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Regionalisation of environmental impacts and emissions models in agricultural LCA

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Summary

Regionalised direct (field) emission modelling and life cycle impact assessment (LCIA) have rapidly evolved in recent years. Available literature reveals that spatial differentiation can be crucial to achieving adequate and accurate results for emissions and environmental impacts at both the midpoint and endpoint levels. Regionalised LCIA also helps to identify the regions where a specific food item can be produced with the lowest environmental impacts. However, many challenges remain in the regionalisation of models, such as the closing of major gaps in the currently used models or determining the appropriate spatial resolution for life cycle assessment (LCA) studies based on their goal and scope.

The present evaluation of emission models and environmental impacts at both the midpoint and endpoint levels aims to fill some of the currently existing gaps. To do so, we conducted a literature review of the currently available modelling approaches. To facilitate the reading of this report, we separated the environmental impact models (Chapter 2) from the emission models (Chapter 3). The text is structured into equal subchapter sections for all analysed emissions and impacts. We present a short introduction, identify the influence of site-specific parameters, and offer an assessment of the current status on how site-specific variables are included in the currently applied approaches. We then highlight the general gaps in the current emission and impact models. For global impact categories, where regionalisation does not improve accuracy (such as greenhouse gas [GHG] potential, stratospheric ozone depletion, and ionising radiation), we only provide a very short description or comment.

Based on this comprehensive review of the regionalisation of both emission and impact models, we discuss some selected aspects in more detail (Chapter 4). First, we emphasise that both agricultural management and pedoclimatic conditions can strongly influence the spatial variation of field emissions and environmental impacts. Agricultural management influences yield, which is often used as a functional unit in LCIA to provide the environmental impacts per kg of product. Further, farm management also directly determines the life cycle inventory (LCI) through the use of fertilisers, pesticides, machinery, and irrigation. However, since agricultural management is largely controlled by farmers' decisions, we do not discuss them in our study. By contrast, the pedoclimatic conditions, which are generally not controlled by the farmer, are comprehensively assessed and discussed. From the review work, we identify key parameters that simultaneously drive several field emissions.

We find that the following key parameters simultaneously drive several emissions: (i) soil texture, determining the percentage fractions of sand, silt, and clay and thus the grain size distribution, (ii) soil organic carbon (SOC), (iii) air temperature, and (iv) precipitation amount. As these key driving parameters typically show large spatial variability, it is crucial to provide them at a sufficiently high spatial resolution fitting to the applied model. Further, the expected increase in accuracy and the time required to implement and run the method has to be in proper relation to each other. We also stress that increasing the degree of detail does – depending on the selected model – not necessarily increase the overall accuracy of the results.

In contrast to agricultural field emissions, the impact pathways (fate, exposure, and effect) of several environmental impacts are critically influenced by the vulnerability of the concerned ecosystem, the spatial distribution of the human population, and the regional availability of certain resources, such as water (determining water scarcity) and land. For instance, the biodiversity score is prone to the occurrence of endangered species in the ecosystem. The spatial distribution of the human population has a direct impact on the number of people exposed to toxic substances and is thus a crucial parameter for human toxicity, and photochemical ozone exposure.

Population density is also of great importance when estimating the impact of water use by competing users on deprived water availability. It is evident that the appropriate spatial resolution of the applied model depends on the spatial variability of the key driving parameters. If, for instance, the population is spatially homogeneously distributed, a high spatial resolution can be dispensed without a loss of accuracy. However, if the population density changes over short distances – as in Western Europe – the spatial resolution has to be high enough to correctly capture the spatial distribution of exposed human beings.

The degree of vulnerability of ecosystems due to nitrogen and phosphorous emissions from agricultural cultivation generally shows high spatial variability regarding species threatened by extinction (e.g. flora, small mammals, amphibians, and insects such as butterflies or grasshoppers). This is related to specific site-dependent characteristics of the ecosystem, spatial variation in biodiversity levels (e.g. characterised by the number of species, the variety of

ecological niches, or increased genetic diversity), and spatial variation in stress levels in aquatic (e.g. rivers, peatlands, and wetlands) and terrestrial ecosystems.

The above considerations indicate that the key parameters driving emissions and environmental impacts differ: The emissions are primarily driven by local soil properties and climatic parameters, whereas environmental impacts are influenced by processes along the entire environmental cause–effect chain. We also show that the choice of adequate spatial model resolution strongly depends on the goal and scope of the study. The objective of a project or study as defined in goal and scope largely determines the extent to which regionalisation of emission models and midpoints will be necessary. A regional differentiation of key driving parameters with high spatial variability is relevant if significant changes in one or several analysed environmental impacts are expected to change substantially, potentially leading to other conclusions depending on the region of production. This is the case when the following three conditions are simultaneously met: (i) the driving parameter has a high spatial variability, (ii) the parameter is key for the emission or the resource (e.g. water), and (iii) the emission or the resource has a major influence on the environmental impact. If these three conditions are not met simultaneously, increased spatial resolution will have little effect on the impact results.

To facilitate the choice of an appropriate spatial resolution in practical applications (LCA studies), we elaborate on some advice provided through the following recommendations:

(i) Ensure that the data used on production techniques, resource use, emissions, and impacts are representative of the regions from which the products originate, where relevant to the objective of the study.
(ii) If expert knowledge and available literature suggest that regionalisation is not relevant for a specific model and/or research question as provided in goal and scope, do not aim at applying models with higher spatial resolution.
(iii) If multiple native spatial resolutions – the spatial scale at which the most influencing modelling can be considered uniform – are suggested through physical principles, try to find a compromise between scientific rigour and practical considerations.
(iv) Site-specific and management factors often cannot be separated in practical and case studies. They often also interact with each other. In certain situations, however, management can be adapted to reduce the environmental impacts (e.g. by avoiding cultivation of erosion-prone arable crops such as maize in hilly areas or water-intensive vegetables in dry areas).

In quantifying the appropriate spatial differentiation of emission models and pathways relevant to environmental impacts, there is much room for further development and investigation. We identify the following research and development issues that need to be addressed:

(i) Compile spatially highly resolved data for parameters at sufficient accuracy identified as key drivers for multiple emissions and environmental impacts such as soil texture, SOC, soil pH and precipitation/temperature, but also freshwater availability, endangered species/ wild fish or the population density
(ii) Consolidate impact modelling through consensus findings (as done, e.g. in the Global Guidance on Environmental Life Cycle Impact Assessment Indicators (GLAM) initiative)
(iii) Generalise models that are tuned to a specific limited region (e.g. continent or climate zone) to allow global application
(iv) Address relevant knowledge gaps through interdisciplinary research and compilation of better data by combining various but also novel data sources, such as satellite imagery.

Successful application of regional models requires sophisticated software and IT tools. The implementation of regionalised models requires input data at sufficient spatial resolution. Further, the models should be appropriate for the geographic region under consideration. The spatial resolution between the LCI and the impact assessment method must also be coordinated. Certain study frameworks should adapt the native resolution of the impact assessment method to the spatial resolution of the available LCI data. For instance, the native resolution of the water scarcity method AWARE (Available WAter REmaining) is the water catchment area. Considering this spatial resolution requires knowledge of water use in specific production systems. However, production data are often not available at this level of detail but rather at the country level. Therefore, generally, only national characterisation factors for AWARE are given in common LCA software, such as SimaPro. To increase the flexibility in practical application, it should be aimed at modular structure of IT tools allowing the use of characterisation factors at different spatial resolutions, for example, country and watershed in the case of freshwater scarcity.

To summarise, this study provides comprehensive insights into the state-of-the art of regionalised models for both agricultural field emissions and environmental impacts. The main challenges are addressed and discussed, providing information on major gaps still existing and key parameters that drive local emissions and environmental impacts. We also elaborate on key variables simultaneously driving multiple emissions or environmental impacts, thereby showing how the accuracy of agricultural LCA studies can be improved based on the emission, impact, and goal and scope of the study.

Zusammenfassung

Sowohl die Modellierung regionalisierter Feldemissionen als auch die Wirkungsabschätzung (Life Cycle Impact Assessment, LCIA) haben sich in den letzten Jahren rasch entwickelt. Die Literatur zeigt, dass eine räumliche Differenzierung entscheidend sein kann, um ausreichend genaue Ergebnisse sowohl für Emissionen als auch Wirkungsabschätzungsmethoden zu erzielen. Eine regionalisierte Wirkungsabschätzung erlaubt, Regionen zu ermitteln, in denen ein bestimmtes Lebensmittel mit den geringsten Umweltwirkungen produziert werden kann. Bei der Regionalisierung von Modellen bestehen jedoch noch viele Herausforderungen wie etwa der Schliessung grösserer Lücken in den aktuell angewandten Methoden oder der Bestimmung einer geeigneten räumlichen Differenzierung je nach Ziel und Untersuchungsrahmen der Ökobilanzierung.

Die vorliegende Studie von Emissionsmodellen und Wirkungsabschätzungsmethoden zielt darauf ab, einige Lücken zu schliessen. Zu diesem Zweck wurde eine Literaturübersicht über die derzeit verfügbaren Modellierungsansätze erstellt. Für eine bessere Übersichtlichkeit werden die Wirkungsabschätzungsmethoden (Kapitel 2) und Emissionsmodelle (Kapitel 3) im vorliegenden Bericht getrennt analysiert. Der Text ist für alle Emissionen und Umweltwirkungen in dieselben Unterkapitel gegliedert. Anschliessend an eine kurze Einführung diskutieren wir den Einfluss standortspezifischer Parameter und zeigen auf, wie standortspezifische Variablen in die aktuellen Ansätze einbezogen werden können. Anschliessend werden allgemeine Lücken in aktuell angewandten Emissionsmodellen und Wirkungsabschätzungsmethoden aufgezeigt. Für globale Wirkungskategorien, bei denen eine Regionalisierung zu keiner erhöhten Genauigkeit führt (z. B. Treibhausgaspotenzial, Abbau der stratosphärischen Ozonschicht und ionisierende Strahlung), beschränken wir uns auf eine sehr kurze Beschreibung oder einen Kommentar.

Auf der Grundlage dieses allgemeinen Überblicks zur Regionalisierung von Emissionsmodellen und Wirkungsabschätzungsmethoden werden einige ausgewählte Aspekte ausführlicher behandelt (Kapitel 4). Zuerst zeigen wir auf, dass sowohl landwirtschaftliche Methoden als auch Boden- und Klimabedingungen die räumliche Variation von Feldemissionen und Umweltwirkungen stark beeinflussen können. Das landwirtschaftliche Management beeinflusst den Ertrag, der in Ökobilanzstudien oft als funktionelle Einheit verwendet wird, um die Umweltwirkungen pro kg des Produkts anzugeben. Auch die landwirtschaftliche Betriebsführung wirkt sich durch die Verwendung von Dünge- und Pflanzenschutzmitteln, Maschineneinsatz und Bewässerung direkt auf die Ökobilanz aus. Da das landwirtschaftliche Management jedoch weitgehend von den Entscheidungen der Betriebsleiterinnen und Betriebsleiter bestimmt wird, gehen wir in unserer Studie nicht weiter auf diesen Aspekt ein. Im Gegensatz dazu werden die Boden- und Klimabedingungen, die von den Betrieben im Allgemeinen nicht beeinflussbar sind, umfassend bewertet und diskutiert. Anhand der Ergebnisse dieser Übersicht wurden Schlüsselparameter ermittelt, die gleichzeitig mehrere Feldemissionen beeinflussen.

Die Analyse zeigte, dass die folgenden Faktoren mehrere Emissionen gleichzeitig massgeblich beeinflussen: (i) die Bodentextur, die durch den prozentualen Anteil von Sand, Schluff und Ton und die Korngrössenverteilung bestimmt wird, (ii) der organische Kohlenstoff im Boden, (iii) die Lufttemperatur sowie (iv) die Niederschlagsmenge. Da diese Schlüsselparameter in der Regel eine hohe räumliche Variabilität aufweisen, ist es zentral, diese mit einer ausreichend hohen und an das verwendete Modell angepassten räumlichen Auflösung bereitzustellen. Ausserdem muss die erwartete höhere Genauigkeit und die für die Implementierung und Durchführung der Methode erforderliche Zeit in einem angemessenen Verhältnis zueinander stehen. Wir zeigen auch, dass ein grösserer Detaillierungsgrad – je nach gewähltem Modell – die Genauigkeit der Schlussergebnisse nicht unbedingt erhöht.

Im Gegensatz zu den landwirtschaftlichen Emissionen werden die Umweltwirkungen durch die verschiedenen Wirkungspfade (Verweildauer, Exposition und Wirkung) entscheidend von der Empfindlichkeit des betreffenden Ökosystems, der räumlichen Verteilung der Bevölkerung und der regionalen Verfügbarkeit bestimmter Ressourcen wie Wasser und Land beeinflusst. Die Bewertung der Biodiversität hängt zum Beispiel vom Vorkommen gefährdeter Arten im Ökosystem ab. Die räumliche Verteilung der Bevölkerung wirkt sich unmittelbar auf die Anzahl der Personen aus, die toxischen Stoffen ausgesetzt sind, und ist somit ein entscheidender Parameter für die Humantoxizität und die durch photochemische Reaktionen verursachte Ozonbelastung.

Die Bevölkerungsdichte und der damit verbundene Wasserbrauch beeinflusst auch die für weitere Nutzung verbleibenden Wasserressourcen. Es ist klar, dass die geeignete räumliche Auflösung eines Modells von der räumlichen Variabilität der wichtigsten Einflussparameter abhängt. Ist die Bevölkerung beispielsweise räumlich

homogen verteilt, kann auf eine hohe räumliche Differenzierung verzichtet werden, ohne dass die Genauigkeit darunter leidet. Ändert sich jedoch die Bevölkerungsdichte über kurze Entfernungen (wie zum Beispiel in Westeuropa), muss die räumliche Auflösung hoch genug sein, um die räumliche Verteilung der exponierten Menschen korrekt zu erfassen.

Die Anfälligkeit von Ökosystemen aufgrund von Stickstoff- und Phosphoremissionen aus der Landwirtschaft in Bezug auf die lokale Artenvielfalt (z. B. Flora, kleine Säugetiere, Amphibien und Insekten wie Schmetterlinge oder Heuschrecken) weist im Allgemeinen eine hohe räumliche Variabilität auf. Beeinflusst wird diese Anfälligkeit durch standortabhängige Merkmale des Ökosystems, die räumliche Variation der Artenvielfalt (z. B. gekennzeichnet durch die Anzahl der Arten, die Vielfalt der ökologischen Nischen oder die erhöhte genetische Vielfalt) und die räumliche Variation der Belastung in aquatischen (z. B. Flüsse, Torfgebiete und Feuchtgebiete) und terrestrischen Ökosystemen.

Die oben genannten Überlegungen zeigen, dass sich die entscheidenden Faktoren von Feldemissionen und Umweltwirkungen unterscheiden: Während die Emissionen in erster Linie von den lokalen Boden- und Klimabedingungen abhängen, werden die Umweltwirkungen durch Prozesse entlang der gesamten ökologischen Wirkungskette beeinflusst. Wir zeigen auch, dass die geeignete räumliche Auflösung des Modells stark vom Ziel und dem Untersuchungsrahmen der Studie abhängt. Das für ein Projekt festgelegte Ziel und dessen Untersuchungsrahmen bestimmen weitgehend, inwieweit eine Regionalisierung der Emissions- und Umweltwirkungsmodelle erforderlich ist. Eine regionale Differenzierung der wichtigsten Variablen mit hoher räumlicher Variabilität ist nur dann sinnvoll, wenn bei einer oder mehreren analysierten Umweltwirkungen je nach Produktionsregion substantielle Veränderungen zu erwarten sind, die zu anderen Schlussfolgerungen führen können. Dies ist der Fall, wenn die folgenden drei Bedingungen gleichzeitig erfüllt sind: (i) der untersuchte Parameter weist eine hohe räumliche Variabilität auf, (ii) die Emission oder die Ressource (z. B. Wasser) wird entscheidend von diesem Parameter beeinflusst, und (iii) die Emission oder die Ressource hat einen grossen Einfluss auf die Umweltwirkungen. Wenn diese drei Bedingungen nicht alle gleichzeitig erfüllt sind, hat eine höhere räumliche Auflösung kaum Auswirkungen auf die Ergebnisse.

Als Unterstützung bei der Wahl einer geeigneten räumlichen Auflösung in praxisnahen Anwendungen (Ökobilanz-Studien) sind nachfolgend einige Empfehlungen zusammengestellt:

(i) Sicherstellen, dass die verwendeten Daten zu Produktionsmethoden, Ressourcenverbrauch, Emissionen und Umweltwirkungen für die Region, aus denen die Produkte stammen, repräsentativ sind, sofern dies für das Ziel der Studie relevant ist.
(ii) Wenn Expertenwissen und verfügbare Literatur darauf hindeuten, dass eine Regionalisierung für ein bestimmtes Modell und/oder eine bestimmte Forschungsfrage gemäss Ziel und Untersuchungsrahmen der Studie nicht relevant sind, kann auf Modelle mit höherer räumlicher Auflösung verzichtet werden.
(iii) Wenn physikalische Grundsätze unterschiedliche räumliche Auflösungen nahelegen, sollte ein Kompromiss zwischen wissenschaftlicher Genauigkeit und praktischer Umsetzung angestrebt werden.
(iv) In Praxis- und Fallstudien können standortspezifische Faktoren und Managementfaktoren oft nicht getrennt werden. Zudem beeinflussen sie sich häufig gegenseitig. In bestimmten Situationen kann das betriebliche Management jedoch so angepasst werden, dass sich die Umweltwirkungen verringern (z. B. durch den Verzicht auf den Anbau erosionsanfälliger Ackerkulturen wie Mais in hügeligen Regionen oder wasserintensiver Gemüsekulturen in Gebieten, die unter Wasserknappheit leiden).

Zur Frage einer geeigneten räumlichen Differenzierung von Emissionsmodellen sowie der für Umweltwirkungen relevanten Pfade besteht noch viel Raum für weitere Entwicklungen und Analysen. Dabei haben wir die folgenden noch zu untersuchenden Forschungs- und Entwicklungsfragen identifiziert:

(i) Bereitstellung räumlich hoch aufgelöster Daten für Variablen mit ausreichender Genauigkeit, die als Schlüsselfaktoren für mehrere Emissionen und Umweltwirkungen identifiziert wurden, wie Bodentextur, organischer Kohlenstoff im Boden, Boden-pH und Niederschlag/Temperatur, aber auch Wasserknappheit, Anzahl gefährdeter Arten oder Bevölkerungsdichte
(ii) Konsensfindung hinsichtlich neuer Wirkungsabschätzungsmethoden, wie z. B. im Rahmen der Initiative Global Guidance on Environmental Life Cycle Impact Assessment Indicators (GLAM)
(iii) Verallgemeinerung von Modellen, die nur in einer räumlich begrenzten Region (z. B. ein bestimmter Kontinent oder eine Klimazone) gültig sind, auf eine globale Anwendung
(iv) Schliessung von Wissenslücken durch interdisziplinäre Forschung sowie Verbesserung der Datengrundlage durch kluge Kombination verschiedener Datenquellen wie etwa Satellitenbilder.

Die erfolgreiche Anwendung regionaler Modelle erfordert hochentwickelte Software und IT-Tools. Die Umsetzung regionalisierter Modelle setzt die Bereitstellung von Inputdaten mit ausreichender räumlicher Auflösung und Genauigkeit voraus. Ausserdem sollten die Modelle für die betreffende geografische Region angepasst sein. Die räumliche Auflösung der Inventardaten und der Modelle zur Berechnung der Umweltwirkung müssen aufeinander abgestimmt sein. Gewisse Anwendungen verlangen, die anfangs gewählte räumliche Auflösung einer Wirkungsabschätzungsmethode an die Auflösung verfügbarer Inventardaten anzupassen. Die aus physikalischen Gründen am besten geeignete Auflösung der Methode zur Bestimmung der Wasserverfügbarkeit (AWARE, Available WAter REmaining) sind Wassereinzugsgebiete. Die Berücksichtigung dieser räumlichen Auflösung erfordert Kenntnisse über die Wassernutzung in bestimmten Produktionssystemen. Die Produktionsdaten stehen jedoch häufig nicht in dieser Detailtiefe, sondern nur auf Länderebene zur Verfügung. Daher werden in gängiger Ökobilanz-Software wie SimaPro in der Regel nur nationale Charakterisierungsfaktoren für die Methode AWARE berücksichtigt. Um eine hohe Flexibilität in praktischen Anwendungen zu erlauben, sollten IT-Modelle möglichst modular aufgebaut werden, um die Verwendung von Charakterisierungsfaktoren unterschiedlicher räumlicher Auflösung zu ermöglichen, z. B. Staat und Wassereinzugsgebiet im Fall von Wasserknappheit.

Zusammenfassend lässt sich sagen, dass diese Studie einen umfassenden Einblick in den aktuellen Stand regionalisierter Modelle sowohl für landwirtschaftliche Feldemissionen als auch Umweltwirkungen bietet. Die wichtigsten Herausforderungen werden angesprochen und erörtert. Zudem werden die wichtigsten noch bestehenden Lücken und die wichtigsten treibenden Parameter beschrieben, welche die lokalen Emissionen und Umweltwirkungen bestimmen. Wir gehen auch auf Schlüsselfaktoren ein, die gleichzeitig mehrere Emissionen oder Umweltwirkungen entscheidend beeinflussen, und zeigen, wie die Genauigkeit landwirtschaftlicher Ökobilanzstudien je nach Emission, Auswirkung sowie Ziel und Untersuchungsrahmen der Studie verbessert werden kann.

Résumé

La modélisation régionale des émissions directes (sur le terrain) et l'évaluation de l'impact sur le cycle de vie (en anglais: Life Cycle Impact Assessment, LCIA) ont rapidement évolué ces dernières années. La littérature disponible révèle que la différenciation spatiale peut être cruciale pour obtenir des résultats corrects et précis en matière d'émissions et d'impacts environnementaux. La LCIA régionalisée permet également d'identifier les régions où une denrée alimentaire spécifique peut être produite avec les impacts environnementaux les plus faibles. Cependant, de nombreux défis restent à relever en matière de régionalisation des modèles, notamment pour combler les principales lacunes des modèles actuellement utilisés ou pour déterminer la résolution spatiale appropriée pour les études d'analyse du cycle de vie (ACV) en fonction de leur objectif et de leur portée.

La présente évaluation des modèles d'émissions et des impacts environnementaux vise à combler certaines lacunes. A cet effet, nous avons procédé à une revue de littérature pour identifier les approches de modélisation actuellement disponibles. Afin de faciliter la lecture de ce rapport, nous avons séparé les modèles d'impact environnemental (chapitre 2) des modèles d'émission (chapitre 3). Le texte est structuré en sous-chapitres égaux pour toutes les émissions et tous les impacts analysés. Nous présentons une brève introduction, identifions l'influence des paramètres spécifiques au site et proposons une évaluation de l'état actuel de la prise en compte des variables spécifiques au site avec les approches actuellement appliquées. Nous soulignons ensuite les lacunes générales des modèles d'émission et d'impact actuels. En ce qui concerne les catégories d'impact global, pour lesquelles la régionalisation n'améliore pas la précision (comme le potentiel des gaz à effet de serre [GES], l'appauvrissement de la couche d'ozone stratosphérique et le rayonnement ionisant), nous ne fournissons qu'une très courte description ou un commentaire.

Sur la base de cet examen complet de la régionalisation des modèles d'émission et d'impact, nous examinons plus en détail certains aspects préalablement sélectionnés (chapitre 4). Tout d'abord, nous tenons à souligner que le mode d'exploitation agricole et les conditions pédoclimatiques peuvent fortement influencer la variation spatiale des émissions sur le terrain et des impacts environnementaux. Le mode d'exploitation agricole influence le rendement, qui est souvent utilisé comme unité fonctionnelle dans la LCIA pour indiquer les impacts environnementaux par kg de produit. En outre, il détermine directement l'inventaire du cycle de vie (ICV) par le biais de l'utilisation d'engrais, de pesticides, de machines et par l'irrigation. Cependant, le mode d'exploitation agricole dépendant largement des décisions des agriculteurs, il n'est pas pris en compte dans notre étude. En revanche, les conditions pédoclimatiques, qui ne sont généralement pas contrôlées par l'agriculteur, font l'objet d'une évaluation et d'une discussion approfondies. La revue de littérature nous a permis d'identifier les paramètres clés qui déterminent simultanément plusieurs émissions sur le terrain.

Nous constatons que les paramètres clés suivants influent simultanément sur plusieurs émissions : (i) la texture du sol, qui détermine les fractions en sable, limon et argile et donc la distribution de la taille des grains, (ii) le carbone organique du sol (COS), (iii) la température de l'air et (iv) la quantité de précipitations. Comme ces paramètres clés présentent généralement une grande variabilité spatiale, il est essentiel de les fournir à une résolution spatiale suffisamment élevée afin qu'ils correspondent au modèle utilisé. En outre, l'augmentation attendue de la précision et le temps nécessaire à la mise en œuvre et à l'exécution de la méthode doivent être en harmonie l'un par rapport l'autre. Nous soulignons également que l'augmentation du degré de détail - en fonction du modèle sélectionné - n'augmente pas nécessairement la précision globale des résultats.

Contrairement aux émissions agricoles sur le terrain, les voies d'impact (évolution, exposition et effet) de plusieurs impacts environnementaux sont fortement influencées par la vulnérabilité de l'écosystème concerné, la répartition spatiale de la population et la disponibilité régionale de certaines ressources, telles que l'eau (déterminant la rareté en eau) et la terre. Par exemple, le score de biodiversité est lié à la présence d'espèces menacées dans l'écosystème. La répartition spatiale de la population a un impact direct sur le nombre de personnes exposées aux substances toxiques et constitue donc un paramètre crucial pour la toxicité humaine et l'exposition à l'ozone photochimique.

La densité de la population est également très importante pour estimer l'impact de l'utilisation de l'eau du fait de la concurrence entre les utilisateurs. Il est évident que la résolution spatiale appropriée du modèle appliqué dépend de la variabilité spatiale des principaux paramètres moteurs. Si, par exemple, la population est répartie de manière

homogène dans l'espace, on peut se passer d'une résolution spatiale élevée sans pour autant perdre en précision. Par contre, si la densité de la population change sur de courtes distances – comme c'est le cas en Europe occidentale - la résolution spatiale doit être suffisamment élevée pour saisir correctement la distribution spatiale des personnes exposées.

Le degré de vulnérabilité des écosystèmes dû aux émissions d'azote et de phosphore provenant des cultures agricoles présente généralement une grande variabilité spatiale en ce qui concerne les espèces menacées d'extinction (flore, petits mammifères, amphibiens et insectes tels que les papillons ou les sauterelles). Cette variabilité est liée aux caractéristiques spécifiques de l'écosystème qui dépendent du site, à la variation spatiale des niveaux de biodiversité (caractérisés par exemple par le nombre d'espèces, la variété des niches écologiques ou l'augmentation de la diversité génétique) et à la variation spatiale des niveaux de stress dans les écosystèmes aquatiques (par exemple les rivières, les tourbières et les zones humides) et terrestres.

Les considérations ci-dessus indiquent que les paramètres clés qui déterminent les émissions et les impacts environnementaux diffèrent : Les émissions sont principalement dictées par les propriétés locales du sol et les paramètres climatiques, tandis que les impacts environnementaux sont influencés par des processus tout au long de la chaîne des causes et des effets dans l'environnement. Nous montrons également que le choix de la résolution spatiale adéquate du modèle dépend beaucoup de l'objectif et de la portée de l'étude. L'objectif d'un projet ou d'une étude, tel qu'il est défini dans le champ d'application, détermine en grande partie à quel point la régionalisation des modèles d'émission et des impacts environnementaux est nécessaire. Une différenciation régionale des principaux paramètres moteurs à forte variabilité spatiale est nécessaire si des changements importants dans un ou plusieurs des impacts environnementaux analysés sont attendus et potentiellement susceptibles de conduire à d'autres conclusions en fonction de la région de production. C'est le cas lorsque les trois conditions suivantes sont simultanément remplies : (i) le paramètre moteur présente une forte variabilité spatiale, (ii) le paramètre est essentiel pour l'émission ou la ressource (p. ex. exemple l'eau) et (iii) l'émission ou la ressource a une influence majeure sur l'impact environnemental. Si ces trois conditions ne sont pas remplies simultanément, l'augmentation de la résolution spatiale n'aura que peu d'effet sur les résultats de l'impact.

Pour faciliter le choix d'une résolution spatiale appropriée dans les applications pratiques (études ACV), nous apportons certains conseils qui sont résumés dans les recommandations suivantes :

(i) Veiller à ce que les données utilisées concernant les techniques de production, l'utilisation des ressources, les émissions et les impacts soient représentatives des régions dont sont originaires les produits, lorsque cela est pertinent pour l'objectif de l'étude.
(ii) Si les connaissances d'experts et la littérature disponible suggèrent que la régionalisation n'est pas utile pour un modèle spécifique et/ou une question de recherche telle que définie dans l'objectif et le champ d'application, ne pas chercher à appliquer des modèles présentant une résolution spatiale supérieure.
(iii) Si des principes physiques suggèrent des résolutions multiples - l'échelle spatiale à laquelle la modélisation la plus performante peut être considérée comme uniforme - essayer de trouver un compromis entre la rigueur scientifique et les considérations pratiques.
(iv) Les facteurs spécifiques au site et les facteurs d'exploitation ne peuvent souvent pas être séparés dans les études pratiques et les études de cas. Ils interagissent souvent les uns avec les autres. Dans certaines situations, cependant, le mode d'exploitation agricole peut être adapté pour réduire les impacts environnementaux (p. ex., en évitant les cultures arables sujettes à l'érosion telles que le maïs dans les régions de collines ou les légumes à forte consommation d'eau dans les régions sèches).

La quantification de la différenciation spatiale appropriée des modèles d'émission et des voies pertinentes pour les impacts environnementaux offre de nombreuses possibilités de développements et de recherches. Voici les questions de recherche et de développement qui ont été identifiées :

(i) Compiler des données à haute résolution spatiale pour les paramètres suffisamment précis identifiés comme des facteurs clés d'émissions multiples et d'impacts sur l'environnement, tels que la texture du sol, le COS, le pH du sol et les précipitations/la température, mais aussi la disponibilité de l'eau potable, les espèces menacées/les poissons sauvages ou la densité de la population.
(ii) Consolider la modélisation de l'impact dans une optique consensuelle (à l'instar de l'initiative «Global Guidance on Environmental Life Cycle Impact Assessment Indicators» (GLAM))
(iii) Généraliser les modèles correspondant à une région limitée spécifique (p. ex. un continent ou une zone climatique) pour permettre une application à l'échelle mondiale

(iv) Combler les lacunes en matière de connaissances grâce à la recherche interdisciplinaire et à la compilation de données de meilleure qualité en combinant des sources de données diverses et nouvelles, telles que l'imagerie satellitaire.

Réussir à appliquer des modèles régionaux nécessite des logiciels et des outils informatiques sophistiqués. La mise en œuvre de modèles régionalisés nécessite des données initiales avec une résolution spatiale suffisante. En outre, les modèles doivent être adaptés à la région géographique considérée. La résolution spatiale entre l'ICV et la méthode d'évaluation d'impact doit également être coordonnée. Certains cadres d'étude devraient adapter la résolution de la méthode d'évaluation d'impact à la résolution spatiale des données de l'ICV disponibles. Par exemple, la résolution de la méthode d'évaluation de la rareté de l'eau AWARE (Available WAter REmaining) est le bassin hydrographique. Pour prendre en compte cette résolution spatiale, il faut connaître l'utilisation de l'eau dans des systèmes de production spécifiques. Cependant, les données de production ne sont souvent pas disponibles à ce niveau de détail, mais plutôt au niveau national. C'est pourquoi, en général, seuls les facteurs de caractérisation nationaux pour AWARE sont indiqués dans les logiciels d'ACV courants, tels que SimaPro. Pour accroître la flexibilité des applications pratiques, il faudrait viser une structure modulaire des outils informatiques permettant l'utilisation de facteurs de caractérisation à différentes résolutions spatiales, par exemple au niveau du pays et du bassin versant en cas de rareté de l'eau.

En résumé, cette étude donne un aperçu complet de l'état des connaissances en matière de modèles régionalisés pour les émissions agricoles sur le terrain et les impacts sur l'environnement. Les principaux défis sont abordés et discutés. Ils fournissent des informations sur les principales lacunes encore existantes et sur les paramètres clés qui déterminent les émissions locales et les impacts environnementaux. Nous développons également les variables clés qui déterminent simultanément plusieurs émissions ou impacts environnementaux, montrant ainsi comment la précision des études ACV agricoles peut être améliorée en fonction de l'émission, de l'impact, de l'objectif et de la portée de l'étude.

Riassunto

Sia la modellizzazione delle emissioni sul campo regionalizzate sia la valutazione d'impatto del ciclo di vita (Life Cycle Impact Assessment, LCIA) hanno registrato una rapida evoluzione nel corso degli ultimi anni. Dalla letteratura emerge che una differenziazione spaziale può essere determinante per ottenere risultati adeguati e accurati per le emissioni e i metodi di valutazione d'impatto ambientale a livello di effetto potenziale ed esito finale (midpoint/endpoint). L'LCIA regionalizzato aiuta anche a identificare le regioni in cui una specifica derrata alimentare può essere prodotta con il minimo impatto ambientale. La regionalizzazione dei modelli comporta tuttavia ancora numerose sfide, ad esempio colmare le principali lacune nei modelli attualmente utilizzati o determinare l'appropriata risoluzione spaziale per un ecobilancio (Life Cycle Assessment, LCA) in funzione dell'obiettivo e del raggio d'azione dello studio.

La presente valutazione dei modelli di emissioni e dei metodi di valutazione d'impatto ai livelli midpoint ed endpoint mira a colmare alcune delle lacune esistenti. In questa ottica abbiamo preso in rassegna i testi che trattano gli approcci di modellizzazione attualmente disponibili. Per una maggiore chiarezza abbiamo trattato separatamente i metodi di valutazione d'impatto ambientale (capitolo 2) e i modelli di emissioni (capitolo 3). Il testo è strutturato negli stessi sottocapitoli per tutte le emissioni e gli impatti ambientali oggetto dell'analisi. Dopo una breve introduzione, discutiamo l'influenza dei parametri specifici per il sito e spieghiamo come le variabili specifiche per il sito possono essere incluse negli approcci attualmente seguiti. Infine illustriamo le generali lacune negli attuali modelli di emissioni e d'impatto. Per le categorie d'impatto globali, per le quali la regionalizzazione non migliora l'accuratezza (ad es. potenziale di gas serra, assottigliamento dello strato di ozono stratosferico e radiazione ionizzante), ci limitiamo a una breve descrizione o a un commento.

In base a questa visione d'insieme della regionalizzazione dei modelli di emissioni e d'impatto, approfondiamo alcuni aspetti (capitolo 4). Prima di tutto sottolineiamo che sia la gestione agricola sia le condizioni pedoclimatiche possono avere una forte influenza sulla variazione spaziale delle emissioni sul campo e degli impatti ambientali. La gestione agricola influenza la resa, che viene spesso utilizzata come unità funzionale nell'LCIA per indicare gli impatti ambientali per kg di prodotto. Inoltre, la conduzione agricola si ripercuote direttamente sull'inventario del ciclo di vita (LCI) attraverso l'uso di fertilizzanti, pesticidi, macchinari e irrigazione. Tuttavia, poiché la gestione agricola è in gran parte determinata dalle decisioni del capoazienda, nel nostro studio non approfondiamo ulteriormente questo aspetto. Vengono invece valutate e discusse in modo esaustivo le condizioni pedoclimatiche che non sono generalmente influenzabili dalle aziende. Dai risultati di questa rassegna abbiamo identificato i parametri chiave che influenzano simultaneamente diverse emissioni sul campo.

Dall'analisi è emerso che diverse emissioni sono influenzate simultaneamente dai seguenti parametri: (i) la tessitura del suolo, determinata mediante la percentuale di sabbia, silt e argilla e la distribuzione granulometrica, (ii) il carbonio organico nel suolo (Soil Organic Carbon, SOC), (iii) la temperatura dell'aria e (iv) la quantità di precipitazioni. Dal momento che questi parametri chiave sono generalmente contrassegnati da un'elevata volatilità spaziale, è essenziale fornirli con una risoluzione spaziale sufficientemente elevata e adeguata al modello utilizzato. Inoltre, la migliore accuratezza prevista e il tempo necessario per implementare ed eseguire il metodo devono essere ragionevolmente proporzionati tra loro. Sottolineiamo anche che un maggiore grado di dettaglio, a seconda del modello scelto, non aumenta necessariamente l'accuratezza del risultato finale.

A differenza delle emissioni agricole, gli impatti ambientali sono influenzati in modo critico da diversi meccanismi d'impatto (permanenza, esposizione ed effetto), dalla vulnerabilità dell'ecosistema in questione, dalla distribuzione spaziale della popolazione e dalla disponibilità regionale di determinate risorse, come l'acqua (che ne determina la penuria) e la terra. Ad esempio, il punteggio della biodiversità dipende dalla presenza di specie a rischio di estinzione nell'ecosistema. La distribuzione spaziale della popolazione ha un impatto diretto sul numero di persone esposte a sostanze tossiche ed è quindi un parametro decisivo per la tossicità umana e l'esposizione all'ozono fotochimico.

Anche la densità della popolazione e il conseguente consumo di acqua influenzano le restanti risorse idriche per i diversi usi. È evidente che l'appropriata risoluzione spaziale di un modello dipende dalla variabilità spaziale dei principali parametri di influenza. Se, ad esempio, la popolazione presenta una distribuzione spaziale omogenea, si può rinunciare a una risoluzione spaziale elevata senza penalizzare l'accuratezza. Tuttavia, se la densità della

popolazione varia su brevi distanze (come in Europa occidentale), la risoluzione spaziale deve essere sufficientemente elevata per rilevare correttamente la distribuzione spaziale delle persone esposte.

Il grado di vulnerabilità degli ecosistemi dovuta alle emissioni di azoto e fosforo provenienti dall'agricoltura evidenzia generalmente un'elevata variabilità spaziale per quanto riguarda le specie a rischio di estinzione (ad es. la flora, i piccoli mammiferi, gli anfibi e gli insetti, come farfalle e cavallette). Questa vulnerabilità è correlata a specifiche caratteristiche dell'ecosistema dipendenti dal sito, alla variazione spaziale della diversità delle specie (ad es. caratterizzata dal numero di specie, dalla varietà delle nicchie ecologiche o dall'aumentata diversità genetica), alla variazione spaziale dell'inquinamento negli ecosistemi acquatici (ad es. fiumi, torbiere e paludi) e terrestri.

Quanto suesposto dimostra che i fattori determinanti delle emissioni sul campo e degli impatti ambientali sono diversi: mentre le emissioni sono causate prima di tutto da condizioni pedoclimatiche locali, gli impatti ambientali sono influenzati da processi lungo l'intera catena di causa-effetto. Mostriamo inoltre che la scelta della giusta risoluzione spaziale del modello dipende notevolmente dall'obiettivo e dal raggio d'azione dello studio, che per un progetto determinano in misura significativa fino a che punto è necessaria la regionalizzazione dei modelli di emissioni e d'impatto ambientale. Una differenziazione regionale dei principali parametri con un'elevata variabilità spaziale è rilevante solo se in uno o più impatti ambientali analizzati si attendono cambiamenti sostanziali che possono portare a conclusioni diverse a seconda della regione di produzione. Ciò avviene se sono contemporaneamente soddisfatte le tre condizioni seguenti: (i) il parametro analizzato denota un'elevata variabilità spaziale, (ii) il parametro è determinante per l'emissione o la risorsa (ad es. l'acqua), e (iii) l'emissione o la risorsa ha una notevole influenza sull'impatto ambientale. Se queste tre condizioni non sono soddisfatte contemporaneamente, una maggiore risoluzione spaziale avrà uno scarso effetto sui risultati.

Per facilitare la scelta di un'opportuna risoluzione spaziale nelle applicazioni pratiche (studi LCA) abbiamo sintetizzato di seguito alcune raccomandazioni:

(i) garantire che i dati utilizzati sulle tecniche di produzione, l'uso delle risorse, le emissioni e gli impatti ambientali siano rappresentativi per la regione da cui provengono i prodotti, se è rilevante per l'obiettivo dello studio;
(ii) se il know-how degli esperti e la letteratura disponibile suggeriscono che la regionalizzazione non è rilevante per un determinato modello e/o un quesito di ricerca basato sull'obiettivo e il raggio d'azione dello studio, si può rinunciare a modelli con una risoluzione spaziale più elevata;
(iii) se i principi fisici suggeriscono diverse risoluzioni ottimali (la scala spaziale alla quale la modellizzazione più influente può essere considerata uniforme), è opportuno cercare un compromesso tra il rigore scientifico e le considerazioni pratiche;
(iv) negli studi pratici e di casi è spesso impossibile separare fattori specifici per il sito e fattori di gestione, che non di rado interagiscono tra loro. In determinate situazioni, tuttavia, la gestione dell'azienda può essere adattata in modo da ridurre gli impatti ambientali (ad es. evitando colture arabili a rischio di erosione come il mais nelle zone collinari o gli ortaggi con un fabbisogno di acqua elevato nelle zone aride).

Sulla questione dell'opportuna differenziazione spaziale dei modelli di emissioni e dei rilevanti meccanismi d'impatto ambientale esiste ancora un ampio margine di sviluppo e di indagine. Abbiamo quindi identificato i seguenti quesiti di ricerca e di sviluppo:

(i) predisporre dati con un'elevata risoluzione spaziale per variabili sufficientemente accurate che sono state identificate come parametri chiave per diverse emissioni e impatti ambientali, come la tessitura del suolo, il SOC, il pH del suolo e le precipitazioni/temperature, ma anche la scarsità d'acqua, il numero di specie a rischio di estinzione o la densità della popolazione;
(ii) raggiungere un consenso su nuovi modelli d'impatto, come avvenuto nel quadro dell'Initiative Global Guidance on Environmental Life Cycle Impact Assessment Indicators (GLAM);
(iii) generalizzare modelli che valgono solo in una specifica regione (ad es. un determinato continente o una zona climatica) per consentire un'applicazione su scala globale;
(iv) colmare le lacune conoscitive con una ricerca interdisciplinare e migliorare la base di dati con un'opportuna combinazione di diverse fonti di dati, tra cui le immagini satellitari.

L'applicazione efficace dei modelli regionali richiede sofisticati software e strumenti informatici. Per implementare modelli regionalizzati occorrono dati di input con una sufficiente risoluzione spaziale e precisione. Inoltre, i modelli dovrebbero essere adattati alla regione geografica in questione. È necessario coordinare la risoluzione spaziale dei dati per l'inventario del ciclo di vita e il metodo di valutazione dell'impatto ambientale. Determinate applicazioni esigono che la risoluzione ottimale del metodo di valutazione dell'impatto sia adattata alla risoluzione dei dati d'inventario disponibili. Ad esempio, la risoluzione ottimale del metodo utilizzato per valutare l'impatto sul consumo di acqua AWARE (Available WAter REmaining) è il bacino idrografico. La considerazione di questa risoluzione spaziale richiede conoscenze dello sfruttamento idrico in determinati sistemi di produzione, tuttavia i dati di produzione non sono spesso disponibili a questo livello di dettaglio, ma solo a livello nazionale. Di conseguenza, nei comuni software LCA come SimaPro vengono considerati solo fattori di caratterizzazione nazionali da utilizzare con il metodo AWARE. Per aumentare la flessibilità nelle applicazioni pratiche, gli strumenti informatici dovrebbero avere una struttura modulare in modo da consentire il ricorso a fattori di caratterizzazione con diverse risoluzioni spaziali, ad esempio il Paese e il bacino imbrifero nel caso della penuria di acqua.

Per concludere, lo studio fornisce un quadro completo dello stato attuale dei modelli regionalizzati sia per le emissioni agricole sia per gli impatti ambientali, oltre ad affrontare ed esaminare le sfide più significative. Inoltre descrive le maggiori lacune ancora esistenti e i più importati fattori chiave che determinano le emissioni locali e gli impatti ambientali. Infine, approfondisce le variabili principali che esercitano un'influenza determinante su più emissioni o impatti ambientali e mostra come l'accuratezza degli studi LCA applicati al settore agricolo può essere migliorata a seconda dell'emissione, dell'impatto, dell'obiettivo e del raggio d'azione dello studio.

1 Introduction

In the last two decades, a wide range of literature has been published on regionalised life cycle impact assessment (LCIA). Several studies have shown that the location of the emission may strongly affect impacts such as acidification and eutrophication (Hauschild & Potting, 2005; Norris, 2002). Mutel et al. (2019) published a consensus output of a UNEP-SETAC Life Cycle Initiative on the status of regionalised LCIA methods. They found that the native spatial resolution (the spatial scale at which the most influencing modelling can be considered uniform) often does not reflect the observed spatial variability of a given environmental issue but rather on the input data availability and the limited availability of models for specific impact categories.

The current literature reveals that for all impact categories in which the impact is dependent on the activity location, spatial differentiation can be highly important to achieve a representative assessment of the environmental impacts of a system (Henryson et al., 2018). Hellweg and Milà-i-Canals (2014) stressed that spatial differentiation is considered an important step in improving LCA methodology. This is because the same emitted amount of a substance may cause different impacts depending on where the emission is released. This means that regional differences in source and receptor characteristics may strongly influence the impact of an emission. For each regionalised impact category, the most appropriate spatial resolution is determined by the resolution of the most influential modelling parameter (Bulle et al., 2019).

The spatial resolution of characterisation factors (CF) in available LCIA midpoints is subject to constant change mainly – but not solely – due to the creation of high-resolution datasets. Major factors determining whether regionalised LCIA will be used are the cost-benefit ratio, ease of use and transparent documentation of LCIA methods, and regionalised life cycle inventory (LCI) (Frischknecht et al., 2019b). A critical formulation of the study's "goal and scope" will ensure the appropriate spatial resolution of the applied approaches. The research question of an LCA study determines regional resolution. The level and degree of regionalisation should be adapted to the research question and goal of the study.

When using regionalised LCIA, the spatial resolution of the LCI must match that of the LCIA. Therefore, the challenge is to provide input data that allow for the computation of characterisation factors for LCIA methods at both the midpoint and endpoint levels that are scientifically sound, reflect the appropriate resolution of the underlying physical processes, and are at the required resolution for a specific application. Generally, higher spatial resolution is required if the underlying physical processes exhibit high spatial variation and a strong effect on an emission and if the emission has a high contribution to an impact category relevant to the study. It is evident that a wide range of spatially explicit data, for example, on climate, soil, land use, or management practices, is a prerequisite for deriving CFs at high spatial resolution.

This report investigates the state-of-the art of regionalisation for both emission models and selected environmental midpoints and endpoints. Note that the adequate boundary between LCI and LCIA is not always evident and can be treated in different ways. For pesticide applications, there is some consensus that the LCI should describe the initial emission distribution of active substances within environmental compartments (soil, water, plants) within minutes to hours after their application (Fantke, 2019).

The main objective of this report is to critically evaluate current methods to better account for regional effects where necessary. Thus, we investigate the influence of site-dependent parameters on emission processes and impact pathways. The influence of management, such as different fertiliser application techniques, is beyond the scope of this study, even though agricultural management shows regional differences. The major goal of this report is to provide an overview of LCIA and emission models regarding their potential to increase their expressive power and accuracy through higher-resolution regional processes. LCIA translates resources and emission flows into (environmental) impacts using CFs. Methods that do not (or only to a negligible extent) benefit from regionalisation are also briefly discussed in Chapter 3 but are not further discussed in detail.

Below are some key research questions to be answered within this analysis.

1. What are the key driving parameters at the regional or local level that influence the results from LCIA and emissions models? What is the extent of their impact on emissions and environmental impacts?
2. Which site characteristics affect physical mechanisms that are relevant for the emission or impact category?

3. How are site characteristics considered in the LCA literature for the respective emission or impact categories? Does the potential gain in accuracy justify the resources needed to implement and apply a regionalised method?
4. Are there major gaps in the current methods and models relevant for practical LCA applications?
5. Do common LCIA methods include spatial differentiation? At which level are the characterisation factors provided (global, country, and geospatial regions such as watersheds)?

We stress that the regionalisation of methods should always be analysed in the context of the goal and scope of LCA applications: Methodically sophisticated models or models with very high spatial resolution are generally not required for LCA studies. For example, if for a product only the country of origin is known (e.g. soy from Brazil), increased spatial resolution does not provide additional benefits.

In Chapters 2 and 3, we analyse LCIA methods and emission models regarding their potential to benefit from regionalisation. A separate evaluation of the LCIA methods and emission models is reasonable for the following three reasons:

(i) Involved physical processes (degree of knowledge level, parameterisation) differ.
(ii) Typical spatial scale (spatial variability) differs; for example, nitrous oxide (N_2O) emissions vary strongly spatially, whereas the GHG potential induced – among others – by N_2O, does not.
(iii) Following the Driver-Pressure-State-Impact-Response (DPSIR) framework (OECD, 2003), emission models are ‘pressures’, while midpoints are ‘impacts’; thus, the latter are further down in the cause–effect pathway. The DPSIR model is often used to structure and organise indicators.

Chapter 4 provides a comprehensive discussion based on the findings in Chapters 2 and 3 and further enhancements. We conclude in Chapter 5, which also provides detailed recommendations for practical applications in LCA studies.

2 Regionalisation of impact models

LCIA methods translate resource or emission flows using characterisation factors (CFs) into impacts. To keep the scope of the analysis within reasonable limits and to consider the most important relevant LCIA methods, we limit the analysis to the following LCIA methods, as well as to the most relevant reports on international initiatives, recommendations, and regulations. The basic idea was to select frequently used and broadly accepted LCIA methods and international organisations. Note that the historically relevant method EDIP 2003 has also been considered. The main reason was to gain more insight into the parameters that are relevant to regionalisation. The EDIP 2003 method is no longer recommended (Douziech et al., 2024; Frischknecht et al. 2019a).

The following literature on LCIA methods was considered:

- LC-Impact (Verones et al., 2020a, 2020b)
- ImpactWorld+ (Bulle et al., 2019)
- ReCiPe 2016 (Goedkoop et al., 2009); Huijbregts et al., 2016, 2017)
- PEF (Product Environmental Footprint) (Zampori and Pant, 2019)
- UBP (Swiss method of ecological scarcity, eco-points) (Frischknecht & Knöpfel, 2013)
- CML 2001 (Guinée et al., 2001)
- EDIP 2003 (Hauschild & Potting, 2005)
- UN Life Cycle Initiative
- IPCC2021 (IPCC, 2006, 2019, 2021).

To avoid duplicate information below, we provide a short general introduction to the above-listed methods, leaving relevant details inherent to the specific methods in the following sections. Most approaches provide CFs at both the midpoint and endpoint (damage) levels. Midpoints are typically located "in the middle" of the impact pathway, where the environmental mechanisms are identical for all environmental flows assigned to that impact category (Huijbregts et al., 2017). Endpoints corresponding to the three areas of protection, that is, human health, ecosystem quality, and resource scarcity, are located at the end of the impact pathway. Endpoints are afflicted with higher uncertainty than midpoints but provide more information on environmental relevance (Bare et al., 2000).

LC-Impact
LC-Impact is a spatially differentiated LCIA approach (Verones et al., 2020b). CFs are given at both the global and national level but also at the spatial resolution that is appropriate ("typical") for the impact. The method was developed in the FP7-funded project LC-IMPACT, including state-of-the-art approaches for LCIA methods, at the midpoint and endpoint levels. It is intended to provide regular updates to include the most important developments in LCA. Special emphasis has been placed on appropriate spatial resolution. CFs at the endpoint level are given for (i) human health (unit: disability-adjusted life years [DALY]), (ii) terrestrial/ freshwater/marine ecosystem quality (unit: PDF m^{2}d or PDF·y), and (iii) mineral scarcity (unit: potential kg ore surplus). The method benefits from a new approach that includes impacts on ecosystems by assessing global extinction and from a quantitative uncertainty assessment for selected impact categories (Verones et al., 2020b).
ImpactWorld+
IMPACT World+ is an update of the IMPACT 2002+ (Jolliet et al., 2003), LUCAS, and EDIP (Hauschild and Potting, 2005) methods. The method has a global scope and is available both as midpoint and endpoint (damage level). Most of the regional impact categories are spatially resolved, and all the long-term impact categories are subdivided between shorter-term damages (over 100 years after the emission) and long-term damages. IMPACT World+ also assesses the scale-dependent uncertainty of CFs derived from "fine-scale" models based on different impact pathways. The long-term impacts of climate change are assessed by both global warming potentials (GWP100) and IPCC global temperature potentials (GTP100). Regionalised CFs at the midpoint level are given for (i) freshwater/ terrestrial acidification, (ii) freshwater and marine eutrophication, (iii) freshwater ecotoxicity, (iv) human toxicity non cancer/ cancer, (v) particulate matter formation and (vi) water scarcity, and (vii) land transformation/ occupation (see Fig.1 in Jolliet et al., 2003). The characterisation models at the local and regional scales are based on appropriate spatial scales, such as watersheds for water use impacts or biomes for land use impacts.

IMPACT World+ allows regional assessment of the potential impact of any geo-referenced environmental intervention, providing characterisation factors at four levels of spatial resolution: global default, continent, national, and native. The native resolution scale is defined by the modeller for each impact category and varies among categories.

ReCiPe

ReCiPe 2016 is an updated and extended version of ReciPe 2008 that provides harmonised CFs for midpoint and endpoint (damage) categories (Goedkoop et al., 2009). CFs at the endpoint level correspond to three areas of protection: human health, ecosystem quality, and resource scarcity. At the midpoint level, 18 impact categories are addressed, including climate change, stratospheric ozone depletion, freshwater/marine eutrophication, terrestrial acidification, terrestrial/ freshwater/ marine ecotoxicity, mineral/ fossil resource scarcity, land and water use, etc. As the physical processes and damage models are subject to high levels of uncertainty, three different perspectives are discerned: individualist (I, guided by short-term interests), hierarchist (H, based on most common policy principles), and egalitarian (E, long-term, based on principle thinking).

PEF (Product Environmental Footprint)

PEF defines a standardised method for the application context of product environmental footprinting based on different methodological assumptions. The method recommends applying a broad range of 16 environmental impact indicators (European Commission, 2021). It also provides a set of normalisation and weighting values to calculate a single score (Ramos et al., 2022). The modelling requirements for selected food categories are defined in specific Product Environmental Footprint Category Rules (PEFCRs).

UBP (Swiss method of ecological scarcity, eco-points)

The Federal Office for the Environment (FOEN) has developed a distance-to-target method using so-called eco-factors, based on actual pollution and on critical targets that are derived from Swiss policy (FOEN, 2021; Frischknecht and Knöpfel, 2013). The key metrics of this method are eco-factors, which measure environmental damage in eco-points (UBP) per unit of quantity. It is based on the distance-to-target method. The fourth edition adds eco-factors for the use of marine fish resources and improves water use and biodiversity loss induced by land use, following internationally recommended approaches. Due to changes of environmental targets in Swiss policy, there have been significant changes in the eco-factors between UBP 2013 and UPB 2021, such as the (i) doubling of the GHG eco-factor due to the federal net-zero goal till 2050; (ii) significant lowering of eco-factors for heavy metal emissions due to a new modelling approach based on USEtox (Fantke et al., 2015b; Huijbregts et al., 2010; Rosenbaum et al., 2008); and (iii) tripling of eco-factors for plant protection products (PPP) due to more ambitious goals of the action plan PPP launched by the federal council, which aims to halve the current risks from PPP (Bundesrat, 2017).

CML 2002

The CML method was developed at the “**C**entrum voor **M**ilieukunde” at the University **L**eiden (Guinée et al., 2002; Guinée et al., 2006; Guinée et al., 2001). It is a midpoint approach that models 11 midpoint indicators, including the global warming potential, acidification potential, eutrophication potential, freshwater/ marine aquatic ecotoxicity potential, terrestrial/ human ecotoxicity potential, abiotic depletion, etc. The method is a crucial basis for more recently developed midpoints and endpoints.

EDIP 2003

The EDIP method was derived from a consensus project in Denmark from 1997–2003 (Hauschild & Potting, 2005; Hauschild et al., 2006). The method developed CFs for the following impact categories: acidification, terrestrial eutrophication, photochemical ozone exposure of plants, photochemical ozone exposure of human beings, aquatic eutrophication, human toxicity via air exposure, and ecotoxicity. As with the CML method, EDIP 2003 is a relevant precursor method of more recently developed LCIA methods. It provides spatially resolved CFs for Europe at the country level, allowing for differences in impact from an emission when released in different countries.

UN Life Cycle Initiative

Various guidelines for LCIA indicators have been developed in recent years (UNEP, 2016, 2019). These guidelines follow general International Standard Organisation (ISO) standards, as described in detail in comprehensive reports such as (ISO 1997, 1998a, 1998b, 2006a, 2006b). ISO provides international reference regarding principles, frameworks, and terminology for conducting and reporting LCA studies.

IPCC 2021

IPCC 2021 (IPCC 2019, 2021) is the successor of the IPCC 2013 method, which was developed by the Intergovernmental Panel on Climate Change.

2.1 Climate change

2.1.1 Introduction

The main GHG of agricultural origin are carbon dioxide, methane, and nitrous oxide. Their mean lifetimes in the atmosphere lie between one decade and thousands of years. After such a long period, they are relatively homogenously mixed in the troposphere. Therefore, the location of an emission does not play a relevant role, and a spatial differentiation of the characterisation factors is not needed. Climate change is a global challenge. UNEP (2016) recommends using two different characterisation methods that reflect different time horizons to address the issue of short- and long-lived GHG. It recommends using GWP100 as the default methodology, thus ensuring the comparability of the results and using the global temperature potential 100 (GTP100) to reflect long-term impacts. In GTP100, the weight of methane is considerably lower; for example, in IPCC (2021), the GTP100 impact of methane is seven times lower than its GWP100 (7 vs. 28 CO_2eq/kg CH_4).

2.1.2 Influence of site-specific parameters

As mentioned above, the location of GHG emissions is irrelevant. Notable exceptions are emissions from aviation. Emissions of NO_x, particulate matter, and water vapour in the upper troposphere lead to cloud formation (cirrhus clouds), contributing to global warming. According to Jungbluth and Meili (2019), emissions from aviation have a higher impact on climate change than other sources of GHG. Neu (2021), based on Lee et al. (2021), recommended a factor of 3 for GWP*, 1.7 for GWP100, and 1.1 for GTP100.

2.1.3 Current status of the inclusion of site-specific parameters

Generally, there is no need for spatial differentiation of CFs for global warming. High CFs for emissions from aviation are not considered in standard impact assessment methods. However, scientific evidence seems to be clear that emissions from aviation have a high impact.

2.1.4 General gaps in the current models

Recently, the GWP100 was controversially debated in the scientific community and by stakeholders, who argued that the main GHGs have different lifetimes in the atmosphere and that their cumulative impacts in CO_2eq is therefore problematic. Alternative metrics have been proposed, such as GWP* and CGTP (Neu, 2022), which can be spatially and temporally differentiated by taking the evolution of emissions during the last few years (typically 20) in a given area. This leads to characterisation factors that differ between countries. However, this is not a spatial differentiation in the sense of LCA, since the impact on the atmosphere does not depend on the location of the emission. From the perspective of LCA, these methods are not suitable for use in most LCA studies for the following reasons:

1. The GWP* values for CH_4 can become negative, which would not make sense for most LCA applications, particularly if related to products.
2. The GWP* values can differ between regions and countries, although their impact on the atmosphere is the same. This would, for example, be the case if methane emissions were decreasing in one country while increasing in another. The impact calculated with GWP* would be higher in the country with increasing emissions. This is not consistent with the LCA principle that the LCIA should reflect the environmental mechanism, since the impact of 1kg of methane does not depend on the location of the emission.

2.2 Stratospheric ozone depletion

2.2.1 Introduction

The ozone layer in the stratosphere is crucial for the protection of life on earth, since it absorbs a large part of the harmful UV radiation coming from the sun (https://www.epa.gov/ozone-layer-protection/basic-ozone-layer-science). Therefore, the ozone layer has an important function in protecting plants, animals, and human health. Ozone is continuously formed and destroyed, and it has a relatively short lifetime. A number of manmade chemicals increase the rate of destruction, leading to a reduction in the thickness of the ozone layer. They are called ozone-depleting substances (ODS). ODS are mainly fluorine-, chlorine-, and bromine-containing substances, but N_2O also has an ozone-depleting effect, which is of utmost importance in agri-food systems, since it dominates ozone depletion for these systems. In earlier LCIA methods, N_2O has been ignored, which led to completely different results for agricultural systems. The ODS result in more UV-B radiation reaching the earth's surface, provoking adverse human health effects, such as skin cancer and cataract, with effects on ecosystems (Verones et al., 2020a). The midpoint indicator expresses the ozone depletion potential of 1kg of a given compound relative to the ozone depletion potential of 1kg of CFC-11.

2.2.2 Influence of site-specific parameters

The reduction of stratospheric ozone is unequally distributed throughout the globe, with a tendency to be less important in equatorial regions and more important in polar and mid-latitude regions. However, the location of an emission is not relevant for the impact in the stratosphere; therefore, impact assessment for ozone depletion is global, and no spatial differentiation is needed.

2.2.3 Current status of the inclusion of site-specific parameters

Not needed.

2.2.4 General gaps in the current models

Nothing relevant to this report.

2.3 Photochemical ozone formation

2.3.1 Introduction

Ozone is formed in the lower layers of the atmosphere (troposphere) by a chemical reaction of nitrogen oxides (NO_x) with volatile organic compounds (VOCs) and carbon monoxide (CO) initiated by solar radiation (Hauschild et al., 2006). From an agricultural point of view, the emissions of NO_x (from combustion processes and nitrogen (N) fertilisers) and methane are mainly relevant. Considering the entire food supply chain, other VOCs, such as butane or propane, play a significant role. Subsequently, this tropospheric ozone can be inhaled by humans or taken up by plants, leading to an increased number of mortality cases and damage to human health, as well as the disappearance of plant species and damage to terrestrial ecosystems. On the one hand, the emissions of the precursor gases depend on local and regional conditions (see below); on the other hand, the impact depends on the presence of vulnerable human populations and vulnerable ecosystems. Therefore, spatial differentiation is potentially relevant.

2.3.2 Influence of site-specific parameters

Impacts on human health: Spatial differences are caused by different population densities in the different regions. LC-Impact 1.0 (Verones et al., 2020a) uses the population number for the year 2005 for the population aged over 30 years, assuming no effects on younger people (<30 years). The global source-receptor model TM5-FASST (FAst Scenario Screening Tool for Global Air Quality and Instantaneous Radiative Forcing) is used to model concentrations of the relevant substances in the atmosphere after emission by using 56 emission source regions that represent countries or groups of countries. Region-specific concentration-response functions are calculated to estimate human health damage as an endpoint (expressed in DALYs).

Impacts on terrestrial ecosystems: Similar to the impact on human health, LC-Impact 1.0 proposes spatially explicit CFs for the same 56 emission source regions. It accounts for the potentially disappeared fraction (PDF) of species in grassland and forest ecosystems. The fate of these species is determined by the accumulated ozone exposure over a threshold of 40ppb, which is considered to be the effect threshold. Vegetation periods are differentiated by the northern and southern hemispheres. The effect factor takes into account the species richness density of vascular plants and the area of the different vegetation types. Therefore, the regional aspect is determined by the areas of the different vegetation types per region and the species richness density per vegetation type.

2.3.3 Current status of the inclusion of site-specific parameters

The CFs for human health and ecosystem quality vary widely between countries by about two orders of magnitude. Therefore, spatial differentiation could potentially play a highly important role in the results. The CFs for Switzerland are above the global average for NO_x and below for Non-Methane Volatile Organic Compounds (MNVOC). Note that the CFs for NO_x can become negative in some countries, which implies that ozone concentrations decrease with higher NO_x emissions. However, CFs for VOCs tend to be higher in these countries (Verones et al., 2020b). For terrestrial ecosystems, the CFs for Switzerland are above the global average for both substance groups, which means that imports would have potentially lower impacts than domestic production.

ReCiPe 2016 uses region-specific intake fractions for human health impacts, but CFs are provided at the global level only without spatial differentiation. LC-Impact proposes CFs at four different spatial resolutions: global, continental, and country levels. PEF-CR recommends the use of the indicator for human health from ReCiPe 2008, which is also used in Impact World+. An interesting aspect is that the main emission sources of CH_4 and NO_x are different. While CH_4 is mainly of agricultural origin (if we exclude emissions for the fossil energy sector) and NO_x stems mainly from combustion processes (transports, heating, industry), of which the majority comes from non-agricultural sectors. Therefore, methane is mainly formed in rural areas and NO_x in urban areas. This means that the highest ozone formation is likely to occur in agglomerations between urban and rural areas. NO_x and various VOC are relevant precursor substances. Implementing a spatially differentiated method means that all relevant inventory flows need to be spatially differentiated to account for spatially differentiated CFs.

2.3.4 General gaps in the current models

Verones et al. (2020b) listed the uncertainties in fate factor calculations for terrestrial ecosystems based on the AOT40 values, which is the "sum of the differences between hourly ozone concentration and 40 ppb for each hour when the concentration exceeds 40 ppb during a relevant growing season, e.g. for forest and crops" (AOT40 — European Environment Agency (europa.eu)). For values slightly above or below this threshold, a large uncertainty occurs.

2.4 Terrestrial acidification

2.4.1 Introduction

Acidification refers to the effects of the emissions of (inorganic) acid-forming substances into the atmosphere and the resulting deposition of acids in various environmental compartments, such as soil, groundwater, or surface waters. In principle, the deposition of these substances on soil or in water leads to the release of protons (H+), which can result in a decrease in the pH value. However, the actual effects vary depending on the buffering capacity of the receiving medium. For example, the extent of acidification in the soil depends strongly on its lime content (Roesch et al., 2017). At the country level, the most relevant acidifying emissions are releases of N (NO_x and NH_3) and sulphur (SO_2) to air (Hauschild & Potting, 2005). Both ammonia (NH_3) and mono-nitrogen oxides (NO_x) contribute to the acidification potential of agricultural systems, with NH3 (from livestock and fertilisation) typically causing 80-90% of the impact (Kupper & Menzi, 2013). Although NH_3 does not have a direct acidifying effect, it indirectly contributes to terrestrial acidification after nitrification (Wowra et al., 2021). Terrestrial acidification and terrestrial eutrophication are often highly correlated in agricultural systems, as both are largely caused by NH_3 emissions.

2.4.2 Influence of site-specific parameters

Acidification can influence agricultural productivity through both direct and indirect effects. This can be attributed to the fact that all plants have an optimal level of pH, where productivity is at its highest. A significant deviation from this optimum has a negative impact on crop productivity. Direct effects are caused by a changing pH value, which, in turn, can change the availability of nutrients or toxic substances as indirect effects (Roy et al., 2014). The atmospheric deposition of NO_x, NH_3, and SO_2 results in terrestrial acidification by a decrease in soil pH (Roy et al., 2014). A key site-specific parameter in this context is the lime content of the topsoil, which acts as a buffer substance with regard to the pH value. A higher lime content can thus stabilise the pH value and compensate, to a certain extent, for the deposition of acidifying substances.

2.4.3 Current status of the inclusion of site-specific parameters

Both the emission of acidifying substances and the resulting impact from the receiving environment after deposition are directly related to local environmental conditions and are therefore site-specific. Different impact methods for estimating the acidification potential with different levels of regionalisation are available.

- ReCiPe 2016: Calculation of terrestrial acidification in the ReCiPe 2016 method is an updated version of the ReCiPe 2008 method and is based mainly on the work of Roy et al. (2014). At the midpoint level, it considers the fate of an emission in the atmosphere and the soil and calculates changes in soil H+ (Huijbregts et al., 2017). The model provides country-specific characterisation factors and a global average.
- EDIP2003: EDIP 2003 uses the RAINS model to estimate atmospheric dispersion and deposition processes for N and sulphur compounds. The resulting characterisation factors are spatially differentiated in the 44

countries respectively regions in Europe, and a European average (generic CF) is given. Both the background concentrations and buffer capacity of the receiving compartments (e.g. soils) are considered.
- CML2001: Similar to EDIP 2003, CML2001 uses the RAINS model to estimate atmospheric dispersion and deposition processes of acidifying emissions without spatial differentiation.
- Accumulative Exceedence (AE) (Posch et al., 2008; Seppälä et al., 2006): AE takes into account both the emission of acidifying substances and the sensitivity of the receiving environment to the respective emissions. The latter is calculated by means of critical load functions that use a steady-state model to describe ecosystem-specific sensitivity.
- LC-Impact (Verones et al., 2020a). This metric provides CFs for terrestrial acidification, mainly based on the methods described by Albrecht et al. (2014) and Aragão de Mello et al. (2013). Four levels of spatial detail are differentiated: (i) the native resolution of the method, (ii) country averages, (iii) continental averages, and (iv) a global average. The latter should only be used if the origin of an emission is unknown.

2.4.4 General gaps in the current models

ReCiPe 2016 and LC-Impact do not provide a characterisation model for marine acidification. Woods et al. (2016) reported on various studies investigating basic oceanic biochemistry and noted that there are still significant knowledge gaps related to the consideration of non-linear behaviour of global circulation models and the representation of coastal regions in these models. Henryson et al. (2018) developed and applied site-specific characterisation factors for marine acidification in Sweden; however, to our knowledge, a globally applicable model is currently missing.

2.5 Terrestrial eutrophication

2.5.1 Introduction

Terrestrial eutrophication is caused by nutrient enrichment in terrestrial ecosystems due to nutrient deposition mainly from anthropogenic sources (Clark et al., 2017). In agricultural production, this is mainly caused by emissions of the macronutrient N from fertilisation (e.g. in the form of NH_3 (from deposition), NH_4+, or NO_x) which is illustrated by the fact that, at the European level, the N use efficiency rate is only 63% (Hauschild and Potting, 2005; Isbell et al., 2011). Excess nutrients can affect nutrient cycles and, thus, the productivity of crops (Clark et al., 2017).

2.5.2 Influence of site-specific parameters

The emission of eutrophying substances and the impact of eutrophication depend on regional nutrient concentrations and nutrient surplus, which indicates the need for spatially differentiated emission and impact modelling (Isbell et al., 2011; Wowra et al., 2021). The influencing site-specific parameters are as follows (Bouwman et al., 2002a; Bouwman et al., 2002b; Bouwman et al., 2002c; Eichner, 1990):

- Meteorological conditions (e.g. air temperature and precipitation)
- Soil conditions (type and structure, O_2 capacity, SOC stock, pH, N content)

2.5.3 Current status of the inclusion of site-specific parameters

In impact assessment in the context of agricultural LCA, terrestrial eutrophication is considered to different degrees, depending on the impact assessment method. This concerns both the overall level of differentiation of eutrophication into different compartments and the emissions considered (i.e. characterised). Three gradations can be distinguished according to the degree of consideration:

i) Terrestrial eutrophication is not considered at all (e.g. ReCiPe 2008, IMPACT World+).
ii) Aquatic eutrophication and terrestrial eutrophication are combined (e.g. CML 2001).
iii) Terrestrial eutrophication is considered separately (EDIP 2003 and the AE method).

Among the commonly used LCIA methods, only EDIP 2003 and AE consider terrestrial eutrophication as a separate impact category. EDIP 2003 is based on the RAINS model, which assesses exposure to terrestrial eutrophication for 44 regions in Europe based on a combination of regional emission levels and atmospheric transport over long distances (Hauschild & Potting, 2005). In the AE method, country-specific characterisation factors are calculated that take into account the dispersion of an emission in the atmosphere, the deposition of that emission to an ecosystem, and the sensitivity of the receiving ecosystem in regard to the emission. The basis are so-called critical loads of N (Posch et al., 2008; Seppälä et al., 2006).

2.5.4 General gaps in the current models

In addition to the degree of differentiation, there is also a question of completeness. Wowra et al. (2021) examined various impact assessment methods from this perspective and found that the EDIP method covers 5 N-based emissions, whereas the CML 2001 method (Guinée et al., 2001; Guinée et al., 2002) characterises 11 N-based emissions to air with regard to (terrestrial) eutrophication. For example, N_2O and nitrate (NO_3^-) are characterised by CML 2001 but not by EDIP 2003, whereas in the AE method, NH_3, HNO_3, and NO_x are considered (Seppälä et al., 2006).

2.6 Aquatic (marine) eutrophication of nitrogen

2.6.1 Introduction

Marine eutrophication is defined as the reaction of a marine ecosystem to the excessive availability of growth-limiting nutrients in the euphotic zone of coastal waters (Cosme & Hauschild, 2017). Here, we assume that N is the main limiting nutrient in marine waters. The increase in planktonic growth due to N-enrichment fuels the organic carbon (C) cycles and may lead to excessive oxygen depletion in the benthic (bottom) layer of the ocean, which may then lead to loss of species diversity (Levin et al., 2009). These phenomena may eventually cause serious damage to fisheries and biodiversity. Henryson et al. (2018) stressed that eutrophication is commonly assessed using site-generic characterisation factors, despite being a site-dependent environmental impact. They showed that location plays an important role in determining the actual impact of an emission, which means that site-dependent impact assessment could provide valuable information to LCAs and increase the relevance of LCA as a tool for assessing product-related eutrophication impacts.

Specifically, for aquatic eutrophication, characterisation factors have been proposed for large geographical areas (mainly European and North American countries). However, the factors are not sufficiently detailed for countries that present large geographical, climatic, and economic variability (Gallego et al., 2010). The importance of regionalised characterisation factors has also been stressed by Gallego-Schmid and Tarpani (2019).

2.6.2 Influence of site-specific parameters

Specifically, for aquatic eutrophication, characterisation factors have been proposed for large geographical areas (mainly European and North American countries). These factors are not sufficiently detailed for countries that present large geographical, climatic, and economic variability (Gallego et al., 2010). The importance of regionalised characterisation factors has also been stressed by Gallego-Schmid and Tarpani (2019). Through sensitivity studies, Cosme (2016) found that the most relevant parameter for computing CFs is the surface water residence time, which is used to estimate N removal by advection and denitrification in fate modelling. Also of high importance is the primary production rate, which is used for estimating the marine ecosystem exposure factors XF. Bystricky et al. (2017) showed that soil type distinctly affects the aquatic eutrophication of N. Soil type influences N release through mineralisation, as it depends on pore volume and, thus, oxygen supply for microorganisms, as well as soil warming in the spring (Richner et al., 2014).

2.6.3 Current status of the inclusion of site-specific parameters

Cosme and Hauschild (2017) emphasised that N-enrichment (supply of inorganic nutrients to coastal water from anthropogenic sources) in the marine compartment is well reflected in various LCIA methods at the midpoint level (e.g. ReCiPe, EDIP 2003, IMPACT 2002+, and CML 2002). However, the link between emissions and endpoint (damage level) is poorly represented. The authors stressed that a “consistent cause–effect link from emissions to the endpoint of the cascade of effects caused by the N enrichment (impact pathway) is not yet available”. Modelling at the endpoint level requires the estimation of the exposure factor (XF) and the effect factor (EFF), which are generally not sufficiently well reflected in current models.

Cosme and Hauschild (2017) suggested a sophisticated physically based approach for deriving regionalised CFs for marine eutrophication. This method provides global, regionally differentiated fate factors (FFs), XFs, and EFFs for 66 large marine ecosystems. FF expresses the persistence of the exported fraction of the original N emission in each receiving coastal ecosystem, and EFFs the effect on different marine species due to N inputs. The authors estimated new soil and freshwater FF for the river basins of the world and calculated spatially explicit CF at the endpoint (damage) level for 5772 river basins of the world. Inland water (i.e. freshwater) fate modelling is based on the NEWS 2-DIN model (Mayorga et al., 2010) at 0.5° × 0.5° resolution, relating natural and anthropogenic nutrient emission sources as well as natural transformation processes in watersheds to the inputs of nutrients at the level of watersheds. Morelli et al. (2018) concluded that for marine eutrophication, the work of Cosme and Hauschild (2017) is the best available LCIA method, as it fills previously existing gaps in the characterisation model and provides full coverage of the cause–effect chain.

For Europe, spatially resolved EFFs based on a sophisticated model can be derived using the Cause Effect Relation Model CARMEN, as outlined in Hauschild and Potting (2005). This model computes the fraction of nutrient emissions from agricultural soil that will reach and expose marine (and freshwater) waters. It estimates the transport of nutrients to surface water (in Europe) from agricultural supply, through groundwater drainage and surface runoff and through atmospheric deposition with a high spatial resolution based on 124320 grid-elements of 10 × 10 minutes (roughly 100–250km^2, depending on the longitude and latitude location of the grid-element. Site generic EFFs were computed for 32 coastal areas by their country of release. EFFs express the share of emissions that will contribute to the eutrophication of coastal areas. The calculated factors describe a “realistic worst-case scenario”. Emissions from a non-European or unknown region can be characterised using site-generic factors.

LC-Impact: For marine eutrophication, the LC-Impact method was developed based on the ImpactWorld+, ReciPe 2008, and EDIP2003 methods (Cosme & Hauschild, 2017; Morelli et al., 2018). N emissions to 66 different large marine ecosystems are treated separately. The modelled impact pathway is limited to waterborne N loadings from human activities into coastal marine waters, leading to increased N concentrations (Verones et al., 2020a). The model estimates the effects of oxygen depletion on biota. N-losses in marine coastal waters due to denitrification are also considered.

ReCiPe: Huijbregts et al. (2016) described the characterisation factors at the midpoint level for ReCiPe 2016. Morelli et al. (2018) stated that marine eutrophication is only included in ReCiPe 2008 at the endpoint level, whereas ReCiPe 2016 addresses marine eutrophication only at the midpoint level because there are no appropriate endpoint models, such as the one developed by Cosme and Hauschild (2017).

Impact World+: According to Roy et al. (2012) and Bulle et al. (2019), the computation of atmospheric emissions of N-containing substances in Impact World+ is based on a 2° × 2.5° grid resolution FF ($mass_{deposited}/mass_{emitted}$, units: $kg_{deposited}/kg_{emitted}$). CFs are then computed by the product FF × XF × EFF, thus linking the emissions of a substance with its impact in an impact pathway. XF and EFF are given in the unit of PDF in a square meter within one year PDF m^{2}y)/$mass_{deposited}$. For example, a product with an ecosystem quality score of 0.2 PDF m^{2}y implies the loss of 20% of species on 1m^2 of earth surface during one year. Modelling of the impact pathway follows (i) Cosme et al. (2018) – for the formulation of spatially explicit FF (resident mass per unit of emission), which expresses the persistence of the fraction of the initially emitted dissolved inorganic N in coastal large marine ecosystems; (ii) Cosme et al. (2015) – suggesting ecosystem XFs for the ‘conversion’ of the available N into organic matter (biomass) and oxygen consumed after its aerobic respiration; and (iii) Cosme (2016) – for the estimation of EFF to quantify the impact of dissolved oxygen depletion on exposed species.

Spatial differentiation in fate model work for nutrient emissions has been adopted in various other LCIA methods – EDIP 2003, ReCiPe 2008, LUCAS (Toffoletto et al., 2007) and TRACI (Norris, 2002), although at a coarse spatial resolution and limited scope. Cosme and Hauschild (2017) stressed that most other LCIA approaches, such as CML 2003, EPS (Steen, 1999), or MEEuP (VHK–Van Holsteijn en Kemna, 2005), do not provide spatially differentiated CFs at the midpoint and endpoint levels at a global scale or are at a coarse resolution (e.g. European countries in EDIP2003 and ReCiPe 2008, US states in TRACI).

To summarise, only three endpoint methodologies provide spatially differentiated CFs for aquatic eutrophication for the whole globe: Impact World+, ReCiPe 2016, and LC-Impact. However, the effective use of these CFs is limited, as these methodologies have not yet been integrated into commercial LCA software (Patouillard et al., 2018), and the fate of nutrients from agricultural soils to water is not available worldwide. The assessment of marine eutrophication at a finer scale may be critical due to the limited data quality at high spatial resolution (Henryson et al., 2018). Several authors have emphasised that site-dependent characterisation factors will be especially important when investigating the effect of N emissions on a specific coastal area, such as the Baltic Sea (Henryson et al., 2018).

2.6.4 General gaps in the current models

Current midpoints and endpoints generally still lack sufficient spatial resolution of CFs or are restricted in terms of geography (global coverage), depending on the goal and scope of the study (Cosme, 2016). Cosme (2016) indicated that the following issues are still missing and should be improved in current marine eutrophication impact assessment methods: (i) a consistent link between midpoint and damage level, (ii) spatial differentiation at an adequate and relevant resolution, and (iii) global scale coverage. Notably, recent attempts to fill this gap have led to significant improvements in both process modelling and spatially resolved CFs. Cosme (2016) emphasised that excessive depletion of dissolved oxygen (hypoxia) in bottom marine waters and the effects of this oxygen depletion on exposed animal communities is an important pathway that is often poorly accounted for in current midpoint models. Similarly, Vea et al. (2022) stated that the water residence time in the coastal zone is still very uncertain but crucial for the estimated FF used in the LCIA approach.

2.7 Aquatic (freshwater) eutrophication phosphorus

2.7.1 Introduction

The discharge of phosphorus (P) to freshwater systems is generally considered the main driver for the growth of algae and declining freshwater quality and eutrophication (Khan & Mohammad, 2014). The 'Freshwater eutrophication' impact category includes the impacts in the area of protection 'Ecosystem quality' caused by the emission of P into the soil compartment, the transfer of P from the soil into freshwater bodies, and its residence time in freshwater systems (Verones et al., 2020a). CFs are computed by the product of (i) P emissions to the aquatic environment (LCI), (ii) FF for the persistence of P in water bodies, and (iii) EFF, describing the potential decrease in relative species richness due to the P concentration in freshwater.

2.7.2 Influence of site-specific parameters

The location of a P emission can strongly affect its expected fate in freshwater. To date, in LCA, the FF of P emissions, that is, the residence time of P in freshwater, have been derived for continents or large countries, with limited spatial resolution. These FF do not account sufficiently for local variations and are not applicable globally. Therefore, FF for freshwater eutrophication has to be derived for P emissions into freshwater (Helmes et al., 2012). FF and EFF are translated into aquatic freshwater eutrophication by specifying CFs. Helmes et al. (2012) concluded that local hydrologic properties have the largest impact on FF. In addition, they stressed that a spatially explicit and consistent global approach is crucial. Bennett et al. (2001) stated that advection, retention, and water use are the most important processes affecting P fate in freshwater. As P transport via erosion is an important path for its transport into fresh water bodies, considering soil properties (soil texture, soil wetness, soil and surface roughness), vegetation cover, slope, and precipitation intensity at high spatial resolution is crucial. Morelli et al. (2018) stress that the development of nutrient fate and transport models for multiple environmental compartments is important for estimating site-specific P emissions. These authors suggest several watershed models, including CARMEN.

2.7.3 Current status of the inclusion of site-specific parameters

ReciPe 2016 provides CFs for freshwater eutrophication for 157 countries based on the cumulative FF of P developed by Helmes et al. (2012). It is assumed that 10% of all P released into the soil reaches surface waters (Morelli et al., 2018). At the endpoint level, the damage pathway is the loss of aquatic species [unit: PDF] due to increased P concentrations. CFs are given on a global scale with half-degree resolution. In contrast to ReciPe 2008, ReCiPe2016 does not provide midpoint CFs that consider P soil and groundwater fate and transport modelling.

Impact World+: The computation of midpoint CFs in Impact World+ is similar to ReciPe 2016. The computation of CFs at the midpoint level is again based on the cumulative FF for P in freshwater from Helmes et al. (2012). However, FF will not be computed here but must be provided in the LCI phase.

CML: The CML method assesses both terrestrial and aquatic eutrophication using a single indicator. In addition, this method assumes that 100% of emissions will contribute to eutrophication; thus, fate (transport and attenuation) is not modelled (Payen & Ledgard, 2017). Due to its aggregation and "worst-case scenario" ignoring all fate processes, CLM is not appropriate for estimating the aquatic P eutrophication potential.

EDIP2003: The EDIP2003 method (Potting et al., 2005) estimates FF based on the nutrient fate model CARMEN (Beusen et al., 1995), providing data at the country level for Europe. The authors of the method mentioned that P output to surface water bodies is generally dominated by erosion in topsoil, with erosion rates being estimated using a simplified version of the universal soil loss equation. Note, however, that dissolved P is likely to have a higher impact than P bound to (eroded) soil particles. CARMEN assumes that the exclusive transport route for agricultural P to surface freshwaters is via the P attached to eroding sediments (Morelli et al., 2018).

LC-Impact: LC-Impact includes both P transported through erosion into freshwater and emissions of P to soil that reaches the freshwater compartment. Freshwater eutrophication impact is estimated by the FF (residence time in freshwater; persistence in water bodies) and the decline of the richness of freshwater fish to enhanced levels (described by the effect factor) (Verones et al., 2020b). The geographical coverage of the endpoint CF is global. The spatial resolution for the FF is 0.5° × 0.5° and 5 arc-minutes for direct emissions to water and emissions to soil, respectively. The spatial resolution for the EFF is the biogeographical habitat following the ecoregion classification described in Azevedo et al. (2013). The spatial resolution for the endpoint CFs is 0.5° × 0.5°. Morelli et al. (2018) suggested using the model developed by Helmes et al. (2012) for the most appropriate estimate of freshwater FFs. Values are provided at a 0.5° × 0.5° grid, which allows subsequent aggregation at the country and watershed levels.

2.7.4 General gaps in the current models

Helmes et al. (2012) stated that current LCA methods still focus on one continent and operate on a relatively coarse resolution (country or state). They emphasised that FF from different methods should not be merged to achieve global coverage. The effective use of these CFs is limited, as current regionalised methodologies have not yet been integrated into commercial LCA software (Patouillard et al., 2018), and the fate of nutrients from agricultural soils to water is not available worldwide (Helmes et al., 2012). Morelli et al. (2018) recommended providing greater spatial differentiation of FFs, suggesting considering more detailed and robust fate and transport models, and filling existing gaps in the freshwater cause–effect chain by adapting the oxygen depletion midpoint indicator developed by Cosme and Hauschild (2017) for freshwater systems. These authors have also suggested reducing methodological gaps in the characterisation model by computing atmospheric FFs based on Roy et al. (2012). Additional beneficial effects on the accuracy of spatially differentiated soil and freshwater FFs for P at the 0.5° × 0.5° grid scale may be obtained by applying the Integrated Model to Assess the Global Environment Global Nutrient Model (IMAGE-GNM). This model also computes P concentrations in surface freshwater bodies (Beusen et al., 2015).

2.8 Toxicity (ecotoxicity and human toxicity)

2.8.1 Introduction

Agricultural production leads to emissions of various toxic substances, with impacts on aquatic and terrestrial ecosystems as well as human health. Some substances are applied intentionally, such as pesticides used to control weeds, insects, or fungi; others are emitted to the environment as contaminants of inputs. The latter is the case, for example, for heavy metals contained in fertilisers, fuels, or feedstuffs. These toxic emissions have lethal or sublethal effects on various organisms. For toxicity, the USEtox® method is recommended by UNEP (2019) and the European Commission (2017). USEtox (https://usetox.org) is a scientific consensus model endorsed by the Life Cycle Initiative of the UN Environment (Rosenbaum et al., 2008; Westh et al., 2015), the International Reference Life Cycle Data System (ILCD), and the Product Environmental Footprint Category Rules (PEF-CR) of the EU (European Commission, 2017) for characterising the human and ecotoxicological impacts of chemicals. We will discuss the general aspects of toxicity modelling with USEtox, followed by specific aspects for aquatic, terrestrial, and human toxicity.

The model is intended to assess the human and ecotoxicological impacts of substances emitted to the environment and is not limited to pesticides. Organic substances (with some exceptions, such as protein-binding PFAS) and metal ions are covered in USEtox. The characterisation factors are related to emissions in the following environmental compartments (see also Fig. 1):

- Continental rural air
- Continental freshwater (no distinction is made between surface water and ground water)
- Continental soil, agricultural

- Continental soil, natural
- Continental sea water (referring to coastal water)

The impact category of freshwater ecotoxicity quantifies the impacts of toxic substances emitted to the air, the soil, or directly to water on freshwater organisms. USEtox calculates impacts with three factors, which are multiplied to deliver the CFs:

- Environmental fate, which models the distribution and degradation of each substance
- Exposure, which models the extent to which target organisms are exposed to the substance
- Effects, which models the inherent damage to the substance (the toxicity to the target organisms).

The model distinguishes between a continental and a global scale, of which only the continental scale is used for emission input, while the global scale is required for a complete mass balance, that is, accounting for impacts from (continental scale) emissions on the global level. For emissions to air, a distinction is made between rural and urban (outdoor) and urban (indoor). The entire set of compartments considered in USEtox is shown in Fig. 1.

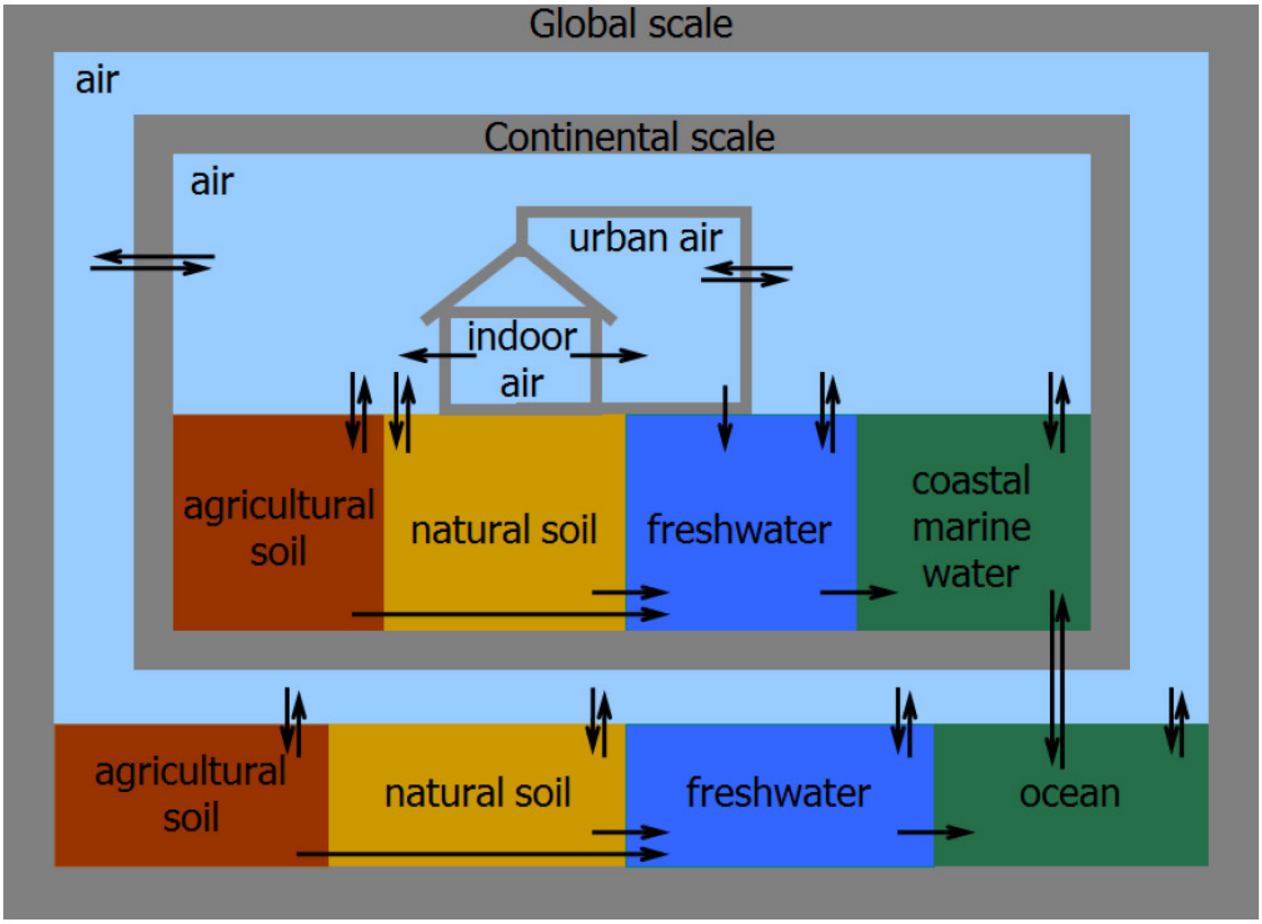

Fig. 1: Emission compartments considered in the USEtox model. (Source: adapted from Rosenbaum et al. 2008, Rosenbaum et al. 2015)

2.8.2 Influence of site-specific parameters

Numerous site-dependent parameters influence the toxicity impacts of different pollutants. The USEtox documentation (Fantke et al., 2015a) lists the so-called continental landscape parameters that are taken into account:

1. Areas of land and sea and the fractions of areas for freshwater, natural soil, and agricultural soil
2. Climate and soil parameters: mean wind speed, mean annual precipitation, mean river flow, runoff, and infiltration rates, soil erosion, irrigation
3. Human population parameters: total human population, population living in urban areas

4. Human ingestion parameters: ingestion of exposed and unexposed produce[1], ingestion of meat, dairy products, fish, human breathing rate, human water ingestion

The first three parameter groups have a spatial variation that can be considered at the continental or subcontinental level, which is still a very low level of resolution. The first two groups influence all toxicity impacts, while the latter two have effects on human health only.

2.8.3 Current status of the inclusion of site-specific parameters

USEtox considers three spatial scales. At the lowest level, urban and rural environments are distinguished for the urban indoor and outdoor air compartments, which are relevant for human health. Next is the continental level, with six environmental compartments (Fig. 1). At the global scale, the model has the same compartment structure but without urban air. USEtox provides global CFs only, but LC-Impact (Verones et al., 2020a) calculated CFs at the subcontinental level, distinguishing 16 world regions. Despite the low resolution at the continental level, implementing these factors can improve the accuracy of the results, for example, when food and feedstuffs are imported from different continents. The variation is especially high for short-lived pollutants (Kounina et al., 2014), because long-lived substances tend to more equally disperse over the globe. A comparison of the CFs from LC-Impact for the different regions reveals a ratio of ~200 between the highest and lowest value, for example, for Cu(II); therefore, the effect could be potentially very relevant when different global regions are compared.

2.8.4 General gaps in the current models

The level of spatial resolution of USEtox is low, even when considering spatially differentiated CFs at a continental and subcontinental scale. This shows that the assessment of toxicity impacts in LCA is not suitable for capturing effects at the level of small geographical units. For this purpose, methods from the field of risk assessment are more suitable. An example is the SYNOPS model (Gutsche & Rossberg, 1997; Gutsche & Strassemeyer, 2007; Strassemeyer & Gutsche, 2010), which can be used to assess pesticide risks at the regional or country level (de Baan, 2020). A simultaneous application of USEtox and SYNOPS with a comparison of the approaches can be found in Waldvogel et al. (2018).

Fantke et al. (2015b) listed the general limitations of USEtox. A groundwater compartment is currently lacking; therefore, emissions to groundwater are considered as with other emissions to freshwater. The intake fractions are constant values and do not take into account differences between populations (e.g. in fish consumption). Only a limited number of ingestion pathways are considered. Missing pathways include breast milk, indoor inhalation, increased exposure due to proximity to the source (e.g. workers handling chemicals), and dermal exposure. Of special importance is the impact of pesticide residues on and in food on human health. This impact can be considered by the dynamiCROP model (Fantke et al., 2011). However, its application in standard LCA studies is not straightforward. Furthermore, the majority of exposure equations are based on empirical regressions instead of mechanistic insights. CFs are not available for all pollutants, which can cause particular problems in modelling pesticides. In such cases, it is recommended to use proxies for missing CFs, as shown, for example, by Furrer et al. (2023).

2.8.5 Aquatic (freshwater) ecotoxicity

The official release of USEtox provides CFs for aquatic (freshwater) ecotoxicity and human toxicity. CFs for terrestrial and marine ecotoxicity are available from LC-Impact. Freshwater ecotoxicity considers the impacts on organisms in freshwater bodies. The midpoint impact is expressed in the potentially affected fraction (PAF) of species as PAF*m^3*d/kg emitted and endpoint impacts in PDF as PDF*m^3*d/kg emitted. Here, m^3 refers to the exposed water volume. The bioavailability of pollutants in freshwater is considered by calculating the fraction of total pollutant that is dissolved (by subtracting the fractions that are associated with suspended matter, dissolved organic C, or biota). Gandhi et al. (2010) showed that water type has a major influence on ecotoxicity impacts, with bioavailability being a key influential factor. Dong et al. (2014) showed that CFs could vary by two to six orders of magnitude for seven archetypes of water bodies in the EU. This shows the importance of considering the characteristics of water bodies. The results of LCA studies show that metals often dominate the impacts over organic chemicals. The modelling of the fate of organic chemicals (which are degraded over time) and metals (which cannot be degraded) differs in

[1] Exposed produce are parts of plants directly exposed to pesticides (grains, leaves, stems), while unexposed produce are typically plant parts in soil (roots, tubers).

USEtox. For this reason, Fantke et al. (2018) recommended analysing the toxicity impacts of metal and organic chemicals separately.

2.8.6 Terrestrial ecotoxicity

The same principles of freshwater ecotoxicity also apply to terrestrial ecotoxicity, with terrestrial organisms being the target. The impacts are expressed in the same units as for freshwater ecotoxicity, but the m^3 refer to the soil volume instead of water. However, USEtox does not provide recommended CFs for terrestrial ecotoxicity, as these CFs are currently considered less reliable than CFs for freshwater ecotoxicity. CFs are provided by LC-Impact 1.0. They are also spatially differentiated, as is the case with aquatic ecotoxicity.

2.8.7 Human toxicity

Similar to ecotoxicity, USEtox also provides recommended impact assessment methods for human toxicity (Fantke et al., 2015a). At the midpoint level, the impacts are expressed in comparative toxic units for human toxicity (CTUh), which quantify the estimated increase in morbidity (the number of disease cases) in the total human population per unit of mass of the chemical emitted. USEtox takes into account toxicity related to ingestion exposure and inhalation exposure. Characterisation factors are available for two impact indicators: carcinogenic and non-carcinogenic human toxicity impacts. The CFs for human toxicity (CF_h [DALY/kg emitted]) are calculated as:

$$CF_h = FF \times XF \times EFF \times DF$$

where FF ($kg_{in\ compartment}/kg_{emitted}$/day) is the fate factor relating the mass in a given environmental compartment to the mass emitted per day, XF ([kg_{intake}/day]/$kg_{in\ compartment}$] denotes the human XF relating the mass taken in per day by a human population to the mass in a given environmental compartment, EFF (disease cases/kg_{intake}) captures the human toxicity EFF relating the likelihood (or potential risk) of developing an adverse health effect expressed as number of cancer or non-cancer disease cases to the mass taken in by a human population, and DF (DALY/disease cases) is the human damage factor relating the number of DALY to the number of cancer or non-cancer disease cases, respectively. The FF and the human XF can be combined into the population intake fraction. USEtox provides global CFs only, but spatially differentiated CFs can be found in LC-Impact (Verones et al., 2020b) for 16 subcontinental zones and 8 continental zones. The exposure factor XF depends on population density. Therefore, exposure is strongly dependent on the population density in a given area, which is the main factor for spatial differences. Direct intake (inhalation of air and ingestion of water), as well as indirect intake through food, is considered. As mentioned above, pesticide residues on food currently cannot be satisfactorily considered in the standard application of USEtox.

2.9 Total water use/water stress

2.9.1 Introduction

Water is a crucial resource for agricultural production: Seventy per cent of freshwater consumption by humans goes to the irrigation of agricultural crops (Motoshita et al., 2018). Most LCIA methods at the midpoint level relate the amount of freshwater used to the prevailing water scarcity. Available “endpoint metrics” estimate the damage occurring at the end of a cause–effect chain (e.g. health or ecosystem damages resulting from water consumption), either by quantifying potential impacts on human health or ecosystem quality or by including vulnerability and resilience (Liu et al., 2017). Note that the water footprint methodology according to the Water Footprint network (www.waterfootprint.org) is not consistent with LCA methodology. On the one hand, water footprinting combines all water-related issues into one indicator, while LCA uses several categories, such as water scarcity, land occupation, aquatic eutrophication, and aquatic ecotoxicity, to quantify the impacts. Thus, combining water footprinting with LCA leads to a potential double count. Furthermore, LCA quantifies water scarcity, while water footprinting only quantifies the amount of water.

2.9.2 Influence of site-specific parameters

Water stress is defined as the ratio between total water withdrawal (industry, agriculture, households) and freshwater availability. Water availability is computed as the difference between precipitation and actual evaporation (Nistor et al., 2022). Actual evaporation is driven by global radiation, temperature, soil moisture, and land cover. Runoff primarily depends on precipitation and soil water content. The aforementioned parameters typically show high spatial and temporal variability. Thus, it is crucial to provide the models with high spatial resolution and at least monthly resolution.

2.9.3 Current status of the inclusion of site-specific parameters

There are several regionalised impact methods available at both the midpoint and endpoint levels.

UBP: The Swiss Ecological Scarcity method (Frischknecht & Knöpfel, 2013) takes into account the current extraction of freshwater and relates this to critical flow (this yields so-called ecofactors). Critical flow is assumed to be 20% of those water resources that are renewed annually.

Pfister: This method, described in Pfister et al. (2011, 2020), calculates a water-stress index from the ratio of current water consumption to renewed freshwater over the same period. Water-stress index values are available worldwide, both for individual countries and for water catchment areas. This method assumes a regionalised impact analysis; that is, the place where the water is extracted must be determined and differentiated according to country or water-catchment area. Pfister et al.'s (2011) method was crucial for the development of the AWARE method.

AWARE: The AWARE method (Boulay et al., 2018b) is a water consumption impact indicator for water scarcity that is applicable in LCA studies. It is a consensus-based midpoint model that has been developed by an international working group of the UN Life Cycle Initiative. AWARE estimates the relative Available WAter REmaining per area once the demand of humans and aquatic ecosystems has been met (Boulay et al., 2018a). The resulting CF ranges between 0.1 and 100 and can be used to calculate water scarcity footprints, as defined in the ISO standard. CFs are available at both the country and crop levels. Crop-specific water consumption was simulated for 26 crops using the Global Crop Water Model (GCMW) (Siebert, 2008). The AWARE model is also recommended in the PEF method (Zampori and Pant, 2019).

ReCiPe 2016: ReCiPe 2016 estimates the reduction in freshwater availability induced by water consumption. Water that has been consumed (by incorporation into products, evaporation, transfer to other watersheds, or disposal into the sea) is no longer available in the watershed of origin. CFs at the midpoint level are the volume of water consumed per volume of extracted water. This means that water-use efficiency has to be estimated. In agriculture, the global mean water-use efficiency amounts to 0.44, with national values given in the supporting material of Huijbregts et al. (2017).

The cause–effect pathway for endpoint modelling in ReciPe 2016 is based on reduced freshwater availability, leading again to reduced crop production, increased malnutrition, and eventual damage to human health. To model the impact of water consumption on human health, a water stress index (WSI) developed by Pfister et al. (2009) was included in the method. WSI describes the water deprivation potential. This index takes into account that water use impacts the environment more negatively in locations with high water stress than in locations with low water stress. WSI is computed as the share of water used in industry, agriculture, and households to total water deprivation, sometimes also described as the (local) freshwater withdrawal-to-availability ratio. It is a widely used CF for water consumption in LCIA.

Impacts on terrestrial ecosystems ("ecosystem quality") are assessed via a potential reduction in vegetation and plant diversity caused by lower soil moisture and, thus, a reduced number of plant species. The highest possible resolution of the derived CFs at both the midpoint and endpoint levels is directly linked to the spatial resolution of the WSI, as presented in Pfister et al. (2009). They used geographic information system (GIS) data to derive WSI at the country and major watershed levels.

Impact World+: Impacts of water consumption at the midpoint level are based on the AWARE model. The estimation of water use impacts on human health follows Boulay et al. (2011). It includes a competition scarcity index (CSI) (expressed in m^3 deprived/m^3 dissipated), an XF which characterises exposure of competing users to deprivation and some function-specific EFF, which are applied to obtain the impacts on human health per m^3 deprived, focusing on the irrigation, domestic use & fisheries functions that are directly affecting human health.

Note here that endpoint scores are not necessarily proportional to the corresponding midpoint. For example, in a region with scarce water that can nevertheless adapt, there are no water-related health impacts, and the endpoint human health impacts of water use are null and therefore not linearly related to the midpoint water scarcity index AWARE.

LC-Impact: LC-Impact addresses both fate and exposure using WSI. The effect model relates the lack of water in food production to malnutrition cases using statistical data analysis and minimum water requirements for personal food provision (Verones et al., 2020b). The damage factor helps translate DALYs from malnutrition to cases of undernourished persons. This method was applied to more than 11,000 watersheds, and country-averaged CFs are also available.

2.9.4 General gaps in the current models

Most methods provide CFs at the country level or at the level of (large) watersheds. This resolution is sufficient for background processes but higher resolution may be appropriate for foreground processes. The resolution of the available input data determines the maximum degree of spatial differentiation. Note that there are methods (e.g. geospatial) available for aggregating both input data and calculated CFs, while disaggregation is generally very demanding and not possible without an error.

Due to model inaccuracies, the highest spatial resolution should not be the goal but the one that best corresponds to the model's parameterisation equations. If small-scale data (e.g. at sub-basin level) is available, this should be used, with subsequent aggregation to a reasonable spatial resolution such as watersheds (Pfister et al., 2009). Another challenge is to incorporate the aspect of water quality, as the availability of water quality data is very heterogeneously distributed over the world and varies tremendously between regions with huge data gaps in developing countries (Liu et al., 2017). However, inclusion of grey water (domestic wastewater), as in the water footprint, does not conform with the ISO standards for LCA due to double counting, as water pollution is covered in LCA by other midpoints such as aquatic ecotoxicity, eutrophication, and acidification. As water scarcity and river discharges show a clear seasonal cycle in many regions, it is crucial to compute cumulative abstraction from rivers to potential water demand (i.e. consumptive water requirements for agricultural, industrial, and domestic use) at a short time step, if possible on a daily basis.

Water scarcity is not only determined by physical parameters, such as precipitation, runoff, and evaporation, but also depends on poverty, which prevents certain countries from adequately accessing their water resources. However, the lack of consensus on which social and economic factors should be used to describe poverty levels prevents adequate consideration of these non-physical variables.

2.10 Abiotic resources

2.10.1 Introduction

Numerous abiotic resources are used in agricultural production systems either directly or indirectly (via upstream chains). Different methods must be applied according to the goal and scope of the study (Frischknecht et al., 2019a). In this chapter, we focus on those that are of particular relevance:

(i) Non-renewable energy resources (fossil fuels: petroleum, coal, natural gas) as well as uranium (basis for nuclear power generation)
(ii) mineral resources (P and potassium)

2.10.2 Influence of site-specific parameters

Abiotic resource use is considered a site-generic impact category (Alvarenga et al., 2016; Verones et al., 2020a). As we focus on regionalisation aspects in this report, we will only describe very briefly one method called abiotic (resource) depletion potential (ADP), which is characterised by a high scientific robustness (Alvarenga et al., 2016) and therefore commonly applied in the LCA community and also recommended by ILCD and PEF (Schneider et al., 2015; Frischknecht et al., 2019a). An overview with a detailed assessment of the individual methods and the recommendation can be found in the ILCD (2011) in the chapter on resource depletion or in other literature sources (e.g. Alvarenga et al., 2016; Rørbech et al., 2014).

2.10.3 Current status of the inclusion of site-specific parameters

In simple terms, the ADP model accounts for declining resource stocks by dividing the resource by the reserve and then normalising the result with the depletion to reserve ratio of antimony as the reference substance. This approach is site-generic, which is in line with the characteristics of the impact category described above.

2.10.4 General gaps in the current models

There are ongoing discussions on which aspects to include in further developments of abiotic resource use indicators and how they should be calculated without reaching a consensus yet (Schulze et al., 2020a, 2020b; Van Oers & Guinée, 2016).

2.11 Biodiversity

2.11.1 Introduction

Biodiversity includes all terrestrial and aquatic organisms and can be considered at different scales, such as genetic diversity within populations or species diversity (Sala et al., 2000). Biodiversity has been decreasing for decades globally, and counteracting this trend is seen as a central challenge in the 21st century (Curran et al., 2011). The main direct drivers of biodiversity loss in general are (i) habitat and land use change, (ii) climate change, (iii) invasive alien species, (iv) overexploitation, and (v) pollution (especially the deposition of N and P) (Millennium Ecosystem Assessment, 2005). Land use and land use change are often cited as major causes of terrestrial biodiversity loss (Millennium ecosystem assessment, 2005; Pereira et al., 2010; Sala et al., 2000). Agriculture is an essential actor in land use and land use change, which is why we refer to the above-ground terrestrial biodiversity of agricultural production systems in the following sections. Nevertheless, biodiversity is included in the methods described below at different levels, and some methods also include aquatic biodiversity, for example.

2.11.2 Influence of site-specific parameters

Teixeira et al. (2016) concluded that site-specific data are necessary for an accurate assessment of biodiversity loss at regional and local levels. Thus, a key challenge in modelling biodiversity in LCAs is that the spatial heterogeneity of biodiversity and its uneven response to land use require a regionalised assessment, whereas LCAs fundamentally consider global value chains and therefore require a global scale for modelling (de Baan et al., 2013). One way to deal with this is to develop regional methods for biodiversity assessment that are integrated into an LCA framework that can be applied at the global level.

2.11.3 Current status of the inclusion of site-specific parameters

Several methods are available for assessing biodiversity loss in LCA with different geographical resolutions. Below, we briefly describe the levels of regionalisation in the most relevant models regarding biodiversity assessment in the LCIA. SALCAbiodiversity is an expert system developed for including biodiversity as a LCIA category on a midpoint level in agricultural LCA and allows assessment of the influence of agricultural management practices on organismal diversity measured for 11 indicator species groups: vascular plants (grassland and crop flora), birds (*Aves*), small mammals (*Mammalia*), amphibians (*Amphibia*), snails (*Gastropoda*), spiders (*Araneae*), carabid beetles (*Carabidae*), butterflies (*Rhopalocera*), wild bees (*Apoidea*), and grasshoppers (*Orthoptera*) (Jeanneret et al. 2014). The method was originally developed for application in grasslands, arable crops, and semi-natural habitats and was further developed for fruit orchards, vegetables, and vineyards (Nemecek et al. 2023). The level of regionalisation is the farm, with a geographical focus on Central and Western Europe.

In the Ecological Scarcity 2013 method (Frischknecht & Knöpfel, 2013), the land use impact category (endpoint) includes biodiversity damage potential (BDP) with a resolution at the level of 14 biomes using CF developed by de Baan et al. (2013), with natural forests used as reference. The impact on biodiversity is expressed as BDP in this method. However, it has been expressly pointed out that this indicator is not suitable for studies that are intended to support decision-making with regard to land management. In these cases, more detailed and site-dependent assessments are recommended (de Baan et al. 2013). In Impact World+, biodiversity loss is assessed at the endpoint level with contributions of 13 midpoint impact categories that vary in their native resolution from 0.5° × 0.5° to 2° × 2.5° respectively refer to biomes or watersheds (Bulle et al., 2019). The impact on biodiversity is expressed as biodiversity loss in PDF·m^2y (Sanyé-Mengual et al., 2022). In addition to the native resolution, Impact World+ provides values on the global, continental, and country levels.

LC-Impact presents seven impact categories that contribute to biodiversity and vary in their levels of spatial differentiation from a very high spatial resolution of 0.05° × 0.05° for water-stress to world regions for photochemical ozone formation (Verones et al., 2020a, 2020b). The impact on biodiversity is expressed as biodiversity loss in PDF·y

(Verones et al., 2020a). In ReCiPe 2016, biodiversity (i.e. species) loss on the endpoint level is influenced by 9 midpoint impact categories. The method provides characterisation factors that vary from national to global resolution, depending on the impact category (Huijbregts et al., 2017). Chaudhary and Brooks (2018) calculated the global species loss potential due to land use by agriculture, forest, settlement, industry, and transport based on a previous updated version of the method (Chaudhary et al., 2016), which is recommended by the United Nations Life Cycle Initiative. The method provides characterisation factors at the country level and for terrestrial ecoregions.

2.11.4 General gaps in the current models

The underlying models in the methods listed above have a sufficiently high spatial resolution and comprehensively consider the impacts on biodiversity, taking into account various impact pathways. However, the influence of specific agricultural management factors on local biodiversity (here, at the farm level) is insufficiently considered in all methods. For this reason, the Ecological Scarcity Method, for example, is not considered suitable for studies intended to support decision-making with regard to land management (de Baan et al. 2013). This also applies analogously to the other methods mentioned above.

The SALCAbiodiversity method is a suitable option for incorporating a detailed assessment of biodiversity at the farm level, taking into consideration the influence of different agricultural practices. A limitation of the method is its geographical limitation to Switzerland. Chaudhary and Brooks (2018) developed a globally applicable method. Although limited in its informative value with regard to the differentiation of various agricultural practices, the method can show how agricultural production within Switzerland and the production of imported products in other countries relate to each other in terms of their effect on global biodiversity or how the effect changes if more is imported. The method contains characterisation factors for three intensity levels in each country. However, it cannot provide a detailed picture of how specific changes in production practices affect individual crops (Bystricky et al., 2020). The combined method makes it possible to assess biodiversity along the value chain and to take into account the influence of land management in a differentiated way.

2.12 Soil quality

2.12.1 Introduction

Soil quality is defined as the “capacity of a living soil to function within natural or managed ecosystem boundaries and to sustain plant and animal productivity" (Legaz et al., 2017). In 1993, the UN Food and Agriculture Organisation (FAO) considered soil quality in the following five criteria for sustainable farming: (i) productivity, (ii) safety, (iii) protection, (iv) cost-effectiveness, and (v) acceptance (Smyth et al., 1993). The ENVASSO (Environmental Assessment of Soil for Monitoring) Project mentions the following dangers for soils: (i) erosion, (ii) decrease in organic matter, (iii) compaction, (iv) contamination, and (v) salinisation (Huber et al., 2007). Soil quality models are often related to the ecosystem damage potential for impacts, such as freshwater purification, food production, or biodiversity loss.

Several soil models only assess subaspects of soil quality (e.g. soil organic matter or soil erosion). However, it is well accepted that soil quality cannot be estimated using a single indicator (Garrigues et al., 2012). Soil models generally act on the plot level, thus accounting for spatially often highly variable soil conditions. In what follows, a few selected soil quality models are briefly described. To show the wide range of available models, models with limited geographical coverage are also presented.

2.12.2 Influence of site-specific parameters

Soil quality is influenced by both soil characteristics (e.g. soil texture, soil wetness, clay/sand content, and pH) and climatic conditions (precipitation and temperature). Soil compaction strongly depends on site-specific parameters, such as soil firmness, soil type (soil texture), and soil water content (Oberholzer et al., 2012). Agricultural practice data (crop: yield, residues; management data; vehicle characteristics: machinery mass, tyre width) also critically affect soil quality. Soil degradation through soil compaction by heavy machinery and livestock modifies the soil structure and limits water and air infiltration. However, agricultural practices are not considered site-specific data per se.

For the discussion of processes related to erosion, the reader is referred to Chapter 3.6.

2.12.3 Current status of the inclusion of site-specific parameters

Garrigues et al. (2012) suggested a globally applicable framework for assessing soil quality impacts within the LCA framework, that is, considering both on-site and off-site agricultural soils. The authors recommended using simple models to estimate erosion, soil organic matter (SOM), and compaction from soil, climate, and management data. They emphasised that input data should be site-specific and as accurate "as possible". Legaz et al. (2017), evaluating 11 models that estimate the impact of land use and land conversion, found that none of the models fully account for all relevant cause–effect pathways. Most globally applicable comprehensive midpoint/endpoint methods, such as LC-Impact, ImpactWorld+, or ReCiPe 2016, do not provide indicators at the midpoint level that are explicitly designed for assessing the impacts of agricultural soil management on soil quality. However, they estimate biodiversity losses (loss of species) related to land transformation and occupation. Nevertheless, some methods are explicitly designed to provide information on the impacts on soil quality at the midpoint level, as described below.

The Land Use Indicator Calculation (LANCA) model covers the following five indicators related to soil quality: erosion resistance, mechanical and physicochemical filtration, groundwater regeneration, and biotic production (Beck et al., 2010). LANCA considers the underlying physical processes in a simplified way. In a recent update, Bos et al. (2020) developed global characterisation factors (CFs) for 75 land use types and all countries of the world. Soil erosion resistance is modelled by the revised universal soil loss equation (RUSLE) (Renard, 1997) using soil type, slope, summer precipitation, and land-use type as factors in the equation. De Laurentiis et al. (2019) presented two options for aggregating LANCA soil indicators into a single score midpoint indicator. This approach considers the redundancy of the two indicators of mechanical filtration and physiochemical filtration by retaining only the former in the aggregated index (De Laurentiis et al., 2019).

SALCA-SQ describes the medium-term impact of land management practices on soil quality using nine soil quality indicators covering soil physics, soil biology, and soil chemistry (Oberholzer et al., 2012). Management measures such as fertilisation, driving, crop rotation design, and soil cultivation serve as input data for estimating the effects on soil quality. SALCA-SQ is calibrated for Swiss conditions with limited transferability to other soils and climates. Only some of the current state-of-the art soil quality models take into account detailed information on soil characteristics, such as soil texture, clay content, pH, and soil water content. However, this gap is constantly narrowing with the generation of even higher-resolution GIS-based datasets (Legaz et al., 2017). More generic models with global geographic coverage, such as LANCA, do not take into account detailed soil physical properties but approximate key land properties through land use data.

For the discussion of processes related to erosion, the reader is referred to Chapter 3.6.

2.12.4 General gaps in the current models

A consensus method with a standardised selection of impact categories for soil quality is still missing. This is partly due to the manifold definitions of the term soil quality. Numerous different methodological approaches hinder the assessment of soil quality. Legaz et al. (2017) revealed that a clear and consistent impact path to connect LCI data with midpoints and endpoints is still missing.

Two major gaps can often be identified in the current models:

(i) Limited number of soil functions or impacts considered and
(ii) Insufficient spatial resolution of input soil parameters (soil structure)

Although sometimes recommended as a stand-alone indicator for soil quality, attempting to describe soil quality using only SOM is not sufficient to assess soil quality impacts at the midpoint level. Higher spatial resolution leads to more accurate prediction of impacts but at the cost of collecting local (site-specific) data (Legaz et al., 2017), thus hampering its applicability in LCA studies. Using GIS software in LCA may help here to implement appropriate solutions. In addition, current models often lack sufficient discriminating power for different land use (intensities) and management practices. There is a clear need to build a consensus towards a suitable land use classification.

Instead of determining physical, biological, and chemical soil properties when assessing soil quality, some authors recommend designing a framework for the effect of management practices on soil functions, such as biotic production, groundwater recharge, or mechanical filtration (Bos et al., 2016; Saad et al., 2013). For future developments, it may be beneficial to comply with suggestions from the United Nations FAO, which has identified a set of the 12 following soil functions: (1) regulating water flow and storage, (2) regulating air circulation and temperature, (3) providing nutrients and minerals for plant growth, (4) providing organic matter for plant growth, (5) stabilising and supporting plants, (6) acting as a filter, (7) breaking down and recycling organic matter and minerals, (8) preventing erosion, (9) hosting microorganisms that contribute to plant growth, (10) storing C, (11) moderating the effects of pollutants, and (12) providing aesthetic value. However, quantifying the impacts on soil functions remains challenging due to complex soil processes and the spatial and temporal variability of soil processes.

Very detailed physical process models are available for both providing spatially highly resolved input data and assessing adequate and complete pathways. This includes, for example, the calculation of soil moisture using simple water balance models or the estimation of changes in macropores caused by heavy machinery. However, these sophisticated models are not suited for LCA due to their high degree of complexity and the high amount of input data required. Finally, some available soil quality models for use in LCA studies are based on site-specific case studies, thus requiring additional efforts for adaptation to other locations (Burkhard et al., 2012).

For the discussion of processes related to erosion, the reader is referred to Chapter 3.6.

3 Regionalisation of emission models

Field emissions play a crucial role in agriculture. Many physical processes that control released fluxes are influenced by parameters that exhibit significant spatial variations. The aim of this chapter is to describe the current status of models for describing field emissions and to identify the processes and their controlling parameters that show (high) spatial variability. The findings are based on both the Swiss Agricultural Life Cycle Assessment (SALCA) concept (Nemecek et al., 2023) and the literature on further approaches that are implemented in current emission models. The SALCA concept comprises – besides concepts for analysis, interpretation, and communication – detailed models on emission models for gaseous N, nitrate leaching, P emissions to water, soil erosion, pesticides, heavy metals, and emissions from animal production (Nemecek et al., 2023).

This chapter presents an analysis of models for the following emissions: CO_2, N_2O, methane (CH_4), pesticides, heavy metals, P, nitrate, NH_3, and nitrous oxides (NO_x). Land occupation, land competition, and LCI-related indicators are also addressed.

3.1 Emission of CO_2 (without combustion)

3.1.1 Introduction

The release and removal of carbon dioxide (CO_2) from agricultural fields largely contributes to total GHG emissions from farmed land. Long-term C storage in soil is an important lever for mitigating climate change. Carbon sequestration (C sequestration) is defined as (long- and mid-term) removal of C from the atmosphere in, inter alia, vegetation or soil (Olson et al., 2014). C sequestration potential is directly related to changes in SOC stock. The main goal of C sequestration is climate change mitigation by removing CO_2 from the atmosphere as well as the improvement of soil quality. Goglio et al. (2015) pointed out that C sequestration is one of the most promising climate change mitigation options for agriculture. Zomer et al. (2017) estimated that cropland soils could sequester between 0.9 and 1.85Pg of C per year. C in soils is predominantly stored in the form of soil organic matter (SOM). SOM contains approximately 50% C by weight. While SOM contents are typically a few percent in mineral soils, organic soils (peatlands) and upper forest soils predominantly contain SOM. SOM generally increases with increasing clay and silt fractions by occluding organic materials, making them inaccessible to degrading organisms (Plante et al., 2006). This reduces the biological decomposition rate.

This chapter addresses C sequestration induced by both land occupation (related primarily to management practice) and land transformation (land use changes, i.e. land is converted to a new land-use category). Therefore, we focus on changes in SOC stocks and the associated emissions and removal of CO_2 induced by changes in land use and management. SOC stocks depend on climate, soil type, land cover (vegetation type), and land management (mineral fertilisers and manures). For example, land transformation from forest to other land-use types or from grassland to cropland typically results in substantial C losses.

Drained organic soils (drained peatlands) are hotspots of CO_2 emissions from agricultural soils (Drösler et al., 2008). The drainage of organic soils usually releases large amounts of CO_2, but this is accompanied by a decrease in CH_4 emissions (Nykanen et al., 1995). CO_2 emissions from lime application depend on the dissolution rate of the applied liming materials, which again depends on the soil properties and climate conditions (Cho et al., 2019). The impact of climate parameters on CO_2 emissions from urea can also be ignored within LCA, as C in urea is typically lost in the form of CO_2 within a short time. The temperature dependence of CO_2 emissions from the combustion process of agricultural machinery can be ignored. Thus, we conclude that the emissions factors provided by the IPCC (IPCC, 2019) do not profit from spatial differentiation. However, Cho et al. (2019) questioned the IPCC assumption that all C in agricultural liming material is released as CO_2 into the atmosphere. The processes related to this release are also dependent on soil pH. Kim et al. (2017) revealed that only a part of the C in urea is emitted into the air, thus suggesting a revision of the current IPCC default emission factor in temperate upland soils.

3.1.2 Influence of site-specific parameters

Land transformation (land use change)

The land use category is a driving determinant for the total C stock, as land use changes often lead to substantial emissions or removals of CO_2. Since organic soils emit large amounts of CO_2, spatially highly resolved maps for (drained) organic soils are crucial. Soil type and soil parameters (clay content, soil water content, and soil pH) also affect SOC stocks. Since these parameters are subject to high spatial variations, high-resolution data on soil types and related soil parameters are essential for the accurate modelling of CO_2 fluxes. Climate parameters (temperature and precipitation) also exert a certain effect on SOC stocks, as SOC decomposition affects them. By analysing long-term observations, Keel et al. (2019) revealed that soil management has a more pronounced effect on SOC changes than increasing temperatures. Further, detailed spatially resolved information on forest growth is essential, as trees and woody plants can accumulate large amounts of C. For drained organic peat soils, the amount of CO_2 emissions strongly depends on the height of the water table, with high emissions from organic soils with low water tables, as is typically found in drained organic soils. However, this parameter is often not accounted for in the models.

Land occupation

Farm management (amount of applied fertilisers and manure, tillage, amount of plant residues left in the field) may also substantially modify the soil's capacity to store C, but such farm management practices are not counted as site-specific parameters. For mineral soils, the RothC model (Coleman et al., 1997) provides a list of input parameters that affect the evolution of total C stocks in mineral soils: Besides the monthly inputs of plant residues, farmyard manure and precipitation, soil's clay content and soil moisture as well as vegetation cover are also important. Further, the time horizon should be considered, as it is generally important for soil C dynamics. Several studies have stressed that at least 20 years is required to reach a soil C equilibrium after a change in management practices (Goglio et al., 2015; Hillier et al., 2012). Peterson et al. (2012) recommended a 100-year time horizon for cooler climates.

3.1.3 Current status of the inclusion of site-specific parameters

LCA generally sticks to the IPCC guidelines (IPCC 2006, 2019) for the computation of CO_2 emissions from land use occupation and transformation. To estimate changes in CO_2 emissions from land use occupation and transformation, the IPCC distinguishes three levels or tiers with increasing complexity. The most generic method is defined by Tier 1. The basis of the methods following the IPP guidelines is to assess the C stocks depending on the factors of climate, soil type, land cover (vegetation type), and land management.

Tier 1

The IPCC guidelines (IPCC, 2006, 2019) suggest treating aspects related to C sequestration of mineral and organic soil separately, since the physical processes of C stock characteristics differ. For mineral soils, CO_2 emissions and removals are derived from changes in C stocks relative to a reference C stock, while for organic soils, annual C emission factors are specified. Tier 1 methods consider changes in C stock resulting from both land occupation (i.e. farm management practices) and land transformation (or land use change) in a very generic and simplified way. IPCC (2006, 2019) specifies for the Tier 1 approach how to estimate changes in soil C stocks (only topsoil) using a 20-year default time period. It is based on the definition of the default values of C stocks for a set of soil, land cover, and climate conditions. The default values of C stocks are modified according to the applied management system, considering changes in land use, management practices, and inputs. When the last change in crop management occurred more than 20 years ago, IPCC (2019) assumed that soil C content is in equilibrium (steady state, that is, CO_2 emissions from organic matter decomposition is equal to the organic matter added to soil). However, long-term field studies have shown that, in reality, changes may last much longer.

Tier 2

Tier 2 largely represents an extension of Tier 1 but substitutes the default reference values with country-specific data. Therefore, the spatial resolution will be increased compared to Tier 1. Assessing the impact of rotational tillage systems on soil C stocks requires Tier 2 models.

Tier 3

In Tier 3, inventory data or (complex) models are used to estimate CO_2 emissions and removals.

Examples of soil C models that have been used to quantify land management net CO_2 emissions and removal:

(i) The C-TOOL model (Petersen et al., 2013) considers three C pools: (i) freshly added soil matter (crop residues and manure), (ii) humus, and (iii) slowly decaying matter to a soil depth of 100 cm. The model also simulates the transport of C from the topsoil to the subsoil.

(ii) The Rothamsted Carbon Model (RothC) simulates C turnover in non-waterlogged topsoil, which includes the effects of clay content, temperature, moisture, and plant cover (Coleman et al., 1997). It uses monthly time steps to calculate the total organic C.

The IPCC (2019) provides the following updates to the IPCC 2006 guidelines for soil C:

- Tier 1 C stock change factors have been updated for tillage management, grassland management, and land use based on an improved understanding of management impacts on soils. Many of the updated factors show a smaller impact of anthropogenic activity on soil C sequestration than the default factors provided in the 2006 IPCC guidelines.
- Update of reference C stocks based on an analysis of a global dataset that produces more representative reference stocks for different soil types by climate region.
- Tier 2 and Tier 3 methods have also been refined to estimate the impact of biochar amendments on soil C stocks in mineral soils for cropland and grassland.

Despite detailed IPCC guidelines, several authors have stressed that there is no common standard procedure for accounting for all processes related to soil C in agricultural LCA (Joensuu et al., 2021; Goglio et al., 2015; Petersen et al., 2013). Joensuu et al. (2021) stated that despite the lack of consensus, recommendations are provided by the UN Life Cycle Initiative and a technical standard (ISO 14067: 2018). Goglio et al. (2015) concluded that the level of the assessment (site-specific, site-dependent, and site-generic) should be consistent with the objectives of the LCA. The authors also stressed that site-specific approaches require the necessary data and user expertise.

3.1.4 General gaps in the current models

Current LCA methods for computing C stocks in soils (and thus emissions and removal of CO_2 into the atmosphere) are often kept very simple and typically belong to Tier 2 approaches. In their review, Goglio et al. (2015) concluded that the use of Tier 1 emission factors in LCA studies should be avoided, as they do not adequately reflect spatial and temporal variability because they do not take into account local climate conditions, soil type, and crop management. Therefore, the results may differ significantly from those developed using local (site-specific) data. Dynamic crop models capture small-scale, site-specific aspects well, but they are often too complex for use in LCA studies due to the high data effort and expertise required. Joensuu et al. (2021) emphasised the lack of consensus on how to compute changes in the C stock induced by land use conversion and land management. They also showed that model initiali**s**ation for the initial SOC soil pools plays a crucial role in the evolution of the C stock and, thus, the amount of CO_2 emission or removal. However, some guidelines are provided by the UN Life Cycle Initiative, as described by Koellner and Geyer (2013). Therefore, in addition to the lack of spatially highly resolved soil data with sufficient accuracy, scientific consensus about methodical issues should be addressed.

3.2 Emissions of nitrous oxide (N_2O)

3.2.1 Introduction

Here, we distinguish emissions of N_2O from soil (including fertiliser application), livestock and manure management, grazing animals on pasture, and induced emissions, given that the dependence on site-specific parameters differs between these processes. N_2O is formed as a by-product during nitrification and denitrification processes in the **soil** or manure (Xing et al., 2023). Nitrification is the process of oxidation from ammonium (NH_4^+) to nitrate (NO_3^-), while denitrification refers to the transformation of NO_3^- into N in its elemental form (N_2). Both processes are driven by microorganisms and therefore require suitable conditions for microbial activity (temperature, moisture) (Li et al., 2022). However, they occur under different conditions: while denitrification requires anaerobic conditions, nitrification is an aerobic process.

Emissions of N_2O from **manure storage** and treatment depend on the N and C content of manure, the duration of storage, and the type of treatment. N_2O is formed during nitrification and therefore requires aerobic conditions. The emissions are calculated by the amount of N excreted, the animal category, and the manure management system, which are less likely in liquid manure than in solid manure. **Induced (indirect) emissions** are emissions of N_2O that take place through two indirect pathways: 'off-site' N_2O emission from N volatilisation/deposition and N leaching. They should be taken into account for all emission sources.

3.2.2 Influence of site-specific parameters

Numerous factors drive the N_2O formation in the **soil**. First, the presence of inorganic N in soil is a prerequisite for N_2O emissions. This N can stem from N additions into the soil by mineral or organic fertilisers, farmyard manure, crop residues, and sewage sludge or from mineralisation of soil organic matter. The latter process is related to land use and land use changes and, therefore, to changes in SOC. The formation of N_2O depends on numerous soil and climate parameters, such as soil organic C content, soil texture, soil pH, bulk density, temperature, precipitation, and soil moisture.

Emission factor 1 (EF1) (IPCC, 2019) captures the emission of N_2O-N per kg of N applied to the **soil**. As a default, EF1 is set to 1%, but the revised guidelines also provide disaggregated factors for mineral fertilisers in wet climates, other N inputs in wet climates, and N inputs in dry climates.[2] The IPCC emission factors for N fertilisers are distinguished between flooded rice fields and other crops. Emissions from flooded fields are lower (e.g. 0.3% for continuous flooding), since anaerobic conditions prevail. IPCC (2019) provided a detailed analysis of the emission factor based on a set of experiments, yielding the following results:

- The N application rate per area had no significant effect; no clear trend was found. However, a more recent analysis revealed relationships between soil N and N_2O emission rates (Li et al., 2022); thus, these findings remain contradictory.
- Significantly higher emissions were found in wet than in dry climates. In dry climates, irrigation led to significantly higher emissions. No significant differences were found between temperate and tropical climates.
- Mineral fertilisers led to higher emissions than organic fertilisers. However, this difference was only significant in wet climates.

The IPCC guidelines suggest further disaggregation based on (1) environmental factors (soil organic C content, soil texture, drainage, soil pH, and climate, such as temperature and freeze-thaw cycle) and (2) management-related factors (N application rate per fertiliser type; fertiliser type, liquid, or solid form of organic fertiliser; irrigation and type of crop with differences between legumes, non-leguminous arable crops, and grass).

Manure management: The emission factors for the different manure management systems vary widely between 0% and 7%, so manure management systems are of crucial importance. However, there is no clear evidence that site-specific parameters are relevant.

Pasture: Wet climates lead to higher emissions. The revised IPCC guidelines (IPCC, 2019) propose lower and more differentiated EFs for pasture (EF3PRP for pasture, range, and paddock) then the previous guidelines from 2006. For cattle, a generic EF of 0.4% is proposed. This is further disaggregated into 0.6% for wet climates and 0.2% for dry climates. However, these EFs do not differentiate between emissions from dung and urine, although there is clear evidence that emissions from urine are ~4x higher than from dung (Nemecek and Ledgard, 2016), as confirmed by IPCC (2019). As long as the ratio of excretion in urine and dung is constant, this does not affect the final result. However, the proportion of N excreted in urine varies between 30% and 70% as a function of the N concentration in the diet (Nemecek & Ledgard, 2016).

3.2.3 Current status of the inclusion of site-specific parameters

Bamber et al. (2022) reviewed LCA studies of organic agriculture and analysed the use of emission models. Most studies used IPCC Tier 1 emission factors, whereas Tier 2 methods were rarely used. Alternative models to IPCC guidelines have been proposed in the literature. We distinguish two main types of models:

1. Statistical models, mainly regression models, relating emissions to a number of parameters
2. Mechanistic models of the N cycle and related emissions

Stehfest and Bouwman (2006) analysed ~1000 emission measurements for N_2O and ~190 measurements for NO under different conditions. N_2O emissions were significantly influenced by the N application rate, crop type, fertiliser

[2] "Wet climates occur in temperate and boreal zones where the ratio of annual precipitation: potential evapotranspiration > 1, and tropical zones where annual precipitation > 1000 mm. Dry climates occur in temperate and boreal zones where the ratio of annual precipitation: potential evapotranspiration < 1, and tropical zones where annual precipitation < 1000 mm." (IPCC, 2019)

type, SOC stock, soil pH, and texture. N_2O emissions per ha increased with the N application rate and with SOC, while they decreased with a higher pH. For the fertiliser type, ammonium nitrate phosphate and calcium ammonium nitrate showed the largest differences from the other types, but no simple relationship could be derived. Coarse (sandy) soils lead to higher emissions than fine soils (with a high clay content). Temperature and precipitation had a significant influence, with the highest emissions in subtropical regions. The differences were small for the other climate zones. Albanito et al. (2017) derived EF1 factors for different continents, ranging from 0.9% to 1.4%. Their data do not support a non-linear response of the emission factor to the N application rate. Cayuela et al. (2017) found lower emission rates in Mediterranean climates, supporting the finding of lower emission rates in dry climates. Emissions were higher in irrigated crops. Rochette et al. (2018) analysed N_2O emissions in Canada and found that precipitation during the growing season was a dominant factor.

Furthermore, soil texture (coarse, medium, and fine), type of N (synthetic and organic), and crop type (perennial and annual) influenced the emission rates. Li et al. (2022) analysed data from ~6000 field observations. They found positive correlations between soil N_2O emission rates and the mean annual air temperature, soil pH, cation exchange capacity, soil moisture, soil organic C, total soil N, dissolved organic N, ammonium, nitrate, available P concentrations, microbial biomass carbon (MBC), and microbial biomass nitrogen (MBN) on a global scale. Soil bulk density, C:N ratio, and MBC:MBN ratio were negatively correlated with soil N_2O emissions. Although climate and soil parameters caused large variability, soil N content accounted for more than 50% of the variation. The CoolFarm tool (Hillier et al., 2011) uses Bouwman's (2002c) model to estimate N_2O emissions.

As explained above, the IPCC (2019) used a large dataset of measurements by combining data from several sources. They concluded that some of the factors that had a significant influence in previous publications were not significant after reanalysing all data. This shows that the statistical regression models also have limited robustness and that N_2O emission are particularly difficult to model due to the nonlinearity and complexity of influencing factors and to the high variability of the emission data.

Mechanistic models of the N cycle are also sometimes used in LCA studies. They can consider more influential parameters and reflect environmental processes more accurately than simple emission factors or regression models, such as those presented above. For example, Xu et al. (2020) used the process-based soil-crop model WHCNS, and Deng et al. (2017) used the DeNitrification-DeComposition (DNDC) model. Nitschelm et al. (2018) compared the results of the Syst'N model to standard approaches in AGRIBALYSE. Henryson et al. (2020) and Xing et al. (2023) compared different modelling approaches, revealing considerable differences. However, the application of such models in LCA has several limitations:

- They are considerably more complex, and their use is relatively time-consuming.
- They need numerous parameters, many of which are not easily available, for example, site-specific soil data. Default values or proxies should be used instead, which markedly reduces their accuracy.
- Their predictive power is often lower than that of simple empirical models.
- The results of mechanistic models often lack robustness.

This explains why these models are not frequently used in LCA. Agroscope's previous experience with the soil-plant-atmosphere continuum system (SPACSYS) model in the European Union (EU) project CANTOGETHER showed that the use of mechanistic models considerably increases the workload and complexity of the study, without remarkable improvement in the accuracy of the results.

Manure management: Although temperature influences some of the processes involved in the emissions of N_2O, there seems to be no simple relationship that would allow it to be included in the emission calculations.

Induced emissions: EF4 for N volatilisation and re-deposition is given as 1% by default, and EF5 for leaching runoff amounts at 1.1%. EF4 is further disaggregated into 1.4% for wet climates and 0.5% for dry climates. Switzerland's national inventory report 2022 (FOEN, 2022) uses a value of 2.6% for indirect emissions from volatilisation, which is significantly higher than the default for wet climates (1.4%). According to the authors, this is a result of the much higher emission factor for semi-natural habitats and a high share of this type of land cover.

3.2.4 General gaps in the current models

Emissions from soil are estimated with high uncertainty for local conditions. For a larger geographical scale, local differences are partly levelled out, so that the estimate is more reliable. EFs are associated with considerable uncertainty. For example, the uncertainty range of EF1 (default value 0.01) is given as 0.001–0.018 (IPCC, 2019).

The EF for grazing animals does not consider soil characteristics, although these can play a role. Current scientific evidence is insufficient for a reliable estimate. EFs for induced emissions also show high uncertainties due to the complexity of the processes.

3.3 Emissions of methane (CH_4)

3.3.1 Introduction

The main sources of methane emissions are livestock production, rice cultivation, and emissions from flooded land. The latter is not relevant to agricultural production and therefore is not further addressed. Methane emissions from **rice cultivation** occur as organic substances are degraded under anaerobic conditions in flooded paddy rice fields. These are calculated by the daily emission rate and the harvested area (IPCC, 2019). Livestock production and manure management are the most important sources of methane from agricultural production. Enteric fermentation dominates, followed by emissions from animal excretions and subsequent management.

Enteric fermentation: Methane is produced by microorganisms in the digestive system of ruminants. The amount of methane formation depends on the quality and quantity of feed consumed, the type of digestive tract, the age, and the weight of the animal. The quantity of feed is described by dry matter intake or gross energy intake. According to IPCC (2019), methane from enteric fermentation is calculated as a percentage of gross energy intake and ranges from 3–7% for cattle and buffalo. The rate depends on the digestibility of the feedstuffs and the milk yield of dairy cows. The most important parameter is the feed intake and – from an LCA perspective – its ratio to the milk or meat output. In systems with low productivity and low quality of feed, higher enteric emissions per unit of output are produced than in systems with high productivity and high-quality feed.

Manure management: Methane is formed as a by-product under anaerobic conditions by microorganisms using biomass as a source of energy, a process called methanogenesis. Different processes of manure management are considered, leading to differences in emissions (IPCC, 2019):

- Liquid manure storage: Much higher emission rates result from liquid than from solid manure, as anaerobic conditions prevail in liquid storage. For liquid manure storage, the duration of the storage and the temperature play important roles. Furthermore, emissions also depend on the coverage of the slurry tanks.
- Solid manure storage: These emissions are generally much lower than those from liquid storage because the conditions are partly aerobic. The same applies to dry lots, composting, and pasture.
- Daily spreading: No methane emissions are expected.
- Dry lot
- Composting
- Pasture, range, or paddock
- Anaerobic digestion (biogas production): Compared to liquid storage, the emission rates are lower. However, effective emissions strongly depend on the management of the digestion process.

3.3.2 Influence of site-specific parameters

Rice cultivation: The emission rates in paddy rice fields depend on several factors:

- Cropping practices, particularly flooding patterns
- Multiple cropping (e.g. two crop cycles per year)
- Water regime, defined as a combination of ecosystem type (irrigated, rainfed, deep water rice production) and flooding pattern (e.g. continuous or intermittent). The water regime is a key parameter with a highly significant influence on emission rates.
- Input of organic materials
- Soil type: IPCC (2019) recommended considering the soil type in the national GHG inventories but does not provide any factors. However, Annex 5A.2 provides an equation to estimate methane emissions from rice fields considering soil pH and SOC.

The abovementioned factors are management parameters that depend on the cropping system and the type of management, not site conditions, with the exception of soil type. However, there is an indirect dependence of management on site conditions, for example, to determine the need for irrigation. A good grasp of the main mechanisms responsible for spatial variability is essential to improve the upscaling and modelling of water methane emissions (Rehder et al., 2021). The determining factors for **enteric methane** emissions are related to the livestock production system and not, or only indirectly, to the site conditions. Differentiation is needed for production systems, which in turn can be influenced by the natural conditions of the region.

Manure management: While most determining factors depend on management, the climate plays a major role in the emissions from manure stores. This is because methane-generating microorganisms are more active in warmer climates.

3.3.3 Current status of the inclusion of site-specific parameters

Rice cultivation: IPCC (2019) provides default baseline EFs per continent, ranging from 0.65kg (North America) to 1.56kg CH_4/ha/day (Europe). This differentiation should be taken into account when modelling rice production in different continents, which, for example, can be relevant for rice imports from different countries.

Manure management: Temperature plays a key role in methane emissions. For a liquid manure store below animal confinements, the methane conversion factors (MCF) range from 21% to 74% for a storage duration of six months, which can be considered a typical duration in cool and temperate climates. Note that for tropical conditions, the MCFs are much higher; however, manure can be spread frequently due to the absence of a winter period when no manure should be applied. The following definitions apply according to the IPCC (2019):

- Cool climate: Average annual temperature <15 °C (which applies to Europe, except some southern regions)
- Temperate climate: Average annual temperature 15–25 °C
- Warm: Average annual temperature >25 °C

3.3.4 General gaps in the current models

For paddy rice, it is crucial to capture the effects of different cropping systems, notably the water regime.

Methane emission rates from enteric fermentation vary depending on the quality of the feedstuffs. However, the quantity of feed intake is a highly relevant parameter associated with high uncertainties.

3.4 Emission of pesticides

3.4.1 Introduction

Pesticides are used to control the antagonists of cultivated crops, such as insects, pathogens, or weeds. In addition to the intended effects on the target organisms, pesticides have toxic lethal and sublethal effects on non-target organisms. To adequately consider the impact of pesticides on ecosystems and human health, the distribution of the pesticides applied to the environmental compartments should be calculated.

3.4.2 Influence of site-specific parameters

The emissions of pesticides to the environment are determined by many parameters (Fantke, 2019):

- Amount of active ingredients applied
- Formulation – the form in which the active ingredient is applied (e.g. dry or wet) and various additives (e.g. emulsifiers and wetting agents)
- Application technique
- Crop characteristics (e.g. soil cover and properties of the crop surface)
- Weather conditions during and after application (temperature, relative humidity, precipitation, wind speed)
- Soil characteristics
- Drainage
- Topography (field slope)
- Neighbourhood of the field, relevant for off-field emissions

Thus, the amount of emissions to the different environmental compartments depends on a combination of management parameters and site-specific parameters.

3.4.3 Current status of the inclusion of site-specific parameters

In current versions of LCI databases, such as ecoinvent, WFLDB, or AGRIBALYSE, and in many LCA studies, pesticide emissions are modelled as 100% of the applied active ingredient being emitted to the agricultural soil. This means that the subsequent distribution of the pesticides between the compartments and the fate of pesticides is fully accounted for by the LCIA methods (see Chapter 2.8). To cope with this and other challenges, a consensus process was initiated with three scientific workshops (2013 in Glasgow, 2014 in Basel, 2015 in Bordeaux) and a stakeholder workshop (2016 in Dublin), which defined the theoretical framework for pesticide emission modelling (Rosenbaum et al., 2015; Fantke et al., 2018).

To operationalise and harmonise the emission quantification and impact characterisation of pesticides in LCA and product environmental footprinting (PEF) based on this effort, the OLCA-Pest project ("Operationalising Life Cycle Assessment for Pesticides", 2017-2020, co-funded by ADEME, https://orbit.dtu.dk/en/projects/olca-pest) was implemented with nine partner institutions. This resulted in a set of recommendations for implementation in LCI databases and LCA studies (Nemecek et al., 2022). The authors proposed a set of default emission fractions for different crop types and target groups of pesticides. This allows for the estimation of the initial distribution fractions of the applied pesticides used to split the amount applied between the compartments air, agricultural soil, crop, natural soil, and surface water using the PestLCI consensus model and default scenarios. The PestLCI consensus model calculates the fraction deposited on off-field surfaces, which is subsequently distributed among the different compartments, using the shares of the areas in a given region. For the amount deposited on the crop surface, a new emission compartment should be defined. PestLCI consensus was developed based on the PestLCI model (V1.0, Birkved & Hauschild, 2006; V2.0, Dijkman et al., 2012).

This approach has a number of limitations, as discussed by Nemecek et al. (2022). Here, we mention those that are related to spatially dependent factors. Only the initial distribution fraction is calculated in the inventory, and all subsequent processes are considered in the impact assessment or ignored. For the initial distribution, only physical parameters are relevant, such as the application technique, the size of the field, the presence of buffer zones, and the type and stage of the crop. Climate, soil, and topography influence the transport of pesticides, their degradation, and so on, but these processes are not relevant during the first minutes or hours after application. In impact assessment, such processes are considered only by generic factors. For the initial distribution, regional differentiation can be performed for several parameters:

- Share of agricultural, forest, and natural areas, which is relevant for modelling emissions to off-field surfaces
- Presence and width of buffer zones
- Application techniques
- Growth stages, which are influenced by management, soil, and climate.

Only the first and partly the last are related to regional data; the other relate to management parameters only.

PestLCI consensus also allows the modelling of secondary emissions of pesticides, including processes such as wash-off, uptake, volatilisation, re-deposition, leaching, and degradation. Several of these processes strongly depend on soil properties and the climate and are therefore site-dependent. However, the modelling of secondary emissions and their coupling to impact assessment requires further model development and research and is currently not recommended (Nemecek et al., 2022). In summary, although numerous site-specific parameters are potentially relevant, they currently cannot be considered in the modelling of pesticide emissions in agricultural LCA.

3.4.4 General gaps in the current models

The approach does not account for climate and soil conditions or topography. The secondary emission modelling in PestLCI consensus would allow the remedy of several of these shortcomings. However, at the current stage, further development is needed before it can be recommended for a practical application. Nemecek et al. (2022) listed priorities for further research: improving the modelling of pesticide secondary emissions, further extending emission modelling (e.g. additional application techniques, including cover crops), considering metal-based pesticides in emission models, and systematically assessing human health impacts associated with pesticide residues in food crops.

3.5 Emissions of heavy metals

3.5.1 Introduction

Heavy metals have toxic effects on ecosystems and humans when they occur in higher concentrations and are therefore of high environmental relevance (Briffa et al., 2020; Nagajyoti et al., 2010). Some metals, such as copper or zinc, are also essential elements needed to support life functions in low concentrations. In this section, we analyse the inventory phase of heavy metal flows, that is, the modelling of emissions to the different environmental compartments.

3.5.2 Influence of site-specific parameters

To calculate the balance of heavy metals, we need to quantify inputs and outputs at the level of a field or farm. Aerial deposition and agricultural inputs such as seed, fertilisers, and pesticides are the main inputs at the field level. At the farm level, feedstuffs and animals are two relevant input pathways. As outputs, we need to consider harvested crop products, exported animals and animal products, and the emission pathways to water by soil erosion, leaching to groundwater, or drainage to surface water. These flows are influenced by management and site-specific parameters.

- Aerial emissions of heavy metals stem from industry, the energy sector, transport, and households. In addition to the amounts emitted, deposition depends mainly on wind patterns and precipitation. Therefore, deposition has a strong spatial dependence.
- Heavy metal concentrations in the soil are used to calculate the emissions in water through erosion. These concentrations can vary on a small spatial scale, but they are typically unknown for specific fields or for smaller regions. They depend on parent rock and pollution from agricultural and non-agricultural sources. Measurements of soil concentrations are done mainly for polluted soils, which can lead to considerable bias when these values are used for agricultural soils.
- Erosion-induced emissions from soil depend on the amount of soil erosion and therefore are subject to the same dependencies as described in Chapter 3.6.
- Leaching depends on various soil properties, such as texture, pH, and soil water regime. This process therefore has strong site dependence.
- Heavy metal content in biomass concerns inputs such as feedstuff or seed and outputs in the form of agricultural main products and by-products. The concentrations in the biomass depend on the concentration in the soil where the crops are grown, although the relationship is not simple, and clear relationships are found only for some metals. Further, these relationships are typically nonlinear. Soil characteristics, such as pH value, play a major role in the metal uptake by plants.
- Heavy metal content in agricultural inputs: Significant differences exist for some mineral fertilisers depending on the mine, which is relevant for P fertilisers. Therefore, the origin of the fertiliser could be taken into account for more accurate estimates (e.g. based on import statistics).

3.5.3 Current status of the inclusion of site-specific parameters

Considerable differences exist between the emissions and toxicity impacts of heavy metals in different regions. Sydow et al. (2018) assessed the impact of manure application in Europe. Although some changes in the ranking of metals and countries were observed, both mass- and impact-based comparisons between metals agreed that Zn and Cu are dominant contributors to total impacts and that the top contributing countries were those emitting the largest amounts of metals. The authors concluded that spatially differentiated impact assessments are important for the ranking of countries. Owsianiak et al. (2015) calculated terrestrial ecotoxicity CFs for Cu and Ni in 760 soils. They found differences of 3.5 orders of magnitude, mainly explained by the variability in soil organic C and soil pH. They stressed the importance of using regionalised CFs for terrestrial ecotoxicity.

A common model for the calculation of agricultural heavy metal fluxes in the context of LCA was described by Freiermuth (2006). It considers the heavy metals: cadmium (Cd), chromium (Cr), copper (Cu), mercury (Hg), nickel (Ni), lead (Pb), and zinc (Zn). It was recently updated and implemented in SALCAfuture (Nemecek and Lansche, 2022). In the first step, the heavy metal balance of the animal herd is calculated by considering the feed intake, the herd, the housing, the yard, and the manure management, with the aim of estimating the metal concentration in farmyard manure. In the second step, the balance at field level is calculated by considering the inputs of seed, organic, and mineral fertilisers (including the farmyard manure previously calculated), and metal-containing pesticides (mainly Cu and Zn). The model calculates the outputs through harvested main and by-products. It estimates emissions through leaching to ground water, or surface water in the case of drainage, and to surface water through soil erosion. A balance at the field level of inputs, outputs, and emissions is calculated, which is counted as an emission to agricultural soil. To account for metal deposition from non-agricultural sources (industry, transport, household), an allocation factor for each metal is calculated as the ratio of agricultural inputs and total inputs, including deposition. This allocation factor is applied to the emissions by leaching and erosion, the emissions to the soil, and the exports by the harvested products. A detailed description is provided by Nemecek and Lansche (2022).

In the model, aerial deposition is adapted to the regional values. An example is an Austrian adaptation (Bystricky et al., 2015). Metal concentrations are also taken from regional averages; they are differentiated between cropland, grassland, and horticulture. The amounts of eroded soil are calculated by the SALCAerosion model and are therefore site-specific. Leaching is represented by constant values and is subject to high uncertainty. A regional differentiation is currently not possible. Heavy metal concentrations in agricultural inputs and harvested biomass can be adapted to regional values, if available.

3.5.4 General gaps in the current models

The speciation of the metals, that is, their oxidation status, is not considered due to the lack of data, which can cause a bias, as shown by Sydow et al. (2020). In general, there was a strong correlation between the impact assessment results with and without metal speciation. The authors concluded that metals are expected to remain important contributors to soil ecotoxicity impacts in LCA when speciation is considered. Regarding ageing, it is frequently observed that heavy metals are less available after a certain residence time in soil, which is known as ageing. Owsianiak et al. (2015) stated that the availability of metals in the soil depends on pH, soil organic content, and ageing and recommended that time-horizon independent accessibility factors derived from source-specific reactive fractions should be used.

3.6 Soil erosion

3.6.1 Introduction

Erosion is one of the most important causes of soil degradation globally (Panagos et al., 2017). Soil erosion is a process that occurs when the impact of water or wind detaches and removes soil particles, causing the soil to deteriorate. Soil erosion leads to a reduction in soil depth and decreases soil fertility due to the loss of topsoil. Therefore, it negatively affects food production and various soil functions. Both water and wind cause erosion (Song et al., 2005). Alewell et al. (2019) stressed that water erosion is distinctly worsened by the conversion of natural vegetation to agricultural land.

Rain erosion is one of the most significant forms of topsoil degradation triggered by raindrops hitting soil aggregates (Van der Knijff et al., 1999). Most rainfall-induced erosion models rely on the (revised) universal soil loss equation (RUSLE) to predict long-term average annual soil loss (Alewell et al., 2019; Renard, 1997). It takes into account relevant site-specific parameters, such as detailed soil characteristics, topography, land cover, and precipitation. This modelling approach estimates the potential rates of soil displacement caused by water erosion. The method considers the following six factors: R (rainfall erosivity), K (soil erodibility), L (slope length), S (slope steepness), C (cover and management), and P (support practice). The C factor considers changes in erosion related to agricultural practices and thus can be most easily affected by farming activities. What generally distinguishes erosion models is the parameterisation and computation of these six factors.

Wind erosion is the movement of coarse and fine particles by wind across a landscape. Models for wind-induced erosion exist in different complexities for different spatial and temporal scales (Jarrah et al., 2020). The Revised Wind Erosion Equation (RWEQ) also considers information on agricultural fields (Fryrear, 1998). However, these models are applicable only to surfaces with low roughness and relatively low wind speed (de Oro et al., 2016). Due to the complex physical processes driving wind erosion, most available models suffer from distinct uncertainties and limitations. The goal and scope of the study should be considered when selecting the proper model suited to the study's purpose and objectives, as well as the availability of the required input data.

3.6.2 Influence of site-specific parameters

Soil erosion through water is a very local (i.e. site-specific) phenomenon and typically shows high spatial variations. Water-induced erosion is highly dependent on soil characteristics (texture, porosity, particle size, composition, and organic matter), topography, land cover, and precipitation. These parameters typically show high spatial variability. Borrelli et al. (2020) stressed that the spatial distribution of cropland and cropping systems is also crucial for improving the global RUSLE-based estimates for soil erosion. Wind erosion is influenced by various factors, such as wind force, soil wetness, surface roughness, soil texture (aggregation and stability, grain size, SOM, silt/sand content), vegetation cover, and agricultural activities (Chepil & Woodruff, 1963). As some of these parameters generally vary over short distances, wind erosion typically shows high spatial variability.

3.6.3 Current status of the inclusion of site-specific parameters

In recent years, enormous efforts have been made to provide precise gridded datasets for soil erosion risk assessment at high spatial resolutions (Kazamias & Sapountzis, 2017; Polovina et al., 2021; Rellini et al., 2019). This includes not only the factors that are independent of the management (R, K, L, and S) but also the two factors C and P that are dependent on the land management practices. Therefore, farmers can adapt their farming practices and crop rotation to reduce soil losses. Borrelli et al. (2020) presented a RUSLE-based modelling approach for potential erosion rates by water on a 250m × 250m grid for 202 countries by considering (among others) land cover and sub-hourly precipitation records.

RUSLE is the basis of the Sustainability Quick Check for Biofuels (SQCB) model (Faist Emmenegger et al., 2009). This approach splits management factor C into two factors: C1 (crop factor) and C2 (tillage factor). Whereas specific values for factors K, C1, and P are taken from the tables, the erosivity factor (R) and the slope factor (L*S) should be computed. The first is parameterised with a regression equation, depending on the annual precipitation amount, and the latter is calculated using slope and slope length. To further reduce the time used for data collection, mean annual precipitation has been described for each US Department of Agriculture (USDA) soil order. The model can be applied globally.

The framework behind SALCA-Erosion is also the RUSLE equation. The computation of the crop composition factor C depends on several lookup tables that provide correction factors for different crop rotations that are assessed by classification, depending on the percentages of cultivated main and catch crops, as well as special cultivation techniques, such as strip sowing, no-till, or mulch sowing. Wind erosion has not yet been considered in most erosion models used in LCA.

3.6.4 General gaps in the current models

Generally, spatial resolution is too coarse to capture the high variability of soil erosion. Further, most models do not include the characteristics of the precipitation distribution, especially the number and strength of heavy precipitation events. Various authors have indicated that rainfall erosivity dynamics due to heavy rainfall events are still poorly represented in current models, despite it being well-known that short-duration and high-intensity precipitation events substantially contribute to erosion. This is often justified by a lack of accurate global high-resolution (or even field-scale) datasets. Although farmers cannot influence precipitation patterns, it is recommended to estimate rainfall erosivity based on so-called indices that “summarise” the characteristics of extreme precipitation events based on daily and sub-daily data that measure aspects of precipitation frequency, duration, and intensity, as outlined by Alexander et al. (2019).

Soil losses due to rill erosion through small channels – as included in the SALCA-SQ model – is ignored in most erosion models since this process is not considered in the RUSLE approach. In addition, the models generally route downward the displacement of eroded material across grid cells using a transport model. Wind erosion models often suffer from large uncertainties and limitations due to complex processes driving wind erosion (e.g. wind dynamics) and spatially highly varying input parameters (such as soil characteristics (aggregate stability, grain size, vegetation cover, soil wetness) and meteorological parameters (wind speed). RUSLE disregards wind erosion; thus, models using RUSLE may underestimate erosion, especially where wind erosion vulnerability is high (Scherer & Pfister, 2015).

3.7 Emission of phosphorus

3.7.1 Introduction

P is an important macronutrient that is essential for food production (Cordell et al., 2009) and is globally only available in limited quantities. The main P loss from anthropogenic environments to surface water originates from agricultural land induced by excessive fertiliser and manure application (Verheyen et al., 2015). P can be discharged from agricultural land via different pathways, including leaching to groundwater, surface runoff, soil erosion, and drainage losses to surface waters (Cordell & White, 2014; Prasuhn, 2006). Scherer and Pfister (2015) found that groundwater leaching plays a major role in temperate climates. Xavier et al. (2011) indicated that P dynamics in soils are influenced by many factors, including soil type, plant species, and soil management. Generally, soluble P emissions predominate particulate P emissions through erosional processes. P is problematic owing to its eutrophying effect on water systems (see Chapter 2.6).

3.7.2 Influence of site-specific parameters

The amount of P loss is influenced by various spatially highly variable factors, such as soil texture and composition, vegetation cover, slope gradient, and agricultural practices (e.g. tillage intensity: conventional; reduced [mulch, strip]; and no-till, cropping system). However, the latter are not treated as site-specific parameters per se. For drainage into surface water bodies, the distance to surface water bodies and the drainage design (tile spacing, tile depth, and surface inlets) are essential (King et al., 2015). Based on a contribution to variance, Scherer and Pfister (2015) concluded that regionalisation of the LCI is crucial for accounting for spatial variability of the impact at the midpoint level (freshwater eutrophication, see Chapter 2.7). The authors stressed the high sensitivity of P concentration in soil to total P emissions to water. It is evident that the discharge pathway through erosion is affected by the initial P content in the soil and the amount of eroded soil. For the latter, the reader is referred to Chapter 3.6.

3.7.3 Current status of the inclusion of site-specific parameters

Numerous regionalised models exist for estimating P emissions from agricultural land (Pferdmenges et al., 2020). To allow sufficiently high regionalisation, process-based models that aim to represent the processes as accurately as possible should be preferred. However, to include them in LCA studies, constraints on the number of input data and the degree of complexity must be considered. This means that parameterisation (and thus simplification) of the processes is required. Thus, models that include the solution of partial differential equations for transport simulations cannot be applied within the LCA context. Pferdmenges et al. (2020) provided a review of 26 numerical models that simulate P cycles. They found that none of the models provides a realistic approach for P transport through different ecosystems and on different scales. For use within the LCA framework, however, the evaluated models are overly complex and often only consider selected discharge paths.

One model that is ideally framed for use in LCA studies is SALCAphosphorus (Nemecek et al., 2023). It predicts P emissions to water bodies at the plot level. This model is an updated version of the approach described by Prasuhn (2006). The following four relevant discharge paths are taken into account: (i) soil erosion, (ii) surface runoff, (iii) drainage losses to surface waters, and (iv) groundwater leaching. The discharge path via erosion leads to P emissions bound to soil particles (particulate P), while the latter three lead to emissions of soluble phosphate. The calculations are based on mean climatic conditions in line with common LCA practices. Thus, P emissions due to extreme events are not simulated by the model.

3.7.4 General gaps in the current models

The impact pathways for P transport into groundwater and surface water bodies are generally considered in the current models. However, the parameterisation of the involved processes is often (over)simplified due to a lack of site-specific data. This hinders – despite considering site-specific input parameters – adequate modelling of P transport paths to ground water and surface waters. Pferdmenges et al. (2020) indicated that substantial P losses occurring during large runoff events are often neglected when calculating annual P losses. King et al. (2015) pointed out that modelling P movement in tile-drained agricultural land requires significant improvements.

The initial P concentration in soil that is crucial for predicting P losses from eroded soil particles is often not well known. For this reason, current P emission models often assume predefined constant P concentrations in soils, generally distinguishing between different land use types. Further, for P leaching by runoff and drainage, average mean values are typically predefined for a limited number of land use types, such as open arable land, pastures, orchards, and vineyards. This simplification reduces the accuracy of the models, as adequate modelling based on driving physical processes is not taken into account. In some models, it is not evident which fractions of P (i.e. labile inorganic P, intermediately available P, organic P, occluded P, and apatite P) are considered. This is, however, decisive, as generally less than 1% of P is immediately available to plants (Xavier et al., 2011). In addition, whether organic and inorganic P should be treated differently should be considered. The reason is that peaching in soils fertilised with organic P is often higher than in soils fertilised with inorganic P, since organic P is sorbed less strongly than inorganic P (King et al., 2015).

3.8 Nitrate emissions

3.8.1 Introduction

N plays a major role in agricultural systems as the key nutrient for food production as well as different emissions, such as NH_3, NO_3^-, leaching and nitrous oxide (NO_x and N_2O) emissions to air (Bockstaller et al., 2022). Here, we focus on nitrate leaching. Nitrate is a major inorganic groundwater contaminant that is mainly due to fertiliser leaching (Colombani et al., 2020). Different models exist for the assessment of nitrate leaching to ground water with different levels of regionalisation, which are briefly discussed next.

3.8.2 Influence of site-specific parameters

The following site-specific parameters have been identified to be crucial for accurate nitrate modelling: (i) soil characteristics (soil water content, humus content, clay content, root presence, rootable depth, redox condition, etc.), (ii) climatic data (temperature, precipitation, and potential evaporation), (iii) crop rotation, (iv) management practices (tillage, etc.), (v) amount and timing of applied N fertilisers (organic and mineral fertilisers), and (vi) plant growth and N-uptake (Colombani et al., 2020). Given that soil characteristics (soil pH, clay content, and soil bulk density) typically show high spatial variability, nitrate leaching estimations strongly profit from accurate and highly resolved soil data. Zhu et al. (2018) emphasised that spatio-temporal variation of soil water content controls redox coupling among oxidised and reduced compounds, and thus N mineralisation, nitrification, and denitrification. Bockstaller et al. (2022) highlighted that nitrate leaching reacts sensitively to, among others, the available water content, the volumetric field capacity, and the rooting depth. These parameters generally depict high spatial variability. Rakotovololona et al. (2019) used the LIXIM model, which requires soil water content, soil mineral N, climatic data (daily temperature, rainfall, potential evaporation), and soil properties (soil water content at field capacity and at the permanent wilting point). In their study of arable cropping systems in France, Rakotovololona et al. (2019) found that crop sequence and crop management distinctly affect nitrate leaching. However, despite being important, farm management parameters (e.g. crop rotations/sequences, fertilisation strategies) are not considered site-specific parameters in this report (see Section 4.1).

3.8.3 Current status of the inclusion of site-specific parameters

The degree to which site-specific parameters have been considered in nitrate leaching models strongly varies among the current available models. Here, we describe a selected number of models, together with relevant input parameters and their regionalisation. IPCC (2006, 2019, 2021) presented a Tier 1 model that provides a simplistic approach to estimating nitrate leaching. It uses predefined emission factors $EF_{leaching}$ for N losses by leaching for wet climates based on N addition or deposition by grazing animals. $EF_{leaching}$ is assumed to be 0.24, with a wide uncertainty range between 0.01 and 0.73. For a dry climate, the default values are set to zero. Tier 2 models, providing country-specific EF, allow for improved estimates of expected total annual nitrate leaching at the country level. The assumption that leaching depends linearly on N inputs clearly oversimplifies the complex N loss function (that depends on rainfall, soil type, crop rotation, N manure application, and N uptake rate through the plants).

Predictions of nitrate leaching using Richner et al.'s (2014) SALCAnitrate model are based on the difference between the supply of mineralised N from the organic matter of the soil and the N uptake by the plants during the defined time periods and on the leaching of mineral N applied by fertilisation. The model considers crop sowing and harvest dates, soil tillage, timing, and quantity of N fertilisation, as well as several environmental conditions that differ temporally or spatially, such as mineralisation of N from soil organic matter or precipitation levels.

The SQCB-NO3 model uses a simple regression to calculate leaching of NO_3-N taking into consideration precipitation, irrigation, rooting depth, clay content of the soil as well as N supply, N in organic matter, and N uptake by the crop (de Willigen, 2000; Faist Emmenegger et al., 2009; Roy, 2003). The model acts at crop level, but site-dependent parameters such as precipitation plus irrigation, average organic C content, clay content, rooting depth, and unit N uptake per crop are retrieved from lookup tables based on various data sources, such as the FAO database. Crop-specific rooting depth can be retrieved from the FAO database only for selected crops (potato, sugar beet, sugar cane, sweet sorghum, and soybean). The model can be applied worldwide.

Tailleur et al. (2012) developed a simple model to assess nitrate leaching from annual crops for LCA at different spatial scales. It allows for the estimation of the amount of leached nitrate for different agricultural practices. The model is based on the COMIFER (French Committee for the Development of Rational Fertilization) methodology and has been implemented in AGRIBALYSE. The model can be used at different spatial scales (watershed, small agricultural area, production area), but its use is restricted to France, as the nitrate leaching amounts should be estimated from experimental field data for each risk level. Site-dependent input parameters are water retention capacity, soil organic matter content, and volume of drained water.

3.8.4 General gaps in the current models

Nitrate washed from agricultural fields via surface runoff into rivers, lakes, and finally to the ocean is only poorly represented in the current models. For example, SALCA-Nitrate assumes that 100% of N leaving the root area arrives in groundwater or through drainage in surface water. However, F. Liebisch (pers. comm., Feb 7, 2024) points out that the percentage loss depends on the location and lies between 2% and 20%. Also important but often ignored in current models is the previous fertiliser N utilisation, as any N applied but unused by the crop progressively increases the N amount in the soil. Most models could probably profit from a better vertical resolution of the soil, as it is crucial to consider that nitrate N is only available for crop uptake when leaching has not yet reached the root depth (Széles et al., 2012). Further, enhanced irrigation in intensive cropping production may lead to more nitrate leaching (Zhou et al., 2012).

Since short-term fluctuations are usually not included in the development of LCA models, short-term precipitation variations are usually not considered in nitrate models (Wang & Li, 2019). Physically based nitrate models may provide higher spatially resolved results. A typical example is the finite element model HYDRUS-1D (Šimunek et al., 2012), which accurately quantifies the driving mechanism of nitrate leaching, including N mineralisation for both compost and soil organic matter. However, these models require detailed input data, which are generally not available (and not useful to be applied) within the LCA framework. In addition, correct calibrations and interpretations require advanced agronomical expertise, hindering their application within the LCA context (Bockstaller et al., 2022).

3.9 Ammonia emissions to the air

3.9.1 Introduction

NH_3 volatilisation is a significant source of N loss in Swiss agriculture. More than 40,000 tonnes of N are lost in this way each year, which accounts for 94% of national NH_3 emissions. 93% of these emissions come from animal husbandry (Kupper et al., 2022). NH_3 from animal husbandry originates from housing systems, yards, pasture, manure storage, and manure application (Kupper et al., 2022). The nutrient losses due to NH_3 emissions correspond to almost one third of the N accumulated in farmyard manure and result in a financial loss and a reduction in productivity for farmers. Further, NH_3 emissions pollute the environment, especially near natural ecosystems.

In animal production systems, gaseous emissions of NH_3 occur when solutions containing NH_3 and NH_4^+ (total ammonia nitrogen, TAN) come into contact with the air. Examples include slurry storage tanks or walking surfaces in stables or yards soiled by faeces. The magnitude of NH_3 emissions depends on a number of factors, such as the TAN concentration, pH, and temperature of the solution, the size of the interface with the air, the concentration gradient between the solution surface and air, and wind speed (Kupper et al., 2013; Kupper & Menzi, 2013; Sommer & Hutchings, 2001; Sommer et al., 2004).

Nitrogenous solutions in the soil are formed, among other things, after mineral or organic N fertilisation by dissolving the N contained in the fertiliser with soil or air moisture. The composition of the N fertiliser plays an important role in this context. Direct NH_3 emissions result from fertilisers containing NH_4+ and urea. In addition to the fertiliser type, various environmental conditions (temperature, wind speed, precipitation) and soil properties (calcium content, cation exchange capacity, pH value), as well as the application technique (especially for liquid manure), influence the level of NH_3 emissions from fertilisation (Sommer et al., 2004; Wowra et al., 2021). Especially for liquid manure, the application technique can also have a considerable influence on NH_3 emissions (Sommer & Hutchings, 2001; Webb et al., 2010).

3.9.2 Influence of site-specific parameters

Animal production systems

Kupper et al. (2013) and Raschbacher and Offenberger (2006) showed that NH_3 from animal husbandry is significantly influenced by factors specific to the husbandry system, such as type of animals, feeding, and housing system, herd management, type of manure storage, and manure management. In addition, environmental conditions, such as air temperature, precipitation, or wind speed, can also play a relevant role (Schrade et al., 2023), which themselves can vary in time but also depending on the location.

Crop production and soil-based NH_3 emissions

As mentioned above, the level of NH_3 emissions depends, among other things, on soil properties and environmental conditions. The formation and emission of NH_3 from crop fertilisation are influenced by numerous physical (soil pores) and chemical (pH value) soil parameters, as well as meteorological parameters (wind speed, air temperature, and humidity) (Wowra et al., 2021). These can differ over small areas and fluctuate over time (e.g. during the course of the day or seasonally).

For the resulting environmental impacts (see Chapter 2.4 Terrestrial Acidification and Chapter 2.5 Terrestrial Eutrophication), it is important to mention that NH_3 is usually deposited close to the emission source (Asman & van Jaarsveld, 1992). However, NH_3 is also reactive and creates compounds with sulphate or nitrate, which form NH_4^+-containing particles (Asman et al., 1998). These particles can be transported atmospherically over longer distances more easily (Raschbacher and Offenberger, 2006). In addition, NH_3 contributes significantly to the formation of atmospheric particulate matter (Erisman and Schaap, 2004), which is a risk factor for human health, especially in densely populated areas.

3.9.3 Current status of the inclusion of site-specific parameters

A widely applied method of estimating NH_3 and NO_x emissions from fertilisation in agriculture is described in the European Monitoring and Evaluation Programme (EMEP)/European Environment Agency (EEA) air pollutant emission inventory guidebooks (EEA, 2009, 2016, 2019). This method covers manure management and crop production, including emissions from soil, and differentiates among three levels of detail (tiers), depending on the data availability. In the Tier-2 method, EFs for manure management allow for differentiation according to animal species, livestock diets, housing systems, and manure storage systems (Amon et al., 2019). Emission factors for 10 types of (mineral) fertilisers are provided, which are further differentiated according to three climate zones (cool, temperate, warm) and two levels of soil pH (≤7 and >7). Tier 3 methods are those that result in an even more accurate estimation of emissions compared to Tier 2. Such a method is available for Switzerland with Agrammon. This method allows further differentiation of the factors influencing NH_3 emissions by taking into account, for example, the influence of feeding and emission-reducing measures in livestock housing and manure storage. In crop production, site-specific parameters, such as the pH value of the soil or emission-reducing application techniques, can be taken into account (Kupper et al. 2022).

3.9.4 General gaps in the current models

With Agrammon, a NH_3-model with a high level of detail (Tier-3) is already in use, which allows a spatially precise modelling of NH_3 emissions for Switzerland. At the international level, spatial differentiation could be increased for modelling NH_3 emissions from fertiliser use by implementing the Tier-3 level of EMEP/EEA.

3.10 Nitrogen oxides (NO_x) emissions

3.10.1 Introduction

NO_x emissions originate from fuel combustion, the application of N fertilisers, and manure storage. Nitrogen oxides (NO_x) stimulate the increased formation of tropospheric ozone, smog, particulate matter, and aerosols. Deposition on (sensitive) land areas leads to leaching of H^+ due to diminishing buffer capacity and a change in soil parameters. In a literature study that reviewed 160 articles, Kupper (2017) found that the data availability for NO_x emissions from animal production systems, including manure storage, is very limited and partially contradicting. The EEA (2019) stated that contributions from livestock production systems to total NO_x emissions are about 0.1%. Rivera et al. (2017) investigated the impact of NO_x emissions from mineral fertiliser and pesticide application on the overall environmental impact of crop production using barley in Denmark and Italy as examples. The results showed that depending on the impact category, the inclusion of NO_x led to a variation in the overall environmental impacts of up to 7%, except for photochemical ozone formation, where the variation was 18%.

3.10.2 Influence of site-specific parameters

The production of NO_x in soil after the application of N fertilisers is largely caused by microbial activity (nitrification), which is influenced by a number of environmental variables. These include soil temperature, water-filled pore space, and the availability of inorganic N (Hall et al., 1996). These environmental variables can vary over small areas due to natural conditions but are also strongly influenced by agricultural activities such as fertilisation, tillage, or irrigation.

3.10.3 Current status of the inclusion of site-specific parameters

The air pollutant emission inventory guidebook 2019 (EEA, 2019) provides methods for calculating NO_x emissions from livestock and manure management. NO and NO_2, which, such as N_2O, are produced during nitrification and denitrification, are reported in total as NO_x. The Tier-1 method provides emission factors for manure storage for 21 livestock categories and allows differentiation between liquid and solid manure.

3.10.4 General gaps in the current models

Due to the limited importance of NO_x emissions from livestock (as mentioned above), it is sufficient to use simple Tier 1 emission factors.

3.11 Land occupation and land competition

3.11.1 Introduction

According to Roesch et al. (2017), “The concept of ‘land use’ is very comprehensively applied in LCA (Milà-i-Canals et al., 2007), taking into consideration aspects such as the mere use of the land, the biomass production potential of land, the effects of land use on soil quality, biodiversity, and also – in some cases – landscape”. LCA distinguishes between two aspects of land use: (i) land occupation and (ii) land transformation or land use change (Furrer et al., 2023; Lindeijer, 2000). Land occupation impacts are characterised by the fact that, for the duration of land use, qualitative differences potentially occur compared to a reference situation (e.g. natural vegetation) in respect to all areas of protection potentially (de Baan et al., 2013). In contrast, the impacts of land use change result from a change in quality, which can be reversed during a regeneration period (Hellweg & Milà-i-Canals, 2014, de Baan et al., 2013). The qualitative changes comprise the physical, chemical, and biological properties of the land used or transformed.

In this chapter, we deal with land use (occupation) and land use change (land transformation) aspects related to the LCI level. In principle, the LCI-related indicators are discussed here. However, further explanations are also provided in some cases in order to take into account the relationships that exist between the LCI-related indicators and, for example, C-based emissions (see Section 3.1). The impacts of land use on biodiversity and soil quality are dealt with in Sections 2.12 and 2.13, respectively.

In the SALCA method, land occupation (measured in m^2*year) is taken into consideration based on the ReCiPe midpoint method (Douziech et al., 2024). The areas occupied by agricultural production are generally differentiated according to their main use (food production or non-food production) and further differentiated within these categories; for example, in the case of food production, a distinction is made between arable crops and permanent crops. The concept of land occupation and transformation requires the definition of discrete land use categories. This means that each land use has to be assigned to exactly one land use category, which limits the accuracy, for example, when describing a gradient of production intensity, which is a continuum. The CML2001 method (Guinée et al., 2001) proposes the indicator land competition (measured in m^2/year), which was used in the SALCA methodology until 2023. The idea behind this indicator is that occupied land is unavailable as a resource for other uses for the time of occupation. There are other methods in the literature for taking land use into account, which are briefly discussed below.

Food production potential and food–feed competition: To consider the different possible uses and food production in connection with animal production, Mollenhorst et al. (2014) developed a method that quantifies protein production potential for the human diet. In this method, a land-use efficiency (LUE) ratio is calculated as a quotient of the plant proteins that could be produced directly on the arable land for human nourishment instead of forage, and the animal proteins that are actually produced. Ineichen et al. (2023) presented another developed approach that allows to include feed–food competition in the analysis, in addition to land use competition for dairy production. This approach consisted of two methodological components: the human-edible feed conversion ratio (eFCR) and the land use ratio (LUR). eFCR is a measure of the proportion of feed that is suitable for human consumption. LUR places land-related food production potential in relation to the output of milk production. If these two methods are used in parallel, they offer a way to consider the net contribution of a milk production system to human nutrition, taking into account local site conditions.

Biomass production potential (measured in MJ or kg C or kg dry matter): Biomass production potential is of limited significance for food production, since it does not distinguish between renewable resources such as wood, feedstuffs such as grass, and food. Due to this limitation, it will not be discussed further here.

3.11.2 Influence of site-specific parameters

An essential characteristic of land for agricultural production is the SOC content, which both determines the productivity of the land and is a significant factor influencing soil-borne C-based emissions (Lal, 2004). For its part, the SOC content is influenced by the type of vegetation, soil type, and management and varies greatly in spatial terms (Six et al. 2002). In addition, a change in land use (e.g. conversion of grassland to arable land or deforestation) can lead to a depletion of soil C, which in turn results in increased emissions. Rainforest deforestation is a land use change that has a major impact on C emissions, resulting in the release of C stored in above- and below-ground biomass. The variation of land-use change across different regions within a country and the resulting emissions are illustrated by Donke et al. (2020) for 27 regions (i.e. states) in Brazil. It is clearly shown that the amount of C stored in primary forests can vary by up to a factor of five, depending on the region. Consequently, CO_2 emissions from land use change also fluctuate in a corresponding order of magnitude when primary forests are cut down.

Both the impacts from land transformation and land occupation can vary between countries and between certain regions within the same country because they are inherently site-specific. Alexander et al. (2015) used country-level data to assess the main drivers of agricultural land use and land use change and concluded that animal production was the main driver of land use change globally, with major differences regarding the contributions of individual countries. Nevertheless, it should be emphasised that land use as such (in the LCI) is only area- and time-related.

3.11.3 Current status of the inclusion of site-specific parameters

Land occupation and land transformation, according to ReCiPe 2016, are calculated with the amount of area occupied or transformed (in m^2a or m^2, respectively). The same approach is used at the level of the LCI in the ecoinvent database. Sonderegger and Stoikou (2023) reported that datasets using land contain an elementary exchange (“transformation from …”) to reflect the land use type before the land use started and another elementary exchange (“transformation to …”) to reflect the intended land use type after the production cycle (for annual crops, usually about one year). The numerical value for the characterisation factor is identical in both cases, with the difference that in the case of “transformation from …” there is a positive sign, while “transformation, to” gets a negative sign. With that approach, the land use impact will be zero if a production system turns back to the initial land use type once the production cycle is finished, which is usually the case for agricultural production systems. There is no regional differentiation (e.g. for different countries) implemented in this approach, which may be a limitation depending on the use case.

3.11.4 General gaps in the current models

Koellner et al. (2013b) addressed current land use (impact) modelling and mentioned several limitations. One limitation of the approach described above is the simplification that time and area are considered equally. In other words, it makes no difference whether a large area is occupied for a short period of time or a small area for a long period of time, although this can make a difference in terms of ecological impacts (Koellner & Scholz, 2008; Scholz, 2007).

4 Discussion

4.1 Effects of pedoclimatic conditions and agricultural management on environmental impacts

Regional aspects can have various effects on the results of an LCA study (Fig. 2). On the one hand, pedoclimatic conditions (soil, climate, topography) strongly influence emissions and impacts. However, they also have an effect on yields. As the functional units of agricultural LCAs typically depend on the yield, the final impact results per functional unit will also be influenced. The resource use and emissions also strongly depend on crop management: the use of fertilisers, pesticides, machinery, irrigation, etc. has a major influence on the LCI and crop yield. Crop management is driven by socio-economic conditions in the country, such as access to certain technologies or the affordability of inputs. Furthermore, individual factors, such as the education level of the farmer and the choice of a certain farming system (e.g. organic or integrated production), play an important role. Further, crop management influences yields, although management itself depends on pedoclimatic conditions. For example, irrigation is only necessary in regions with a water deficit, and the need for liming is driven by soil pH.

This shows that numerous spatially dependent factors and processes drive the environmental impacts in agricultural LCAs, whereas only the direct influence of pedoclimatic conditions on the LCI and LCIA are considered in this report (red arrows in Fig. 2).

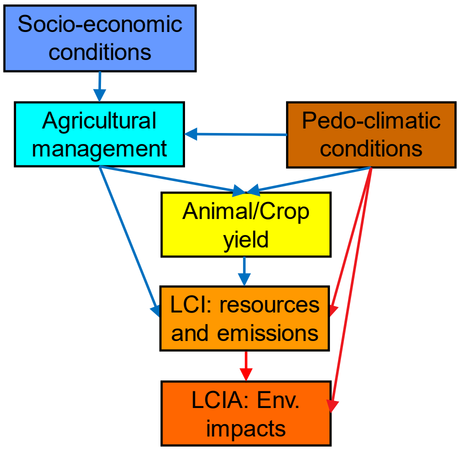

Fig. 2: Influences of pedoclimatic conditions and agricultural management on animal and crop yields, resource use and emissions, and environmental impacts. Red arrows: direct relationships and the focus of this report; blue arrows: indirect relationships.

The distinction between the effects of agricultural management and pedoclimatic conditions is relevant for the optimisation of agricultural systems and policy making. Agricultural management is under the control of the farmer within certain limits. The farmer decides whether to use inputs in certain amounts or in certain management options. The degrees of freedom are comparatively high for agricultural management, and this is also the main focus of agricultural policy and labelled environmental schemes. Agricultural management also depends on socio-economic conditions, such as the education level of the farmer or subsidies.

Natural conditions, by contrast, can only be influenced to a very limited extent. The climatic conditions are beyond the scope of the farmer's management actions. Microclimatic conditions can be influenced to a certain extent, generally with high investments. The temperature can be regulated by shading or protected production (e.g. greenhouses). Some soil properties can be changed easily, such as adjusting a low pH or low nutrient status by liming and fertilisation. Others, such as low SOC or texture, cannot be easily changed in the short term or only to a limited extent.

Even if the natural conditions can be changed only within narrow limits, it is highly relevant to consider them in agricultural LCAs. LCAs can help identify regions where certain foods can be produced with the lowest environmental impacts. Preferably, crops with a high water demand should not be grown in arid regions. An analysis at the product level, however, is not sufficient. We should consider the environmental impacts of a national or global food system to determine the locations to produce a given commodity with the lowest possible environmental impacts.

4.2 Goal and scope: Criteria for relevance of regionalisation

The goal of most LCA studies is to estimate the impacts related to a product, process, or system. A regional differentiation is relevant if one or several environmental impacts are significantly changed; therefore, the conclusions from a study might depend on the production region. LCA models an environmental cause–effect chain from the driving forces over resource use and emissions to the environmental impacts. Regional differentiation is most relevant if the following three conditions are met (see Fig. 3):

1. Driving parameter D shows high spatial variability.
2. A strong relationship exists between the driving parameter D and the emission E or resource R.
3. Emission E has an important contribution to impact I.

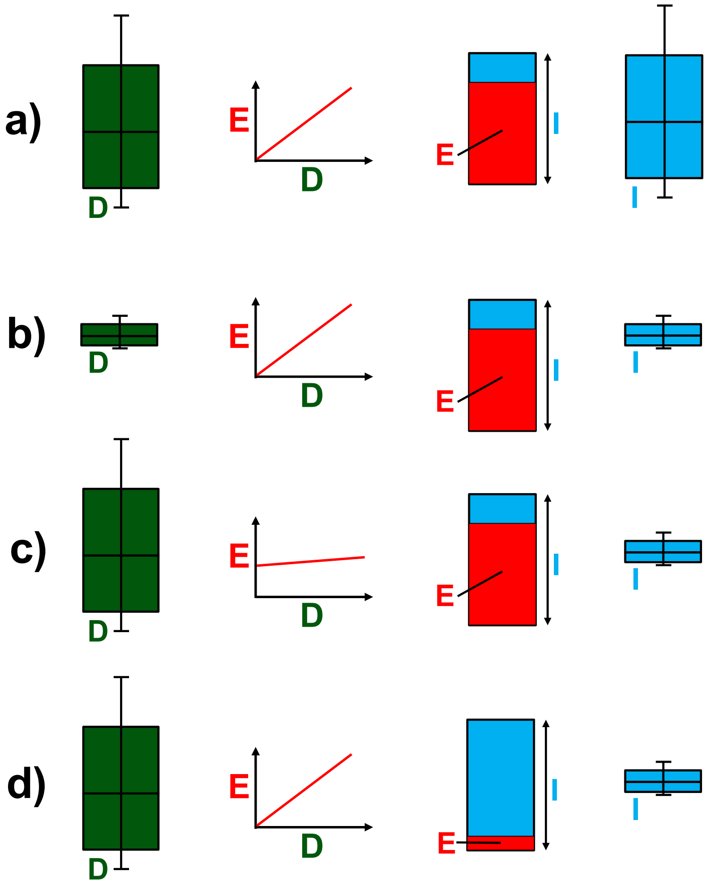

Fig. 3: Schematic representation of the influence of driving force D on resource or emission E and eventual impact I. Case a: D has a large variability and a strong influence on E, which in turn has a high contribution to I. In the other cases, the effect of D on I is minor due to a low variability of D (case b), a low influence of D on E (case c), or a small contribution of E to I (case d).

If one of these conditions is not met, a high spatial differentiation of D or emission E is not needed, as the results for impact I will hardly change. For example, if the spatial variability of driving parameter D is low, its influence on impact I is likely to be low. Similarly, if D has a high spatial variability but only a weak relationship with E, the effect will be small. Further, if D and E are highly variable but the contribution of E to impact I is negligible, the effect on the final results will be small. As the resources to carry out LCA studies are always limited, it is crucial to identify the factors and processes with the highest influence on the environmental impact results and the final conclusions.

The priorities guiding the modelling and analysis efforts should be set relative to the goal of the study. In what follows, we give examples of possible LCA studies and discuss the relevance of regional differentiation.

- *Example A: Comparison of different production techniques or production systems*. In this case, no spatial differentiation is needed unless there is an interaction between pedoclimatic parameters and the technologies or production systems. However, LCA practitioners should try to eliminate the influence of site parameters to avoid biasing the results. This is similar to controlled experiments, in which we try to keep environmental influences constant to isolate pure management effects. For example, if organic and conventional farming should be compared on samples of 2×10 farms, it is preferable to try to eliminate site-specific influences, even if such differences exist, as the goal is to compare farming systems.

- *Example B: Comparison of a food commodity produced in different regions or countries*. In this case, it is likely that regional differences in pedoclimatic conditions could influence emissions or impacts, and regional factors should therefore be considered, unless the area considered is relatively small and homogeneous.
- *Example C: Assessment of the environmental impacts of farms with different management practices in different regional contexts*. Site-specific and regional parameters should be considered in the necessary detail, as the assessment comprises a combination of management and site conditions with possible interactions.

These examples show how the definitions of goals and scopes influence the degree to which regional factors should be considered. This relates to the aspect of data quality related to geographic representativeness (ISO 2006a, b). LCA practitioners should make sure that the data used on production techniques, resource use, emissions, and impacts are representative for the regions where the products come from as far as relevant for the goal of the study.

In comparative LCA studies, the relative differences (in %) between the products or production systems assessed are more relevant than the absolute values, since the relative differences finally determine the conclusions. ISO (2006a, b) allows for skipping processes of low environmental relevance. An LCA study should not spend time on processes, factors, or inputs that will not significantly affect the final outcome. In comparative studies, efforts should be focused on the differences between the systems to be compared.

4.3 Common driving parameters

Here, we discuss the driving parameters that play a crucial role in several emission models or several environmental impacts. To do so, it is beneficial to treat emissions models and LCIA separately. This is because emissions and impacts are often driven by different parameters. Whereas emission models are typically driven by pedoclimatic parameters (climate data such as precipitation, temperature, soil [texture, SOC, pH], and topography [slope, shape]), environmental impacts are driven by environmental cause–effect chains. The CFs in midpoint and endpoint impact methods are primarily influenced by socio-demographic factors, such as the population density (influence on human toxicity), the age structure, or the differentiation between urban and rural areas. For example, sulphur emissions in a big city with a high population density have a much greater influence than the same emissions on a volcano or an island in the middle of the ocean. The age pyramid can play a role, as young/old human beings may react differently to toxic substances. However, pedoclimatic parameters, such as soil pH and lime status in the case of terrestrial acidification, also play a crucial role.

Note that the same process may be parameterised at different spatial resolutions for different purposes. Whereas the modelling of erosion in the UseTox model is performed at the subcontinental level, distinguishing between 16 subregions, SALCAerosion operates at a much higher spatial resolution. This means that different spatial resolutions for the same processes are applied in the different models. This also implies major challenges in its implementation in IT tools and causes certain inconsistencies.

Field and farm emissions

In what follows, we describe the parameters that simultaneously drive several emissions. Soil texture (the proportion of sand-, silt-, and clay-sized particles, often represented by the clay/silt content and particle size) and other soil properties, such as the organic matter content, soil pH, and soil water regime, have been identified to influence several field emissions. Here, we provide an overview of the key influential parameters for the emissions under evaluation.

(i) Erosion is driven by most parameters that are typically used to describe soil properties.
(ii) CO_2 emission mainly depends on the humus content.
(iii) N_2O emission depend on soil texture, SOC, and soil pH.
(iv) Secondary pesticide emissions are driven by several soil properties, such as the presence of drainage, fraction of macropores, soil density, and soil moisture content.

(v) P loss through leaching by surface water and into ground water is driven by soil properties such as grain size, infiltration capacity, and clay silt content.
(vi) Nitrate leaching is influenced by soil characteristics (soil water content, humus content, and clay content).
(vii) Physical (soil pores) and chemical soil parameters affect NH_3 induced by crop fertilisation and NO_x emissions.
(viii) Heavy metal concentrations are influenced by erosion (i.e. point i) and leaching (i.e. point vi), which strongly depend on soil properties.

We conclude that physical and chemical soil properties typically strongly affect the level of the analysed emissions. Of course, there are also differences in the importance of specific soil property factors.

Climate factors such as temperature, precipitation, wind speed, and evaporation influence different emissions to varying degrees. However, the influence is sometimes quite small or even negligible. We provide a short overview of the most influential climatic parameters in the investigated field emissions.

(i) N_2O emissions from soil: precipitation and temperature, freeze-thaw cycles; sensitivity is dependent on the climate zone
(ii) N_2O emissions from grazing animals: precipitation (wetter climate generally leads to higher emissions on pasture), soil moisture, and, to a lesser extent, temperature
(iii) CH_4 emissions from manure storage: temperature (microorganisms are more active in warmer climates)
(iv) CH_4 emission from rice cultivation: no direct link, but flooding pattern/water regimes are a key parameter (mainly irrigation-driven)
(v) Secondary pesticide emissions: volatilisation, re-deposition, and leaching are influenced by precipitation, wind regime, and, of less importance, temperature.
(vi) Rain-induced erosion: precipitation frequency, heavy precipitation events
(vii) Leaching of different substances such as P, NO_3^-, heavy metals, and other pollutants: precipitation and evapotranspiration, determining the amount of seepage water.
(viii) NH_3 emissions from fertiliser application and NO_x-emissions: wind speed, temperature, humidity.

To summarise, the following parameters are crucial drivers of emissions:

- Soil: soil properties (mainly texture [fractions of sand, silt, and clay and particle size]), SOC, and soil pH)
- Climate: precipitation and temperature (air humidity and wind speed are less relevant)
- Slope (only important for emissions into water, such as solid P due to erosion)

As most of the above-listed parameters show high spatial variability, it is crucial to provide these parameters at a reasonably high resolution for the emission model. Agricultural management practices also strongly affect field emissions (see Section 4.1). However, these factors were not treated as site-specific parameters in this study.

Environmental impacts

Here, we identify influencing parameters that are crucial for modelling the impact pathways (fate, exposure, and effect) of several environmental impacts simultaneously. It is evident that sufficient high spatial differentiation of these quantities is of great importance. We provide a list that summarises and synthesises the findings presented in Chapter 2. Note that the effect factors describing the effect of nutrients and pollutants on mankind, land, and marine species, and plants are not discussed, as they are not relevant in the discussion of spatial resolution.

(i) pH: Soil pH is crucial for terrestrial acidification, as all plants have their optimal pH level, and soil pH after deposition of acidifying substances depends on the initial conditions, of course. Soil pH is also a key parameter for modelling soil quality (e.g. the aspect of SOM). This also applies to biodiversity (species act differently on changes in the soil and water pH), which is related to the fact that in various endpoint methods such as LC-Impact and ReCiPe 2016, biodiversity loss is influenced by several impact categories.
(ii) Population structure: Population density (disparities between urban and rural areas) and the shape of the age pyramid (fraction of young people) are key for estimating the exposure of mankind to toxic substances. Therefore, these parameters are of great importance in human toxicity and photochemical ozone exposure. They are also highly important when estimating the impact of water use by competing users on deprived water availability. Therefore, the aim should be highly spatially differentiated data on statistical measures of population structure.
(iii) Atmospheric advection/ wind speed: The air transport of substances is important to calculate the fraction of manifold substances in the different compartments, determining again directly how heavily sensitive

ecosystems are exposed to specific substances. This plays a role in the cycles of substances such as NH_3, SO_2, or toxic compounds from pesticide application, which are directly responsible for environmental impacts such as terrestrial acidification, terrestrial eutrophication, and human toxicity. This means that atmospheric models at the highest possible resolution should be used to thoroughly describe the spatial distribution of the substances.

(iv) Surface water residence time (N, P): Excess N can damage both plant species and aquatic life. The persistence of N in different compartments (fate) crucially determines various environmental impacts, such as terrestrial and marine eutrophication as well as biodiversity. Fate modelling of N is dependent on the surface water residence time, which is used to estimate N removal by advection and denitrification. The residence time of P is a key parameter for aquatic (freshwater) eutrophication. Residence times of pesticides greatly influence the extent to which target organisms (mankind, aquatic life, and plants) are exposed to the substances.

(v) For several abiotic resources, such as rare earth metals, the location of their mining and use is not relevant from an environmental perspective, since these resources are considered global. However, for some resources, such as freshwater or biotic resources (e.g. wild fish populations), the regional availability of the resource strongly determines the impact.

In summary, the following main drivers were identified:

- Vulnerability of the affected ecosystem: for example, occurrence of endangered species (biodiversity), N/P loads (eutrophication), or the pH of soil and water (acidification)
- Human population density/structure for human health impacts
- Regional availability of (land/water) resources (e.g. water scarcity)/regional water consumption

Since the above-mentioned parameters are generally highly spatially variable, it is crucial to use data at the appropriate resolution as inputs for the models to compute the effects along the entire causal chain (either to the level of midpoints or to the level of endpoints) at sufficient accuracy. The degree of appropriate regional resolution is determined by the spatial variability of the driving parameters. This variability is typically not uniform in different regions of the world. For instance, watersheds can span small but also very large regions. The population density in large rural and very sparsely populated regions can be assumed to be uniform over large distances, while this is not the case in Central Europe, which has different population densities.

Note that the main drivers of impact and emissions clearly differ. It is evident that the impact is also affected by the amount of emitted substances. This implies that the impacts are also influenced by the pedoclimatic variables mentioned above as the main drivers of emissions.

4.4 Implementation of IT tools

Numerous elements are necessary to describe an agricultural production system using an LCA. In addition to a variety of data, including management practices and pedoclimatic conditions, a large number of models are required to calculate direct field and farm emissions, as various methods are needed to calculate environmental impacts. These elements result in a relatively complex interaction of data collection, emission calculation, and impact assessment. To address this complexity and the amount of data, sophisticated software and IT tools are crucial.

When implementing regionalised models for emissions calculation and impact assessment in these IT tools, various factors must be taken into account. The most important of these are the availability of data, the applicability of the selected models for the geographical context of the system being analysed and the coordination of the granularity between the LCI and the impact assessment method. In this context, it may be necessary, for example, to adapt the native resolution of an impact assessment method to the data availability or granularity at the level of the LCIs. This can be illustrated by using the environmental impact of water use or water scarcity as an example. The AWARE method (Boulay et al., 2018a) offers an impact assessment method with a very small-scale native resolution (at the level of water catchment areas). The water consumption in the respective water catchment area can thus be offset against water use in the same region to obtain an indicator of the water stress in the respective region. However, this requires identifying the catchment area from which water is withdrawn for a specific production system. Often, the production data are not available at this level of detail for agricultural production systems, but only at the country level.

In common LCA software such as SimaPro (Silva et al., 2017), the AWARE method is therefore implemented with a lower granularity than is available with the native resolution of the original version of the method. Another reason for this simplification is that the complexity of the LCIs can be kept easily manageable on the level of background databases, such as ecoinvent (Donke et al., 2020; Weidema et al., 2013; Wernet et al., 2016). Nevertheless, the correct use of the AWARE method – which is simplified in terms of its geographical resolution – requires the availability of information on the water withdrawal of a production system at the country level. Further, elementary flows must be mapped accordingly in the LCIs. Thus, the application of the simplified AWARE method also requires an increase in the granularity of the LCIs (compared to non-regionalised water flows), and the complexity is significantly increased, as water flows must be included for all relevant countries.

A different level of granularity may be necessary for other environmental impacts (Frischknecht et al., 2019b; Patouillard et al., 2018). This results in the implementation challenge that sometimes different geographical subdivisions of a region must be available, depending on which emission or environmental impact is being calculated. In the case of impact assessment methods, this can be solved, for example, by implementing CFs for larger geographical units (e.g. countries) in addition to small-scale CFs (e.g. different regions within a country). This allows the CF with the proper geographical resolution to be selected, depending on the application and data availability.

In addition to different granularities in the data and impact assessment models used, it may also be necessary – depending on the application – to use different emission calculation models, each of which can be used for a different geographical context. To account for both the necessary complexity and flexibility, it is advisable to pay attention to a modular structure in the implementation, which allows the appropriate level or the right degree of regionalisation to be selected, depending on the application.

4.5 Research needs

The formulation of research needs and gaps in current models have already been identified above. Here, we summarise the findings at an overarching level. Note that the relevance of spatial differentiation depends on the goal and scope of the study (see Section 4.2). The identified research needs can be split into (i) model development and (ii) the provision of high-quality data (collection and preparation) at sufficient spatial resolution. We identified the following key research needs:

Model development

(i) Consolidation of appropriate impact modelling (find consensus methods based on purely scientific criteria). The GLAM initiative (Frischknecht et al., 2019a) will surely help to improve the current situation.
(ii) Effective gain due to the use of detailed regional models instead of more generic global (or continental or national) models
(iii) Generalisation of models that are tuned to a certain limited region (e.g. a country or a continent) to make them applicable worldwide
(iv) Assess the relevance of the uncertainty of regionalised models on the final assessment (as called for by Mutel et al., 2019)

Provision of data

(i) Use of high-resolution climate data for temperature, precipitation, and evapotranspiration as input to emission models
(ii) Compilation of datasets at high spatial resolution for soil texture and further soil properties, such as SOC and soil pH. Here, methods for geostatistical interpolation, such as inverse distance weighted interpolation (Mitas & Mitasova, 1999) or kriging methods (simple kriging, ordinary kriging, universal kriging, cokriging) (Oliver & Webster, 2014), may also help to compile more accurate datasets.
(iii) Use of global GIS-based data with sufficient spatial and temporal resolution to derive regionalised CFs with global coverage. GIS data are generally structured in layers that can be overlaid and analysed to derive insights about spatial relationships and patterns. The application of GIS helps to merge and aggregate variables needed as input for sophisticated methodological approaches. GIS also supports the conversion of data with different spatial resolutions.

5 Conclusions and recommendations

This report details the state-of-the art and the main challenges with respect to the regionalisation of emission models and environmental impacts at both the midpoint and endpoint levels. In addition to the outline of the current status regarding regionalisation, the main drivers are identified for both the field and farm emission models and the environmental impacts (midpoints and endpoints).

We found that the following key parameters simultaneously drive several emissions: (i) soil texture, determining the percentage fractions of sand, silt, and clay and thus the grain size distribution, (ii) SOC, (iii) air temperature, and (iv) precipitation amount. As these key driving parameters typically show large spatial variability, it is crucial to provide them at sufficiently high spatial resolution fitting to the applied model. Further, the expected increase in accuracy and the time required to implement and run the method has to be in proper relation to each other. We also stress that depending on the selected model, increasing the degree of detail does not necessarily increase the overall accuracy of the results.

In contrast to agricultural field emissions, the impact pathways (fate, exposure, and effect) of several environmental impacts are critically influenced by the vulnerability of the concerned ecosystem, the spatial distribution of the human population, and the regional availability of certain resources, such as water (determining water scarcity) and land. For instance, the biodiversity score is prone to the occurrence of endangered species in the ecosystem. The spatial distribution of the human population has a direct impact on the number of people exposed to toxic substances and is thus a crucial parameter for human toxicity, and photochemical ozone exposure. Population density is also of great importance when estimating the impact of water use by competing users on deprived water availability.

It is evident that the appropriate spatial resolution of the applied model depends on the spatial variability of the key driving parameters. For instance, for populations with high homogeneous spatial distribution, a high spatial resolution can be dispensed without loss of accuracy. By contrast, if the population density changes over short distances – as in Western Europe – the spatial resolution has to be high enough to correctly capture the spatial distribution of exposed human beings.

The above considerations indicate that the key parameters driving emissions and environmental impacts differ: The emissions are primarily driven by local soil properties and climatic parameters, while environmental impacts are influenced by processes along the entire environmental cause–effect chain. We also show that the choice of adequate spatial model resolution strongly depends on the goal and scope of the study. The objective of a project or study as defined in goal and scope largely determines the extent to which regionalisation of emission models and midpoints will be necessary. A regional differentiation of key driving parameters with high spatial variability is relevant if significant changes in one or several analysed environmental impacts are expected to change substantially, potentially leading to other conclusions depending on the region of production. This is the case when the following three conditions are simultaneously met: (i) the driving parameter has a high spatial variability, (ii) this parameter is key for the emission or the resource (e.g. water), and (iii) the emission or the resource has a major influence on the environmental impact. If these three conditions are not met simultaneously, increased spatial resolution will have little effect on the impact results.

To facilitate the choice of an appropriate spatial resolution in practical applications (LCA studies), we elaborated on some advice provided through the following recommendations:

(i) Ensure that the data used on production techniques, resource use, emissions, and impacts are representative of the regions from which the products originate, where relevant to the objective of the study.

(ii) If expert knowledge and available literature suggest that regionalisation is not relevant for a specific model and/or research question as provided in goal and scope do not aim at applying models with higher spatial resolution.

(iii) If multiple native spatial resolutions are suggested through physical principles, try to find a compromise between scientific rigour and practical considerations.

(iv) Try to avoid an LCA study framework in which both site-specific variables and management effects significantly impact the findings, as this may lead to problematic discrimination between site-specific and pedoclimatic influences on the results.

6 Abbreviations

AoP	Area of Protection
AWARE	Available WAter REmaining
CF	Characterisation Factor
DALY	Disability Adjusted Life Years
DPSIR	Driver-Pressure-State-Impact-Response
EF	Emission Factor
EFF	Effect Factor
EU	European Union
FF	Fate Factor
FOEN	Federal Office for the Environment
GHG	Greenhouse Gases
GIS	Geographic Information System
GLAM	Global Guidance on Environmental Life Cycle Impact Assessment Indicators
GPT	Global Temperature Potential
GWP	Global Warming Potential
ISO	International Standard Organisation
LCA	Life Cycle Assessment
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
LUR	Land Use Ratio
MBC	Microbial Biomass Carbon
MBN	Microbial Biomass Nitrogen
MCF	Methane Conversion Factor
MNVOC	Non-Methane Volatile Organic Compounds
PEF	Product Environmental Footprint
PEF-CR	Product Environmental Footprint Category Rules
PDF	Potentially Disappeared Fraction
PDF m^2 y	Potentially Disappeared Fraction of species in square meters per year
PPP	Plant Protection Products
RUSLE	Revised Universal Soil Loss Equation
RWEQ	Revised Wind Erosion Equation
SOC	Soil Organic Carbon
SOM	Soil Organic Matter
SQCB	Sustainability Quick Check for Biofuels
UBP	Umweltbelastungspunkte (Swiss Ecological Scarcity Method)
VOC	Volatile Organic Compounds
XF	Exposure Factor

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