category) with the present geography or atmospheric flows at (x, y). $M_{G,i}$ can be modelled as linear (matrix) or nonlinear (functional) operation.

The dynamical dispersion models N_D calculate the accumulated proportion of emissions propagating from and between neighbouring cells (see Figure 3) in the raster. An emission i at cell (ξ, η) and time t with amount $e(\xi, \eta, t)$ is then dispersed as $N_{D,i}(e(\xi, \eta, t))$ which gives the amount of emission i at time $t + 1$ for all (neighbouring) cells within the raster. The considered dispersion models can define velocity, reach and direction of propagation for any emission.

The accumulated emissions after one time step at location a (x, y) is then obtained as the product of geographic/atmospheric model and dispersion model summed over all "origin-cells" in the raster

$$e(x, y, t + 1) = \sum_{\xi, \eta \in \mathcal{R}} M_{G,i}(x, y) N_{D,i}(e(\xi, \eta, t)). \tag{5}$$

As initial emissions, the i-th inventory entry sequence $(g_i(\xi, \eta, 1), g_i(\xi, \eta, 2), \dots)$, distributed in time and designated to the production grid cells $(\xi, \eta) \in \mathcal{P}$, is considered which allows iterative calculation of the emissions at location (x, y) and time $t + 1 \geq 2$:

$$
\begin{aligned}
&e(x, y, t + 1) \\
&= \sum_{\xi, \eta \in \mathcal{P}} M_{G,i}(x, y) N_{D,i}(g_i(\xi, \eta, t)) + \sum_{\xi, \eta \in \mathcal{R} \setminus \mathcal{P}} M_{G,i}(x, y) N_{D,i}(e(\xi, \eta, t)). \quad (6)
\end{aligned}
$$

With the geographical or atmospheric data and resulting maps, the dynamic dispersion is directing the impact, for example, flow direction of a river for emissions transport. The spatial propagation model may help to identify impacts on, for example, land and seascape, water cycles, emissions and impact on climate, weather conditions, and surface interactions.

While the temporal aspect of the method runs over several stages of the life cycle, the spatial aspect is very localised for the operation stages at the study site. Therefore, a selection process identifying localised LCIs is applied. Currently, we use an empirical approach identifying localised processes at the
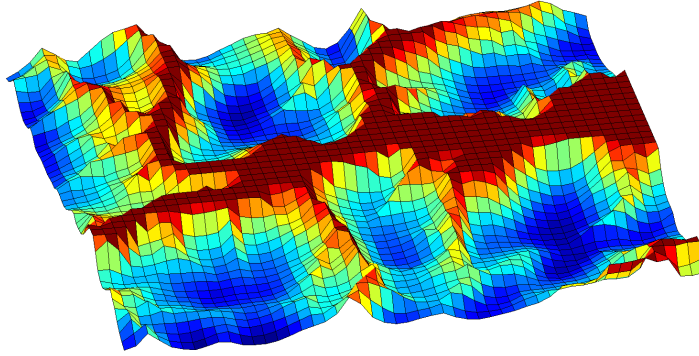
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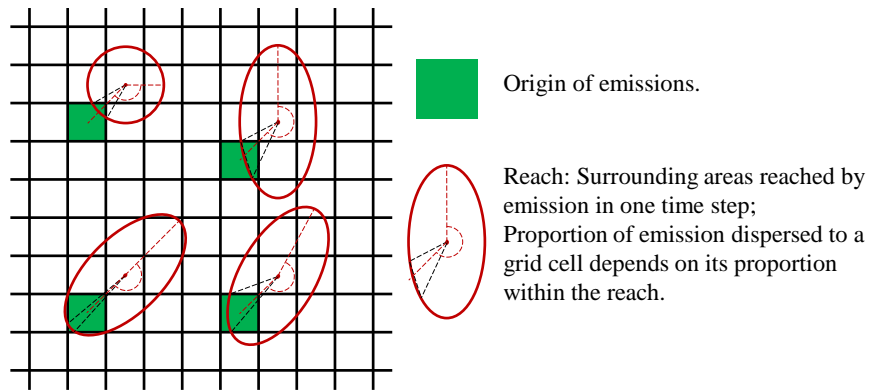Figure 2: Example impact parameter map (red = high impact, blue = low impact).

■ Origin of emissions.

Reach: Surrounding areas reached by emission in one time step; Proportion of emission dispersed to a grid cell depends on its proportion within the reach.

Figure 3: Conceptual propagation model for spatial dispersion of impacts.

study site to rule out "donwstream and upstream" emissions.

4. Case study

4.1. Data

In order to illustrate the proposed theoretical framework a case study on wheat production is chosen. Information for the environmental and process matrices used for the ESPA calculation can be found in the Ecoinvent database 3.1 (process dataset used: Wheat grain (GLO); market for; Alloc Def; U) Weidema et al. (2013). All processes in the A-matrix are assigned into seven main activities:

- Agricultural machinery operations (integrated emissions as used in all other activities)

- Fertiliser application

- Harvesting

- Irrigation

- Pesticides application

- Sowing

- Tillage

All activities are on field operations and upstream or downstream emissions outside the field (such as production of fertilisers and pesticides) are not included in this study. These activities spread over time and several activities (such as irrigation, application of fertiliser) are repeated in possibly different proportions within one wheat production cycle. One cycle of activities is shown in the bar chart 4 where the process distributions accumulate 100% over one production cycle. For the example implementation the production cycle is repeated a number of times (in the presented calculations 5 times) with inactivity of 4 intermediate time steps after each cycle. The temporal occurrence of these

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activities represent an empirical characterisation of process distributions and aim to demonstrate the methodology introduced in Section 3.

In the case of wheat production LCI calculation, matrix B includes a collection of $n = 332$ types of emission during the wheat production cycle while matrix A specifies $m = 71$ flows and exchanges between the sub-processes of the system (Pinsonnault et al., 2014). The demand or scenario vector f collects the cumulated inputs for a specified functional unit of end product or service Mutel and Hellweg (2009). Processes within the B-matrix were assigned to the same seven main activities as the A-matrix in the columns, rows are divided into the chemicals occurrence in air (e.g. CO_2), soil (e.g. chromium) or water (e.g. nitrogen in rivers or salts in ground water) or as a raw material. The chosen chemicals are representatives and only serve as examples to test the framework. These include gas emissions to atmosphere, metal emissions to soil, acids to flowing water and salt in ground water. One year is assumed to be the timeline for a wheat production cycle, with each time step covers a two week period. As mentioned above for this case study a example site in South-West Cornwall was chosen. The top soils in this area are freely draining slightly acid loamy soils and freely draining slightly acid loamy soils over rock closer to the river bed. This loamy soils have a low fertility, and water contaminations with nitrate can be possible. Siltation and nutrient enrichments of streams from soil erosion can occur as well (Cranfield Soil and AgriFood Institute, 2016). Cornwall has a temperate Oceanic climate (Köppen climate classification), with the mildest and sunniest summers in the UK thanks to the southerly latitude and the influence of the Gulf Stream (MetOffice, 2000). Precipitation occurs during the entire year with more rain through winter months. Cornwall is also the second windiest location in the UK (MetOffice, 2015). Using ArcGIS we determined the topography data as well as water flows and ground water resources. Mastermaps with a scale of 1:50000 of tiles SW74NE, SW72NW was used (Edina Digimap, 2015). Within GIS a 50×50 grid cells with $50\text{m}\times 50\text{m}$ measurement was used. The information is then imported into grid cells to create an impact parameter map. Within the case study three locations in the study area
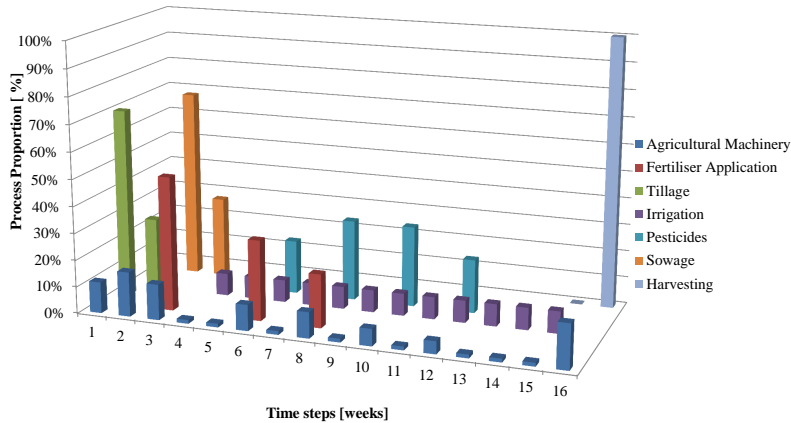
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Figure 4: Main activities of the A-matrix distributed over time, expressed as the proportion of the overall activities, where each activity sums up to 100%, only one cycle shown

for the production of wheat are selected. Therefore, the origin coordinates are identified for the field and time-varying emissions are calculated.

In the considered wheat production case study, the locations (ξ, η) represent the area of an agricultural field, from where the environmental emissions are released and dispersed. The above model may lead to a better understanding of emissions from application of fertilisers and pesticides, harvesting and other processes in the life cycle of wheat production. With harvesting, direct emissions diminish before a new growing season starts, but may have longer-term and slower decreasing repercussions on the surrounding areas.

4.2. Results

In this section we present a qualitative analysis of the spatio-temporal LCI calculations for the considered case study of wheat production. First, the temporal distributions using the ESPA methodology are obtained, see Figure **??**,

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for the cumulative occurrence over a time horizon of 200 weeks of four example inventory entries. The outputs of that temporal calculations are then used for the spatial dispersion model, obtaining the distribution of all inventory entries in the study area at every time step. Figure 5 shows how salts in ground water spread over time, the distribution is visualised at $t = 20n+1, n = 1, \ldots, 8$. Salts in ground water propagate from the location of deployment to the surrounding areas. Emissions spread on land masses first before reaching the rivers from where they are spread into the sea. At a certain point the emissions start to decrease, first at the deployment coordinates then at surrounding areas. Figure 6 shows the cumulative emissions relative to the time-distribution with out spatial dispersal (compare 6 for all chemicals in the study area with CO_2 on the top left, salt in ground water in the top right, nitrogen in river at the bottom left and chromium in soil on the bottom right. A video showing the relative cumulative emissions over time is available in online supporting material. Emission spread slower in soil, but soon follow the flow directions of rivers, sea and groundwater, which confirms the expected outcome.

5. Discussion

In this paper we introduced a new spatio-temporal framework using temporal distributions and spatial dispersion models to obtain localised Life Cycle emissions over time. The aim of the framework is to implement time and spatial information into LCI. Therefore, we developed a spatial propagation model, which runs after the temporally explicit LCI is produced using the existing ESPA method. We then tested the framework using a wheat production as an example. The results show how emissions from an origin spread in soil, air, groundwater and river and how those emissions accumulate over time. This study highlights the accumulation of emissions during the operation stage of a life cycle, and also informs about when emissions occur and spread. The outcome of the proposed method is influenced by the availability of data. While performing a case study we have noticed that Ecoinvent or other LCI databases
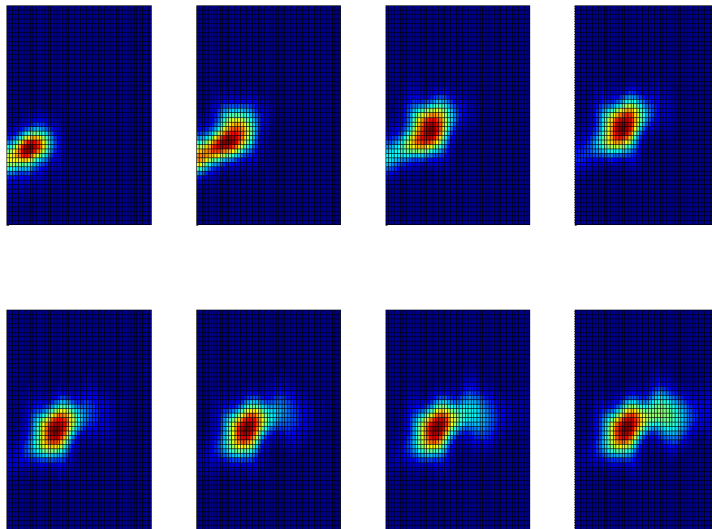
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Figure 5: Emissions results for an example inventory entry at $t = 20n + 1$, $n = 1, \ldots, 8$. The graph shows relative concentrations taken at different time steps
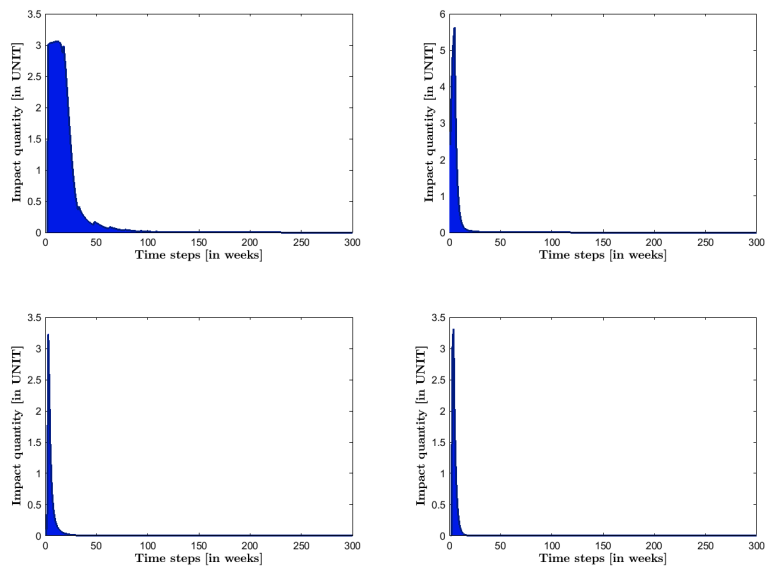
Figure 6: Emissions in time accumulated in study area as proportion of the overall temporal emission distribution for four example inventory entries a) CO_2 , b) Salt, c) Nitrogen and Chromium

are not sufficiently detailed to satisfy all the information spatial LCA as well as temporal LCA require for comprehensive and realistic results. Therefore alternative ways for collecting data needs to be considered. Local data for example can be gathered by regional statistics or surveys. Downscaling of national data is also an option if regional data could not be easily obtained. On the other hand different strategies to fill data gaps are currently used: proxy data sets, extrapolating data and streamlined LCA (Milà i Canals et al., 2011; Nemecek et al., 2011; Roches et al., 2010). Further improvement should also include the integration of soil types and characteristics, more detailed current data and climate data to eliminate the deficiency of the proposed model. Another future step is the mathematical optimisation of the LCI vector g in respect to the scaling vector s. This optimisation step should result in the optimum temporal and spatial allocation of the LCI vector and hence inform implementation time and localisation of processes within the life cycle. In conventional LCI calculations the scenario vector has only one non zero input, the reference flow. The scenario vector ensures the required performance of the studied system, for example the reference flow could be 1000 kg of wheat. Studying the system over time though allows us to spread the total amount of the reference flow into smaller sections over given time without changing the total amount. Therewith, the production of the amount stated in the reference flow can be divided along the time frame and for example production planning to meet emission thresholds can be performed. In this study, the method is only applied to a part of the wheat production life cycle, focusing on activities that happen at the wheat field. Our next step is to expand the application to cover the entire life cycle of wheat production. The spatial propagation model will be used around the locations of the production of raw material such as seed and fertilisers, along the transport links and at other upstream and downstream processes produce a life cycle emission map over time. A further step would be to try and integrate wheat production with the life cycle of other linked system such as livestock production. Both steps will results in significantly improved understanding of environmental impacts with spatially and temporally explicit life cycle emissions.

6. Conclusion

This paper proposed a novel spatio-temporal LCI approach with two main parts in order to address the static nature of conventional LCA. In the first part temporal distributions are used to represent when and how often system processes occur. This information is used to calculate a time dependent LCI vector. In the second part, the time-dependent LCI vector in a spatial propagation model to produce temporally and spatially explicit LCI. The method is then illustrated in a case study of wheat production in Cornwall, UK. The presented results so far only include the agricultural operation stage of the wheat production life cycle and all upstream (e.g., fertiliser production) and downstream production (e.g., wheat transportation) processes are excluded. But the results already show that it is possible to implement both spatial and temporal information in matrix-based LCI. As mentioned the results are not conclusive for wheat production due to the availability of data. With improved LCI databases, the method can be used to get more detailed calculations such as comparing winter and spring wheat, also water flow data can be updated using time-varying and up-to-date data. This could potentially transform the way LCA is currently performed, i. e., in static and spatially-generic way. We believe this framework will offer significantly improved understanding of life cycle environmental impacts and better inform management of processes such as agricultural production that have high spatial and temporal heterogeneity. Further work is needed to fully demonstrate the framework over entire life cycles and much more detailed LCI databases as well as temporally and spatially explicit LCIA methods are required to realise its full potential.

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