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Spatially explicit life cycle impact assessment for soil erosion from global crop production

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ABSTRACT

We derived spatially explicit erosion rates in kg of soil lost per kg of crop as a function of crop choice and management practice on a global scale. These so-called characterization factors (CFs) can be used in product life cycle assessment studies to determine the impact of crop cultivation on soil erosion. We used the biophysical crop model EPIC to determine yields and erosion rates for cassava, corn, rapeseed, soybean, sugarcane, sunflower, and wheat under subsistence, rainfed with fertilizer, and high input (irrigation and fertilizer) farming. Yields varied considerably and contributed to variation in CFs to the same extent as erosion rates. Variation in CFs was mainly attributable to geographic location. Crop type and management scenario still lead to variation in CFs of 2 orders of magnitude, and a factor of 6, respectively. Lowest CFs were predicted for sugarcane worldwide, while largest impacts were seen for rapeseed. Largest median CFs were predicted for subsistence farming, while smallest CFs were obtained for high input systems. Median estimated damage in 2014 erosion costs ranged from 0.5 \$/t sugarcane to 526 \$/t rapeseed. Farmers can minimize erosion by carefully selecting management strategies, while purchasers can carefully select source locations to help reduce erosion related environmental damage.

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1. Introduction

Life cycle assessment (LCA) assesses ecological burden and human health impacts of products and services (e.g. [Hellweg and Mila i Canals, 2014](#)). In the life cycle inventory (LCI) phase, stressors are quantified for the system studied. In the life cycle impact assessment (LCIA) phase, so called characterization factors (CFs) are used to determine the environmental impact that a stressor causes to humans and ecosystems. Over the years, the idea evolved that life cycle oriented methods should encompass ecosystem services (e.g. [Koellner et al., 2013](#); [Saad et al., 2011](#); [Zhang et al., 2010](#)), since these form the basis of planetary activities and human well-being ([MA, 2005](#)). A review by [Zhang et al. \(2010\)](#) shows that

comprehensive accounting for ecosystem services in LCA requires, among other aspects, improved integration of methods, and greater understanding of the role of ecosystems in supporting human activities. An important regulating service is the capacity of ecosystems to stabilize soils, to prevent soil detachment and accumulation of eroded soil material downstream. Human-induced soil erosion is associated with unsustainable land use. Improper management of land, including crop residues and nutrient fertilizer techniques can accelerate soil erosion (e.g. [Bindraban et al., 2012](#)). A main driver is agricultural production, as the cultivation of crops requires loss of permanent vegetation cover, nutrient use, and irrigation, which all contribute to soil loss and degradation ([Adhikari and Nadella, 2011](#); [Pimentel et al., 1995](#)).

Several authors have recently put forward ideas and suggestions on how to include the impact of product life cycles on soil quality and related ecosystem services in the framework of LCA

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(e.g. Garrigues et al., 2012; Othoniel et al., 2016; Koellner et al., 2013), while others have already quantified impacts (Cao et al., 2015; Núñez et al., 2013; Saad et al., 2013; Saad et al., 2011; Quinteiro et al., 2015). Saad et al. (2011) adopted a calculation tool to derive CFs ($\text{t ha}^{-1} \text{a}^{-1}$) for erosion caused by land occupation and land transformation on various spatial levels for a Canadian context. Saad et al. (2013) determined global CFs for, among others, erosion regulation potential of land occupation by permanent and annual crops for 38 ecological regions worldwide. Subsequently, Cao et al. (2015) monetized these factors to compare and aggregate multiple ecosystem service impacts. Núñez et al. (2013) developed a regionalized approach to quantify effects of erosion on the available soil resource stock and on ecosystems' net primary productivity (NPP). Their approach was soil type specific and they applied it to various crop rotation systems of food and energy crops in Spain. To apply their CFs, the LCA practitioner needs to provide in the inventory the amount of soil loss, which varies in space due to climate conditions and agricultural management practices, i.e. fertilizer application and irrigation. Quinteiro et al. (2015) determined CFs for effects of suspended solids on freshwater biota in Europe, but did not base their calculations on actual erosion rates. In a recent case study, Quinteiro et al. (2017) showed the applicability of their work for erosion impacts of *Eucalyptus globulus* stands in Portugal. However, there are no CFs available for erosion in LCA on a grid-specific level worldwide, specifically including potential effects of agricultural management and crop type, up to now.

The objective of this paper was to provide spatially explicit CFs for erosion, as a function of crop and management practice, on a global scale. For this, we used outputs from the biophysical crop model EPIC (Environmental Policy Integrated Climate), which includes relevant biophysical processes such as weather, erosion, and crop growth (Williams et al., 1984), to determine crop and management type specific erosion rates. The derived CFs are provided for seven crops that are cultivated for biofuel and food production purposes, namely cassava, corn, rapeseed, soybean, sugarcane, sunflower, and wheat. Due to the fact that variations in crop management result in different yields, the CFs are expressed in kg of soil lost per kg of crop produced. The CFs are calculated on a 30 arcmin scale and are subsequently aggregated to country-specific factors. Finally, the step from erosion rates to erosion damage in terms of monetary values of onsite and offsite costs was discussed. By valuing the ecosystem service, a step generally lacking in LCA (Othoniel et al., 2016), trade-offs in service provisioning can be quantified.

2. Method

2.1. Characterization factors

Characterization Factors (CFs) for soil erosion (kg soil lost per kg crop produced) were calculated per grid cell i as:

$$CF_{x,s,i} = \frac{\Delta ER}{\Delta Y} = \frac{1}{Y_{x,s,i}} \cdot (ER_{x,s,i} - ER_{0,i}) \quad (1)$$

where $Y_{x,s}$ is the fresh matter yield of crop x ($\text{kg crop m}^{-2} \text{a}^{-1}$) under management scenario s , $ER_{x,s}$ is the erosion rate of crop x ($\text{kg soil m}^{-2} \text{a}^{-1}$) under scenario s , and ER_0 is the erosion rate in the reference situation ($\text{kg soil m}^{-2} \text{a}^{-1}$). The potential natural vegetation (PNV) state, which describes the expected state of mature vegetation with no human intervention (Chiarucci et al., 2010), was selected as the reference situation. Negative CF values indicate lower soil losses under agriculture than in PNV state. To determine fresh matter yields from dry matter yields, moisture contents of the

crops from EPIC were taken (see Supporting Information (SI), Table S1).

Since the LCA practitioners typically do not know the exact location of the crop, but might have information on the source country, CFs were also provided on a country scale, averaged over the total amount of crop produced per grid cell.

2.2. Agricultural production and environmental impact model

2.2.1. Model set up

EPIC is a deterministic biophysically based agro-environmental simulation model operating on a daily time step and driven by spatially explicit information on weather, topography, soil and agricultural management practices (Williams et al., 1984). The major processes simulated in EPIC include biomass production, water, nutrient and carbon cycling, soil erosion, and crop growth. Simplified tillage practices were assumed for all crops in EPIC, including conventional moldboard ploughing and disk cultivation prior sowing, and disking after harvest. The annual crops were simulated in mono-crop rotations, with disked soil surface in-between the growing periods. Model output includes information on, a.o., crop yields, hydrological variables (evapotranspiration, runoff, and percolation), soil loss due to water erosion, nitrogen leaching, greenhouse gas emissions, and soil carbon sequestration (Izaurrealde et al., 2006; Williams et al., 1984).

To simulate erosion rates ($ER_{x,s,i}$ and $ER_{0,i}$), and yields ($Y_{x,s,i}$), a global implementation of the EPIC model (Liu et al., 2016; Pugh et al., 2016; Schaubberger et al., 2017) was used for three different agricultural management intensities:

- i. Subsistence scenario: no fertilization, no irrigation.
- ii. Rainfed scenario: with 90% of crop nitrogen requirements satisfied to a maximum application of $200 \text{ N kg ha}^{-1} \text{a}^{-1}$, without irrigation.
- iii. Irrigation scenario: 90% of crop nitrogen requirements satisfied to a maximum application of $200 \text{ N kg ha}^{-1} \text{a}^{-1}$, and 90% of crop irrigation requirements satisfied to a maximum application of up to 500 mm a^{-1} . Irrigation was set-up as a sprinkler in an automatic schedule i.e. 20–50 mm per application.

The reference situation was simulated with EPIC as well to provide consistency in model outcomes. Ramankutty and Foley (2010) published a dataset representing PNV before human alteration on a $0.5^\circ \times 0.5^\circ$ scale. We ascribed the 17 potential land cover classes either to tree, grassland, or not applicable (see SI, Table S2). For those areas where we had no information, but Elshout et al. (2015) had allocated grassland or forest, we took their classification to supplement our dataset. Subsequently we ascribed either grassland or tree simulated erosion ranges from EPIC to each grid to construct a reference scenario of erosion rates representing the PNV state.

With a daily time step, EPIC calculates, inter alia, water erosion soil loss ($\text{kg m}^{-2} \text{a}^{-1}$), with the revised universal soil loss equation (RUSLE, Renard et al., 1997). Soil nutrient pools (nitrogen and phosphorus), soil organic carbon, applied fertilizers and the total soil depth were reduced on a daily basis by quantity lost with eroded soil material. 10-year EPIC simulation results (1991–2000) were averaged to provide the soil erosion rates in each grid cell i and crop yield estimates ($Y_{x,s,i}$) for each scenario. Availability of nutrients and water in an area was not considered. Soil conservation practices which may prevent soil erosion were not addressed in this study, as well as soil deposition of eroded particles and soil formation.

Grids were only included when agricultural land (cropland or other agricultural land) is currently available in that area. Further-

more, as growing certain crops worldwide may be unrealistic due to climatic conditions, the lowest actual country yield reported by the FAO (2016) (FAOSTAT, 2014 data) was used as a lower threshold for the modeled crop yields. We assumed that farmers will not grow crops at a yield lower than this threshold. Therefore, grids with a specific crop yield lower than the threshold were excluded from the CF calculations for that crop. The threshold values used can be found in Table S3 in the SI.

2.2.2. Input data

A detailed description of the global EPIC input data which was collected during the GEO-BENE project can be found in Skalský et al. (2008). The daily climate data were generated from the Princeton Global Meteorological Forcing Dataset for land surface modeling which provides global meteorological data at 1° spatial resolution and a daily temporal resolution, for the years 1948–2008 (IPCC, 2013). A global soil dataset was created by combining data on global soil distribution (Digital Soil Map of the World, <http://www.fao.org/geonetwork/srv>) with soil profile data (WISE) obtained from the International Soil Reference and Information Centre (ISRIC, NL) and described in Batjes (2006). Digital terrain information was derived from GTOPO sources (Global 30 Arc Second Elevation Data; <http://eros.usgs.gov>).

To organize the spatial data in the global database, a global grid was created as the primary geographical reference. To avoid redundant model runs, model grid cells with homogeneous input data were aggregated following a two-step approach. First, homogeneous response units (HRUs) were spatially delineated as zones of the global grid based on topography and soil characteristics that remain relatively stable over time. The HRU's were defined on the basis of 5 altitude classes, 5 soil textural classes (coarse, medium, heavy, stony, peat), and 7 slope (degrees) classes (Skalský et al., 2008). In a second step, simulation units (SIMUs) were created to form the spatial basis for running the global EPIC simulations. SIMUs were defined as intersections of HRUs with the 30' weather data grid cells and administrative country level delineations. This resulted in 212,707 individual landscape units with homogenous topography, soil and weather conditions. The maximum area of a SIMU is equal to an area of one 30' spatial resolution grid pixel, ranging from about 300,000 ha on the equator to about 30,000 ha in high latitudes. The minimum area of a SIMU is equal to an area of one 5' spatial resolution grid pixel, ranging from about 8500 ha at the equator to about 950 ha in high latitudes.

2.3. Statistical analysis

Results were reported as the median of the grids, with 90 percentile confidence intervals, to not have results affected by outliers. The variance between grid-specific CFs that was attributable to (i) the type of crop produced, (ii) management regime during crop cultivation, and (iii) cultivation location was determined. This variance was calculated using an ANOVA as the sums of squares for crop type and management regime factors, with the residual representing spatial variability. The sum of squares of each factor and the residual were divided by the total sum of squares to provide a measure of the explained variance.

A Spearman and partial rank correlation was also performed to determine the contribution to worldwide variation in CFs by the change in erosion rate and crops yield. Spearman's correlation coefficient is a nonparametric rank statistic which shows the strength of an association between two variables. To remove the interaction effect of the crop yield with the erosion rate, partial rank correlation was performed (Hamby, 1994).

The analyses were conducted using the R statistical software in RStudio, v3.3.2 (R Core Team, 2016), with package ppcor for the partial rank correlation (Kim, 2015).

3. Results

Grid-specific CFs for the irrigation, rainfed, and subsistence scenarios are shown in Fig. 1. Country-specific CFs are provided in the SI (Tables S4–S6). Aggregation from SIMU to country scale was based on the total amount of crop produced (year 2014). For all crops and management scenarios, largest CFs were obtained for South-East Asia. We found most yields simulated below the country threshold value used in our study under subsistence farming, especially for rapeseed. Lowest CFs, including a large number of negative SIMU-specific CFs were predicted for sugarcane, while the largest impacts were seen for rapeseed. Wheat grows more easily around the world as yields are high in many areas and therefore more spatially explicit CFs were calculated, with smaller impacts in the North and larger in subtropical and tropical areas.

Fig. 2 shows the ranges of SIMU-specific CFs per crop and management scenario, for the world as well as for each crop for the 5 top-producing countries in 2014. Smallest median CFs were obtained for sugarcane, i.e. 0.04–0.25 kg soil lost/kg sugarcane produced. Largest median CFs were obtained for rapeseed, i.e. 17.5 (irrigation) to 42.2 (subsistence) kg soil lost/kg rapeseed produced. The largest median CFs were obtained for the subsistence scenario for all crops, while the smallest CFs were obtained for the irrigation scenarios for all crops. Median CFs varied up to a factor of 6.2 (sugarcane) between scenarios per crop.

The smallest 90 percentile ranges of grid-specific worldwide CFs were obtained for sugarcane for all scenarios, i.e. a 90 percentile range between 2.3 and 6.9 kg soil lost/kg sugarcane produced. The largest range was obtained for rapeseed under the subsistence scenario (a 90 percentile range of 779 kg soil lost/kg sunflower produced). In the rainfed and irrigation scenarios, rapeseed also showed the largest range (a 90 percentile range of 504 and 344 kg soil lost/kg rapeseed produced, respectively).

Because most of the top 5 producing countries are large countries, the ranges generally overlap between countries. For each crop of which India is in the top 5 producing countries, largest CFs were shown, i.e. rapeseed, soybean and wheat. The importance of providing CFs on a detailed scale is shown from Fig. 2 as for some country-crop combinations 90% ranges can be large. For rapeseed grown in China for example, CFs range from 0.5 up to 176 kg soil/kg rapeseed in the irrigation scenario.

We investigated the effects of crop type, management system, and location, on the variance in grid-specific CFs. Overall, 93% of the variance in CFs was attributable to differences in location. Crop type accounted for 3%, and management scenario for 2%. Another 1% was due to crop-management interactions. When performing the ANOVA for large countries, i.e. USA, Brazil and China, the same trend was seen, only for Brazil crop type contributed 6% (see SI, Table S7). The partial rank correlation showed that the change in erosion rate and (change in) crop yield equally contributed to the global variation of CFs for each crop-management scenario, i.e. between 47% and 53%.

4. Discussion

4.1. Model performance

EPIC is a field-scale biophysical agronomic production model tracking a number of environmental impact processes in great detail. EPIC has been extensively tested, calibrated and validated against observation under various conditions at the field scale (e.g. Billen et al., 2009; Cabelguenne et al., 1990; Rosenberg et al., 1992; Williams et al., 1989). The EPIC simulations presented here combine a wealth of global data with state of the art in global crop modeling (e.g. Porwollik et al., 2017). Yet, large-scale studies

Fig. 1. Worldwide grid-specific characterization factors (CFs in kg soil lost·kg⁻¹ crop produced) for the subsistence scenario (no fertilization, no irrigation), rainfed (fertilization, no irrigation), and irrigation scenario (fertilization and irrigation). The grids shown in white were deemed unsuitable for agricultural land use beforehand (i.e. wetlands, deserts, snow and ice). Grids shown in grey are areas where yields are below the minimum country-specific yield for 2014.

include some limitations especially with respect to insufficiently captured heterogeneity in crop management practices, such as cultivation practices or distribution of crop varieties (Balkovic et al., 2014), under-performing calibration with respect to different climatic conditions (Xiong et al., 2016), insufficiently captured soil heterogeneity (Folberth et al., 2016) or uncertainty of crop yield aggregations (Porwollik et al., 2017). Nevertheless, quality and validation status of such large-scale applications is continuously being improved (see e.g. Wriedt et al., 2009; Van der Velde et al., 2010; Balkovič et al., 2013). Balkovič et al. (2013) showed for corn and wheat in Europe that EPIC performed reasonably in the simulation of regional yields, with long-term averages predicted better

than inter-annual variability. Simulated variability was smaller than reported variability, and better regionalization of certain input parameters like N fertilization distribution and irrigation scenario is suggested. Wang et al. (2012) calibrated and validated the EPIC model and performed a case study for corn. Model performance ratings for runoff, calculated on an event basis, were strong, EPIC was shown to perform well in predicting corn grain yield with r^2 around 0.73 for average corn yield predictions over 34 years. Model validation is still needed for other crops. Comparing our modeled average yields with FAO yields shows that for all crops, our 90 percent ranges are within the reported minimum and maximum country yields, except for sunflower, where our 95

Fig. 2. SIMU-specific characterization factors (CFs in kg soil/kg crop) for the world and the 5 top producing countries in 2014 of each crop for (A) the subsistence scenario (no fertilization, no irrigation), (B) the rainfed scenario (fertilization, no irrigation), and (C) the irrigation scenario (fertilization, irrigation). The center of each box equals the median score, the edges of each box represent the 25th and 75th percentiles, and the whiskers represent the 5th and 95th percentiles.

percentile for the rainfed and irrigation scenarios is around 1.6 times larger, and for sugarcane under irrigation management, where the 95 percentile is slightly larger. Specifically designed conservation practices taking into account local conditions may limit erosion and have not been addressed by our modelling and assessment. At the same time, the influence of these conservation practices on crop yields would also need to be accounted for. Gao et al. (2015), for example, showed for soybean cultivation that a loss of soil also results in a loss of yield. The impact of conservation practices on soil lost per unit crop produced will require further study. Longer term burial of eroded sediment with significant implications for soil carbon storage (e.g. Wang et al., 2017), may also contribute to soil formation downstream. This is not accounted for in our calculations as EPIC has no routing functionality, and may thus result in overestimated erosion impacts.

4.2. Characterization factors

We derived grid-specific CFs for erosion due to crop production that were subsequently aggregated to country-specific CFs. Results showed that most variability in CFs is caused by location, i.e. climate and soil specifics, which justifies the need for regionalization in LCA. Crop type and management scenario are of minor influence. However, most crops included in the present study were annual crops, of which the frequent harvest, tillage and decreased soil cover between growing seasons can lead to more erosion. Perennial grasses and crops with constant cover provide better soil protection and generally also produce higher yields (for example oil palm). Sugarcane, the only semi-perennial crop in our study, was indeed found to have an average yield of around 10 times larger, and smaller CFs than the other crops. To better reflect current practices, alternative soil conservation practices as well as crop rotations should be included in the modeling (e.g. Mitter et al., 2015). In intercropping systems, for example, crop yields can overall be higher (e.g. de la Fuente et al., 2014). For LCA practices, it is advisable to develop CFs for several crop archetypes. Differences between median crop-specific CFs varied up to a factor of 6 between management scenarios. Total environmental impacts of crop production will, however, include e.g. toxicity due to pesticide use, eutrophication due to fertilizer use, and impacts due to water withdrawals in irrigated systems as well. A decision on the agricultural management type to use should therefore not only depend on impacts due to erosion.

Erosion rates were generally larger for the subsistence scenario due to a lower soil cover under poorly developed canopy. Well-established crops on similar lands can reduce soil loss by almost 90% compared to the sparse crop canopy without any conservation practices (Labrière et al., 2015). Because yields were lower for the subsistence scenario, the CFs were largest for the subsistence scenario. Differences between management scenarios were up to a factor of 5.0 for the median yield of corn, with the smallest yield ranges for the subsistence scenario. This variation shows the importance for the farmer to carefully consider the management strategy applied at the farm. The yield ranges are displayed in the SI, Fig. S1.

Our median simulated erosion rates for 7 crops and 3 management strategies worldwide were between 0.4 and 6.2 kg m⁻² a⁻¹, but they could be as low as 0.002 kg m⁻² a⁻¹ (5th percentile for sugarcane irrigation scenario) and as high as 59.5 kg m⁻² a⁻¹ (95th percentile cassava subsistence scenario). See Fig. S2 in the SI. Various studies measuring or modeling region-specific erosion rates showed the large possible variation. Labrière et al. (2015) showed, for example, for the Jhagrabaria Watershed in India, erosion rates between 0.008 and 5.4 kg m⁻² a⁻¹, while (Pugh et al., 2016) calibrated and validated modeled erosion rates for the East river basin in China of 2.5 kg m⁻² a⁻¹ (annual average) up to a

maximum of 40.9 kg m⁻² a⁻¹. A comprehensive assessment of soil erosion in the humid tropics was published by Labrière et al. (2015), who showed that soil loss in established croplands without conservation practices can be up to 0.3 kg m⁻² a⁻¹, and in recently planted crop fields with undeveloped crop cover it can be up to 2.4 kg m⁻² a⁻¹.

Saad et al. (2013) determined erosion resistance potentials of land occupation of “permanent and annual crops” with a spatial scale of 38 climatic geographic world zones. Their CFs were between 0.05 ((sub)tropical thorn woodland) and 15.4 (subtropical wet forest) kg m⁻² a⁻¹, with a world average of 3.1 kg m⁻² a⁻¹. In our work we showed variations between more than 130,000 SIMUs worldwide, 7 crops and 3 management types. Median CFs in kg m⁻² a⁻¹ were between 0.2 and 6.5, but they could be as low as -0.8 kg m⁻² a⁻¹ (5th percentile for sugarcane irrigation scenario) and as high as 59.3 kg m⁻² a⁻¹ (95th percentile cassava subsistence scenario). This shows the importance of including spatial detail as well as differences between crops and management scenarios.

4.3. Application

The erosion impacts from the production of crops in an LCA case study can be determined by multiplying our CFs with the crop yield. Because different management practice of the crops results in different crop yields, the CFs express the damage caused per kg of crop, and not per m² of land use, which has been more common up to now (e.g. Saad et al., 2013). Our factors are provided in fresh matter amounts of crop, matching inventory data in databases such as Ecoinvent (Frischknecht et al., 2007). Also, land management and intensity has already been included in databases (Koellner et al., 2012). Crop yields are expected to increase in the future as a result of enhanced farming technologies, and changes in climate and atmospheric carbon dioxide (Ewert et al., 2005; Jaggard et al., 2010). Related to the first, it is important to include the amount of crop harvested rather than the area used for harvesting in the erosion CFs. Yield increases due to physical processes are not accounted for in the EPIC model, adding uncertainty to the model outcomes for future use. When no information on management is available at inventory level, and no assumption can be made, the spread in the CFs of the management strategies can be used as input for a sensitivity analysis of the results.

We derived CFs on a midpoint level, expressing the amount of soil lost per kg of crop. To go to endpoint level, expressing final environmental damage due to erosion, there are various options. An important endpoint indicator for ecosystem quality is biodiversity (see e.g. Curran et al., 2011). However, currently, there is no method on the effect of erosion to terrestrial biodiversity that is applicable. Núñez et al. (2013) determined effects to NPP, but a solid step from NPP to biodiversity is still lacking. When knowing the amount of soil entering specific water systems, the framework of Quinteiro et al. (2015, 2017) can be used to derive impacts on freshwater biota. Another option is to determine erosion as damage to natural resources, within that area of protection. Núñez et al. (2013) showed how this could be done expressing damage as surplus energy needed to make the resource available at some point in the future, using emery units, i.e. megajoule solar equivalents. These factors can be coupled to our soil loss factors. Also, exergy estimates of various erosion remediation technologies, as determined by Rocco et al. (2016) could be coupled to our erosion values. To have an indicator comparable to other impacts related to (natural) resources, costs could be used as an indicator, since this indicator outlines the extra costs associated to the loss of soil. Cao et al. (2015) monetized erosion CFs with the costs of the available technologies tackling hydric or wind erosion. Pimentel et al. (1995) and Crosson (1995) estimated the onsite costs of water

applied and lost due to erosion at $2 \$ t^{-1}$ and nutrients loss at $3 \$ t^{-1}$, while de Groot et al. (2012) estimated the costs of erosion prevention between 5 and $44 \$ ha^{-1} a^{-1}$. More recent reviews regarding erosion costs show that the numbers of Pimentel et al. (1995) still hold (Kuhlman et al., 2010; Santos Telles et al., 2011). Kuhlman et al. (2010) estimated the offsite costs to be around 1.8 times lower than onsite costs, which matches the estimate by Pimentel et al. (1995) of $3 \$ t^{-1}$. We therefore estimated the total costs of erosion to be $8 \$ t^{-1}$ in 1995. Correcting this number for inflation (Bureau of labor statistics, 2017), leads to a cost of $12.45 \$ t^{-1}$ to remediate erosion losses in 2014 (the latest year for which FAO data were available). Applying this factor to our CFs leads to median damage scores of $0.5–3.1 \$ t^{-1}$ sugarcane up to $217–526 \$ t^{-1}$ rapeseed. Although this approach is promising, further research to spatialize the soil economic value in function of e.g. soil types or countries' wealth, is needed.

Our factors can be used to compare ecosystem impacts to benefits, to see the trade-offs in ecosystem services of crop production. One way to do this is to compare the erosion costs to the benefit of food provisioning in terms net production value. These are available for each crop for between 64 (sunflower) and 116 (corn) countries (FAO, 2016) in 2004–2006 international dollars. To convert these to 2014 \$ we used a factor of 1.20 (Bureau of labor statistics, 2017). For corn, for example, country-specific costs of erosion are then estimated between 0.3 and $18.5 \$ t^{-1}$, while the net production values are between 2.2 and $1494 \$ t^{-1}$. Financial benefits are clearly larger than erosion costs for crop production. However, it should be noted that for this example we only valued erosion impacts, neglecting potential impacts on other ecosystem services, such as water regulation.

5. Conclusions

We developed spatially explicit CFs for environmental damage due to erosion caused by crop cultivation of 7 crops on a global scale. To account for variation in management scenario and variation between crops it is important to include the amount of crop harvested in the CFs. Our CFs allow for a more-detailed spatial and crop-specific assessment of soil loss than was possible earlier. The smallest worldwide ranges of grid-specific CFs were obtained for sugarcane. Geographic location was found to be the most important factor controlling the amount of soil lost with crop cultivation in the present study, while crop type and management scenario were of smaller influence, but still lead to variation in CFs of a factor of 6 for management scenario and 2 orders of magnitude for crop type. Spatial variation in CFs is determined for half by variation in erosion rate changes, and for half by variation in yields. Our determined CFs allow for coupling to damage scores in terms of monetary values to be used in endpoint assessment in LCA. Farmers can minimize erosion rates by careful selection of irrigation and fertilization strategy. Because of the large spatial variability in erosion impacts, careful selection of growing locations is important to help reducing erosion related environmental damage. In this respect, more global trade could be a powerful policy tool to minimize global erosion.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.ecoser.2017.08.015>.

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