BAYER CROP PROTECTION ENVIRONMENTAL IMPACT REDUCTION (CP EIR)

Methodological Report

/////////// December 2024

Crop Science Division of Bayer

Reducing impacts of crop protection product application on the environment

Currently limited to aquatic organisms

Version 1.4 – Post 3rd review cycle

Disclaimer

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AI	Active Ingredient
BBCH	Biologische Bundesanstalt, Bundessortenamt and Chemical Industry
Bayer	Bayer used in this report references the Crop Science division of Bayer
CAS	Chemical Abstracts Service
CF	Characterization Factor per active ingredient (PAF m^3 d/kg emitted: Model output of USEtox®)
CP	Crop Protection
CPP	Crop Protection Product
CP EI	Crop Protection Environmental Impact
CP EIR	Crop Protection Environmental Impact Reduction
EC	Effect Concentration
EI	Environmental Impact (freshwater ecotoxicity impact of crop protection applied on a field as determined by the combination of the models, PestLCI and USEtox®)
EI/quantity	Environmental Impact per quantity (PAF m^3 d/Kg applied)
EI/ha	Environmental Impact per hectare (PAF m^3 d/treated area)
EI/scenario	Environmental Impact per scenario (PAF m^3 d/country/year) [Note: To facilitate readability and understanding, Crop Science divison of Bayer labels this 'EI/scenario' metric as 'EI'; see description of 'EI' above]
EIR	Environmental Impact Reduction
Ha	Hectare
LCA	Life Cycle Assessment
LCIA	Life Cycle Impact Assessment
LCM	Life Cycle Management
PAF	Potentially Affected Fraction of species
PDF	Potentially Disappeared Fraction of species
DTU	Technical University of Denmark
UN SDGs	United Nations' Sustainable Development Goals

1. Context and Objectives

1.1. Context

Bayer is a Life Science company with a more than 160-year history and core competencies in the areas of health care and agriculture. Contributing to sustainable development has become a core element of Bayer's corporate strategy. For the Crop Science division of Bayer, sustainability focus areas and goals were developed to fulfill the target to shape the future of sustainable agriculture. The Crop Science division of Bayer sustainability focus areas were developed to address the field-to-field-gate[1] impact of agriculture. These targets complement Bayer's sustainability objective for its own operations, such as the target to become climate neutral by 2030 (scope 1 & 2 emissions) and reach net zero including its entire value chain by 2050 or earlier (Scope 1, 2 & 3). The field-to-field-gate scope focuses on the sustainability impacts at the farmer-level (i.e., the product use stage). The Crop Science division of Bayer also has the target to enable farmers to reduce field GHG-emissions by 30%, reduce the environmental impact of crop protection[2] (see below the scope of environmental impact in the context of this report) by 30%, improve water use per kg of crop by 25% and strives to improve the livelihoods of 100 million smallholder farmers through access to education and tailored solutions. This report focuses exclusively on one of Crop Science division of Bayer sustainability focus areas: a transformational target on the environmental impact reduction (EIR) of crop protection (CP) by 30% by 2030.

In the last few decades, the environmental impact of crop protection has decreased while ensuring yield and helping growers produce more with less (McDougall, 2018). However, with new tools and innovations, the Crop Science division of Bayer has the opportunity, and responsibility, to continue reducing this impact. **The Crop Science division of Bayer targets reducing the treated-area-weighted environmental impact per hectare of Bayer's global crop protection portfolio by 30% by 2030 against a 2014–2018 average baseline**. Bayer is currently using a combined model based on PestLCI and USEtox®, that can calculate Bayer's global potential environmental impact of crop protection.

In this report, the term 'potential environmental impact of crop protection uses' is defined in accordance with the current scope of PestLCI and USEtox®. More specifically, Bayer relies on the midpoint USEtox® impact unit that expresses freshwater ecosystem toxicity as "potentially affected fraction (PAF)" of freshwater species exposed to a chemical in a freshwater environment. More details on the interpretation and calculation of this unit follow in later sections. In this report, **the combination of emissions according to PestLCI and potentially affected fraction of exposed species according to USEtox® is called crop protection environmental impact (EI)**. Bayer decided to use the term EI for internal and external communication to facilitate general understanding among customers (farmers) and other internal and external stakeholders who might lack the understanding of strict LCA terminology and the differences between environmental impact categories. **Therefore, this report will also mainly use the term 'EI'**. By using this impact unit, Bayer ultimately aims to reduce the impact of crop protection uses on environmental non-target species. Bayer aims to integrate additional

[1] Field-to-field-gate refers to impact measured based on product use activities within the farm field, excluding impact from crop protection products manufacturing and use outside the farm field.

[2] The designation "environmental impact of crop protection" has been adopted for the purpose of Bayer corporate communication. Any external communication will disclose the limitation of this designation to freshwater ecotoxicity or any other scope according to further methodological developments in the context of the present study.

environmental impact categories, such as soil organisms and pollinators, once the USEtox® consortium integrates these categories in the scientific consensus model.

The Crop Science division of Bayer has partnered with the Technical University of Denmark (DTU) on this CP environmental impact assessment project.

The main objective of this report is to document how Bayer is utilizing the combined model based on PestLCI and USEtox®, that can calculate Bayer's global EI of crop protection. To illustrate how Bayer and DTU have calculate the global CP environmental impact, mapped the different data sets, describe the required input data, limitations and the boundaries of the calculation, this report is based only on 2018 CP application data. However, all steps outlined in this report are applicable to their entire data set used to track the progress of Bayer against its target. Bayer emphasizes that it only considers the EI of crop protection during its use phase on the field in this report while excluding further upstream and downstream impacts. Other impact categories relevant for crop protection such as potential human health impacts resulting from the ingestion of CPP residues in crops, or greenhouse gas emissions, and climate change impacts are not in the scope of this specific report but are considered by other sustainability targets Bayer has made.

Besides the CP EIR target, Bayer has established various separate internal sustainability initiatives and taskforces to set up measurement approaches and improvement levers for other targets such as reducing greenhouse gases (GHG) for Bayer's own operation, value chain, and at the field level, water conservation and improving smallholder livelihood. In addition, initiatives have also been established towards biodiversity and soil health, and product responsibility (e.g. empty container management, safe use trainings) towards achieving globally harmonized safety standards for our crop protection products focused on operator safety. We are aware of potential unintended trade-offs from such ambitious sustainability targets therefore moving forward, we are striving to take a full systems-based perspective on our approach with regenerative agriculture and to treat a farm as an ecosystem in itself – with its unique soil and environmental conditions.

In the context of this report, Bayer does not conduct a full-fledged LCA according to ISO 14040/44 but intends to use the standard as a framework to document the project in the present report. With a critical review of this report by external experts, Bayer aims to verify that it uses the PestLCI and USEtox® models in a reasonable approach and that the baselining and performance tracking methodology is adequate.

1.2. Reducing the environmental impact of crop protection uses requires a holistic approach at crop system level. A review of main drivers and impact reduction levers

Bayer aims to reduce the global environmental impact from the use of its crop protection products. A starting point will be to understand the main drivers of this impact and identify our main impact reduction levers. An EI driver refers to the factors that significantly influence impact on the environment from the use of CPP. Levers are methodologies or activities that can be deployed towards the reduction of environmental impact. Based on our preliminary results, we have identified the following main drivers of environmental impact from CPP uses:

- the amount of all crop protection substances applied per hectare (ha) per growing seasons in a given crop and country,
- the environmental impact of the crop protection applied on the field itself driven by the intrinsic substance properties, and

- factors contributing to emissions of crop protection applied on the field into the environment. For example, the type of CPP application equipment used.

Thus, the main impact reduction ‘levers’ can be categorized as follows:

- Optimize crop protection amounts required per hectare through tools like:
  - Precision application: data-driven tools that ensure that the right amount of crop protection is applied in the right place and at the right time.
  - Seed treatment: seed-applied crop protection tools can dramatically reduce the volume of chemicals used and potential exposure to wildlife and the environment.
  - Seeds and traits: crops bred and designed to better fight the pests and diseases that attack them, ensuring that less chemical crop protection is needed.
  - Biologics: complement chemical crop protection with biologics to enhance integrated management practices and reduce pest resistance.
  - Integrated crop management practices such as crop rotations, cover crops, integrated pest management strategies which help to control weeds, pests, and diseases and therefore reduce the need for crop protection products.
- Reduce the environmental impact of the crop protection product itself:
  - Better environmental profile of the active ingredient (lower effect on non-target plants and species)
- Reduce the emissions into the environment:
  - Mitigation measures such as drift reduction and buffer strips
  - Digitally enabled precision application

Bayer analysis of the major levers starts with the drivers of the environmental impact of crop protection uses in a given crop and country in terms of specific crop protection products relative against the baseline (see section 4.1). Bayer then assesses its existing portfolio, the innovation pipeline, and alternatives in the market to understand how CP EI hotspots can be mitigated. In this analysis, it became apparent that levers can be categorized further into overarching levers, which are relevant for all indications (i.e., herbicides, fungicides, and insecticides) and levers which are mainly relevant for a specific indication as outlined in Figure 1 below.

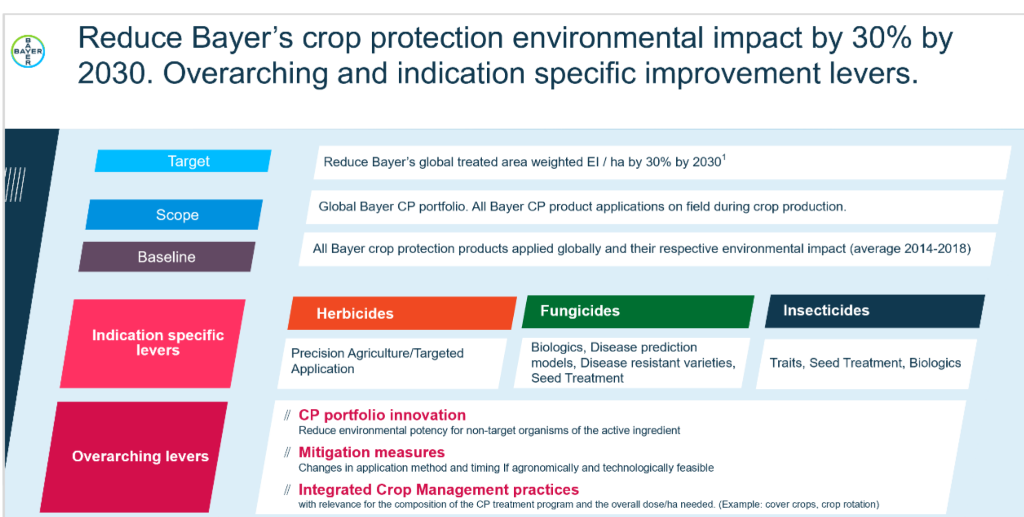

Figure 1: Bayer's crop protection environmental impact reduction framework

1.3. International frameworks considered to define Bayer goal of 30% EIR of CP by 2030

We are at a tipping point where both consumers and our planet demand a fundamental change in the agricultural system. With the world population expected to meet the 10 billion mark by 2050, the demand for food and biomass production is steadily increasing (Ray et al., 2013). However, crop cultivation is becoming increasingly challenging for farmers due to changing environmental conditions, raising regulatory requirements, and other challenges. Furthermore, the amount of available agricultural land is declining due to increasing urbanization, higher salinity levels and soil erosion. For Bayer, all of these factors culminate into a so-called **'agricultural paradox'**: on the one hand, farmers are challenged with the need to produce more food and biomass to meet global demand while, on the other hand, this need must be met while preserving resources and the environment. Agriculture must strike a balance between the need for tools like crop protection, which enable farmers to keep meeting the world's growing agricultural demands while using less land and resources, and potential trade-offs posed by increasing the use of such tools. With new products and technologies, we aim to ensure that our solutions serve farmers' needs and wellbeing, while also protecting the environment and contributing to food security. Overall, the 'agricultural paradox' is based on the following premises (see also (UNEP, United Nations Environmental Programme, 2021)):

- **Development of dietary choices in agricultural system**: The world population is growing, and dietary habits are changing. The world population is expected to grow from about 7.8 billion in 2020 to 9.8 billion by 2050. Global income is increasing, and the global middle class is expanding. In spite of the emerging trend towards plant-based meat and other alternative sources of protein, the per capita consumption of meat, refined fats, refined sugars, alcohols, and oils is expected to rise with the increasing wealth along with demand for consumer products that also depend on agriculture. CPPs are an essential tool in securing higher yields to help limit the amount of land being converted to arable land.
- **Development of output demand in agricultural system**: Demand for food, feed, fibers, fuels, and feedstocks is growing. By 2050 demand for food is projected to grow by 60 percent, meat production by nearly 70 percent, aquaculture production by 90 percent, and production of dairy products by 55 percent. Furthermore, cropland is increasingly used for purposes such as production of livestock feed, fibers, biofuels, and feedstocks for the chemical industry.
- **Development of agricultural system's vulnerability to climate change**: Crop cultivation is becoming increasingly challenging for farmers due to climate change affecting growing conditions. For example, climate change will intensify global water scarcity and change the distributions of pests, which could lead to increased and more widespread use of CPPs.
- **Development of agricultural system's vulnerability to land degradation**: The amount of available agricultural land is declining due to increasing urbanization, higher salinity levels, and soil erosion.

To overcome the 'agricultural paradox', Bayer decided to set an ambitious goal that orients towards the UN Sustainable Development Goals (SDGs), specifically SDG indicator 2.4.1. In addition, this goal also relates to the planetary boundary concept (especially, the planetary boundary of "novel entities"; (Rockström, et al., 2009)). As a result, Bayer made the public target of reducing the environmental impact of Bayer's crop protection portfolio by 30% by 2030. Overall, Bayer defined this 30% in light of established conceptual frameworks and based on internal expert judgement by critically reflecting our technological capability to live up to this target. After defining this ambitious goal, Bayer decided to use PestLCI and USEtox® as consensus models to assess and verify its progress towards the 30% goal.

1.4. Bayer's goal in light of the UN Sustainable Development Goals and Planetary Boundaries

Bayer's CP EIR goal aims at contributing to attain the **United Nations' Sustainable Development Goals**. The United Nations agreed on 17 SDGs to build a better world for people and our planet by 2030. The 2030 Sustainable Development Agenda emphasizes that development should be compatible with all three dimensions of sustainability: economic, social, and environmental. Implementing the 2030 agenda presents an opportunity for collaborative action by many diverse actors at all levels to minimize the adverse environmental impact of CPP uses. Therefore, Bayer's CP EIR target is at the interface with several goals of the 2030 Agenda to contribute to a sustainable management of CPPs (see also UNEP (2021)).

- SDG 1 - No poverty: Increased need for efficient, profitable and sustainable use of CPPs.
- SDG 2 - Zero hunger: Increased need for effective pest management; Need to increase quality and sustainable use of CPPs in certain parts of the world; Wider adoption of sustainable agricultural production practices.
- SDG 3 - Good health and well-being: Ensure access to sufficient, safe and nutritious food.
- SDG 6 - Clean sanitation and water: Minimization of water pollution from CPPs.
- SDG 9 – Industry, innovation, and infrastructure: Development of innovative and sustainable pest management approaches and technologies.
- SDG 12 - Responsible consumption and production: Wider adoption of sustainable pest management practices; Minimization of impacts of CPPs on natural resources; Further strengthening of sound management of the entire life cycle of CPPs; Further support for and implementation of sustainable pest management technologies by the CPP industry; Improvement of information provision about the risks of CPPs and ways to minimize these risks.
- SDG 13 - Climate action: Wider adoption of integrated practices in agriculture that enhance farmers' sustainable productivity as well as climate resilience.
- SDG 15 - Life on land: Minimization of environmental impacts of CPP uses; Ensuring sustainable control of invasive pest species; Mainstreaming ecosystem and biodiversity values in national and regional pest management policies.
- SDG 17 - Partnerships for the goals: Improvement on sharing of CPP management knowledge among relevant stakeholders; Enhancing partnering among UN organizations active in the sound management of chemicals.

As indicated earlier, Bayer's CP EIR goal also takes into account the planetary boundary concept. According to Steffen et al., (2015), "the planetary boundaries framework defines a safe operating space for humanity based on the intrinsic biophysical processes that regulate the stability of the Earth system". Bayer aims at staying within planetary boundaries, especially, within the **planetary boundary of novel entities'** (Rockström J. W., 2009; Steffen, et al., 2015). The planetary boundary of chemical pollution has been expanded and renamed as novel entities which are defined as "new substances, new forms of existing substances, and modified lifeforms that have the potential for unwanted geo-physical and/or biological effects" (Steffen, et al., 2015). The introduction of novel entities to the environment by human is of concern at the global level when these entities exhibit persistence, mobility across scales with consequent widespread distribution, accumulation in organisms and the environment, and potential impacts on vital Earth system processes or subsystems (Steffen, et al., 2015; Persson, et al., 2022). Novel entities can adversely affect human and ecosystem health, which has most clearly been observed at local and regional scales but is now evident at the global scale. Novel entities qualify as a planetary boundary because they can influence Earth system functioning: (1) through a global, ubiquitous impact on the physiological development and demography of humans and other organisms with ultimate impacts on ecosystem functioning and structure and (2) by acting as a slow variable that affects other planetary boundaries. For example, novel entities may influence the biodiversity boundary by reducing the abundance of species and potentially increasing organisms' vulnerability to other stresses such as climate change (Jenssen, 2006; Noyes, et al., 2009). Novel entities can also interact with the climate-change boundary through the fact that most industrial chemicals are currently produced from petroleum, releasing CO2 when they are degraded or incinerated as waste.

The main aim of this report is to assess the potential environmental impact of crop protection when applied on a field, rather than to directly quantify impacts on biodiversity. Bayer acknowledges that a quantification towards the planetary boundary of novel entities (including chemical pollution) is currently not possible mainly due to methodological constraints (Rockström J. W., 2009; Jenssen, 2006; Noyes, et al., 2009; Steffen, et al., 2015). However, this Bayer target further helps to stay within this planetary boundary by assessing as a first step the environmental impacts of chemical stressors for the environment.

1.5. Objectives of the report

In order to achieve the sustainability target of reducing the CP EI by 30%, Bayer has set the foundations of its EI measurement and performance tracking method using input dataset sourced via the Agrowin database and models based on PestLCI and USEtox®. This report objective is to document a method to quantify Bayer's global CP EI, based on application scenarios from 2018. The data from 2018 serves as a reference. For tracking progress against its target,.

Bayer has calculated a five-year average baseline CP EI (from 2014 to 2018), in order to track performance against the 30 % reduction target of the EI by 2030. A baseline on a 5-year-average (2014 – 2018) is established to account for the specificities of agriculture such as inter-annual variability, seasonality, or dependence on climatic conditions.

1.6. Critical review

This report is structured in line with the Life Cycle Assessment (LCA) methodology (according to the ISO 14040 and ISO 14044) as a template for documentation of methodological choices, results, and interpretations as well as limitations. However, Bayer acknowledges that this report only focuses on the field-to-field gate life cycle stage and on CPP emissions' impacts due to CPP uses. Consequently, Bayer does not claim that this report complies with ISO 14040/44. As Bayer intends to communicate to the public its sustainability targets and achievements, a critical review has been performed through a series of repeated consultation with external experts and external auditors in order to demonstrate that the quantification methodology, baselining and performance tracking approach is adequate. This report provides an overview of the external review-panel composition (see Table 1). The report reflects the panel's feedback.

Table 1: Critical external review-panel composition

Members	Country	Area of expertise
Thomas Nemecek	Switzerland	Deputy Lead Life Cycle Assessment Research Group Agroscope. Worldwide known researcher on Life Cycle Assessment, specifically in its applications on agriculture.
Jeffrey Jenkins	U.S.A.	Professor at Oregon State University. Expertise in environmental analytical chemistry, ecological risk assessment, and agronomically based ecohydrologic modeling to characterize watershed scale pesticide use and the potential impact on water quality.
Valery Forbes	U.S.A.	Dean and Professor at Florida Atlantic University. Broad expertise in mechanistic effect modeling and ecological risk assessment of pesticides and other chemicals.
Assumpció Anton	Spain	Researcher at Food and Agricultural Research Institute, IRTA. Expertise in the development and application of LCA methodology in agriculture.
Tiago Rocha	Brazil	Consultant|Partner at ACV Brasil and PhD in Environmental Technology. Extensive experience in life cycle assessment, specifically in the area of carbon footprint.
Lorie Hamelin	France	Researcher at the Federal University of Toulouse (France), studying the environmental impacts related to large-scale transitions towards low fossil carbon use
Anne-Marie Boulay	Canada	Associate Professor in Chemical Engineering at Polytechnique Montreal and co-Director of CIRAIG. Expertise on water footprint methodologies and impact assessment associated with plastic litter in LCA.
Jessica Hanafi	Indonesia	PhD in Life Cycle Engineering. Established the Indonesian Association of Life Cycle Assessment and Sustainability Professional. ISO Technical Committee on Life Cycle Assessment (TC 207/SC5), environmental labelling (SC3), Greenhouse Gas (SC7) and project leader for ISO/TS 14074 LCA normalization and weighting. Applied LCA based on ISO 14040/44 to various industrial sectors, including agriculture.
Laura Golsteijn **(Chair of the panel)**	Netherlands	Senior LCA Consultant at PRé. PhD in Toxic Impact Modelling. Supporting clients to understand, develop and embed environmental metrics to improve the sustainability of supply chains and products.

1.7. Organization of the study

The study is based on data from 2018 which serves as a reference to describe the methodology. The CP EIR target is based on a data set covering multiple years. The methodology outlined in this report applies to all years in scope of the CP EIR target.

the overall impact assessment calculation process can be summarized as follows (see also Table 2 below):

- For the compilation of inventory data, Bayer provided the underlying crop protection application data sourced from Agrowin to DTU.
- For the subsequent impact assessment, DTU used the crop protection application data to calculate primary distribution fractions of CPP emissions in PestLCI and calculated the characterization factors for the active ingredients in USEtox®.
- Finally, DTU combined the primary distribution fractions from PestLCI with the characterization factors from USEtox® to calculate the CP EI scores. The CP EI calculation methodology established by the DTU serves as the basis for subsequent EI scores calculation (more details on the compilation of inventory data, impact assessment, and interpretation follow in later sections of this report).

Table 2: Contact information for all parties

Organization	Contact	Role	Tasks
Bayer Crop Science	Daniel Glas, daniel.glas@bayer.com	Project lead Bayer	• Develop roadmap to deliver against Bayer's target. • Assess how to integrate learnings into CPP development (R&D governance). • Create IT tools to enable Bayer organization to work with EI data.
Technical University of Denmark	Olivier J. Jolliet, ojoll@dtu.dk	Project lead DTU	• Apply PestLCI and USEtox® model to generate global CP EI baseline. • Advance models further (both on the emissions and impact side).

1.8. Use of the study and target audience

The results of this study are intended to transparently and publicly describe the CP EI calculation method, baseline and performance tracking. The main target audience are investors, press, academic partners, and the general public. Potentially, this report might also be used in the future for auditing processes, and as background-information material for peer-reviewed publications in scientific journals.

This report is not Bayer's main vehicle for informing external stakeholders. Bayer is continuously developing other internal and external training and communication materials and channels that will be specifically tailored to the information-needs of the respective stakeholder group.

2. Scope of the study

2.1. System studied

The system of this study includes Bayer's entire CP portfolio applied on its customers' fields globally which can be characterized in the models PestLCI and USEtox®, as reported in the Agrowin system. For example, in the analyzed inventory data, from 2018 , this covers 270 active ingredients which are used in 2,056 CPPs in 82 countries and 54 crops (at crop group level, see Table 3 below).

Table 3: Crops categories and sub-categories covered in the data set (at crop main group and crop group level)

Crop Main Group	Crop Group
BEETS	BEETS
CEREALS	BARLEY
	CEREALS-OTHER
	OATS
	RYE
	WHEAT
CORN/MAIZE	CORN-TRADITIONAL
	CORN-TRANSGENIC
COTTON	COTTON TRADITIONAL
	COTTON TRANSGENIC
ENVIRONMENTAL MARKETS (only covering farm level)	TREES
	TURF+GROUND-MANAGEMENT
FRUITS & NUTS	BANANAS
	BERRIES & SMALL-FRUITS
	CITRUS
	FRUITS: OTHER
	FRUITS: TROPICAL&SUBTROPICAL
	POME-FRUITS
	STONE-FRUITS
	TREE NUTS
GRAPES/VINES	GRAPES/VINES
OILSEED-RAPE/CANOLA	OILSEED RAPE TRADIT.
OTHER CROPS	FALLOW-LAND/SET-ASID
	FIBER CROPS: OTHER
	FORAGE CROPS

	GROUNDNUTS/PEANUTS
	OILSEEDS: OTHER
	OTHER-CROPS UNSPEC.
	SORGHUM & MILLET
	SPICES
	SUNFLOWER
PLANTATION	CACAO
	COFFEE
	OIL PLANTATIONS
	RUBBER
	TEA
	TOBACCO
POTATOES	POTATOES
RICE	RICE
SOYBEANS	SOYBEANS TRADITIONAL
	SOYBEANS TRANSGENIC
SUGAR CANE	SUGAR CANE
VEGETABLES & FLOWERS	FLOWERS+ORNAMENTALS
	VEG: BRASSICAS
	VEG: BULB
	VEG: FRUIT-CUCURBITS
	VEG: FRUIT-OTHERS
	VEG: FRUIT-SOLANACEAE
	VEG: LEAFY&FRESH-HERBS
	VEG: LEGUMES
	VEG: ROOT&TUBER
	VEG: STALK&STEM
	VEGETABLES-OTHER

2.2. Key metric of the system

The key metric of the studied system in this report is the potential environmental impact of all Bayer CPPs such as fungicides, insecticides, herbicides, and seed treatments applied per ha (EI/ha). Using a land based key metric helps in minimizing the environmental impacts per area, and it is measured per hectare and year. Therefore, Bayer defines the key metric as-

- treated-area-weighted EI/ha

Bayer has decided to use a land based key metric i.e. per ha as opposed to considering the yield (per kg crop produced) to reflect societal, political, and shareholder expectations, to reduce the environmental impact of the Bayer crop protection portfolio without compromising yield.

Bayer aims to reduce the environmental impact of crop protection products without compromising their benefits to the farmer which is helping to secure and increase yield.

2.3. Scenario elements

A scenario refers to a unique combination of the following variables: country, crop, crop growth stage, application method, product, indication, distributor, active ingredient, and dose. This section describes those elements along with additional information that is leveraged to understand the environmental impact. The information can be grouped into four categories, namely: Agrowin data input, PestLCI output values, USEtox® compartment distribution and output values, and EI score. Further details on these are described below:

1. Agrowin[3] data input:

General scenario information:

- Scenario ID: running number
- Year: 2018
- Country: Spain
- Region: Europe
- Crop: e.g., Apple
- Crop group: e.g., Pome fruits
- Crop main group: e.g., Fruits & nuts
- Crop growth stage: according to BBCH classification[4]

Market/product information:

- Name of Distributor Group and specific (sub) distributor: e.g., Bayer
- Indication: e.g., Fungicide
- Product Name: e.g., Flint 500WG
- Active ready mix: names of active ingredients if multiple active ingredients are contained in a product

[3] Agrowin is a database-software by Lexagri which generates a complete view of the entire crop protection market by harmonizing multiple data sources (for further details c.f. section 3.2).

[4] BBCH - Biologische Bundesanstalt, Bundessortenamt and Chemical Industry. The BBCH scale provides a framework to develop scales for individual crops wherein similar growth stages of each plant species are allocated within the same BBCH code.

- Active ingredient name: e.g., Trifloxystrobin. *Note:* The term 'active ingredient' (or active substance) refers to the chemically active part of a manufactured CPP which is majorly responsible for the targeted action; i.e., defeating pest and suppressing weed.
- CAS registration number of active ingredient: e.g., 141517-21-7

Application data:

- Treated area (ha per year): 'Treated area' refers to the hectares or size of farmland on which CP was applied during the cultivation of a crop.
- Applied mass (kg of active ingredient applied per year)
- Applied dose (kg of active ingredient applied per ha)
- Application Method (translated into application methods included in PestLCI): e.g., Boom-sprayer-conventional-nozzle

2. <u>PestLCI output values (PestLCI input parameters not listed here. See section 3.3.2):</u>

Primary distribution fractions [kg emitted/kg applied] for environmental compartments:

- Air
- Field Soil
- Field Crop
- Off-field surface

3. <u>USEtox® compartment distribution and output value per active ingredient (USEtox® input parameters not listed here. See section 3.3.5):</u>

Compartment distribution: Area fraction for off-field surfaces per country [m^2 compartment/m^2 total]:

- Off-field agricultural soil
- Off-field natural soil (*Note*: Natural soil means non-agricultural soil)
- Off-field water

Freshwater characterization factors (CF) [PAF m^3 d/kg emitted] for the environmental compartments:

- Air emission
- Agricultural soil emission
- Natural soil emission
- Freshwater emission

4. <u>EI output score combining PestLCI primary distribution fractions, USEtox® CFs and Agrowin information:</u>

Final freshwater impact scores per environmental compartments and in total (CP EI score):

- PAF m^3 d/kg applied (Bayer label = EI / quantity)
- PAF m^3 d/ha (Bayer label = EI / ha)
- PAF m^3 d/country/year (Bayer label = EI)*

*The final EI used per scenario is the sum of the EI from the four compartments i.e (Air, Agricultural soil, Natural Soil and Freshwater).

2.4. System boundaries

The system boundaries comprise the off-field surface area. The assessment builds upon currently available consensus models, combining PestLCI Consensus as the emission assessment model and USEtox® as the impact assessment model. Consensus models are defined as models that were developed not only on state-of-the-art science, but additionally on broad agreement among scientific and user communities regarding aspects that cannot be entirely addressed through science alone, but that require choices, such as the delineation of the technological and environmental system under study (see e.g. Hauschild et al., (2008) and Rosenbaum et al., (2015)). PestLCI is a model that was developed to simulate initial CPP distribution directly after field application until different CPP fractions reach the environment, i.e. PestLCI is a life cycle emission inventory model. USEtox® is a model that simulates the environmental distribution after emission, subsequent exposure to humans, and ecosystem with its toxicity-related effects. Both models reflect state-of-the-science in environmental impact assessment of CPPs.

Figure 2 below illustrates how emissions of pesticide active ingredients applied to agricultural field crops as crop protection products reach the environment. The environment is further divided into different emission compartments namely, air, field soil surface, field crop surfaces, and off-field surfaces that include agricultural and natural soil as well as water surfaces. The active ingredient mass reaching the environment as emissions within minutes after application, following primary partitioning are defined by the PestLCI consensus model as primary emission distribution fractions. These are then linked to USEtox® for impact assessment. See Section 3.3 for more information.

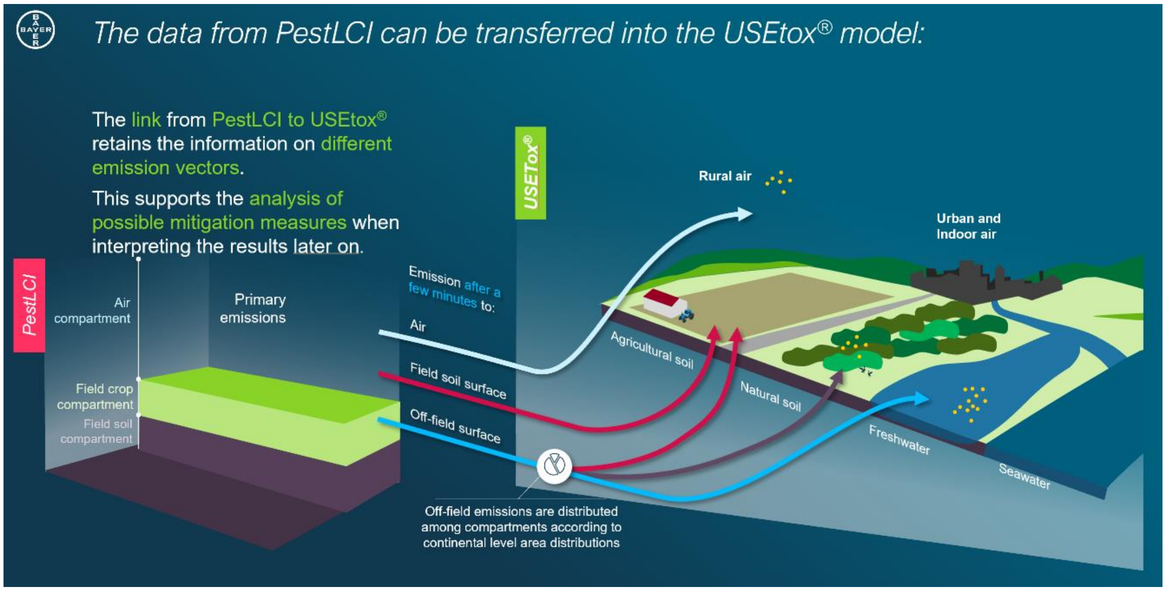

Figure 2: Primary emissions based on PestLCI and their emission vectors to off-field surfaces

3. Method

For the CP EI reduction target baseline and continuous progress tracking, a process and database has been established to accommodate the overall impact assessment calculation. The process can be described as follows: (See Figure 3 below)

1. Bayer receives the global crop protection application data from Lexagri Agrowin currently on an annual basis.
2. Bayer receives Primary Distribution Fractions based on PestLCI, characterization factors and off-field fractions based on USEtox® 2.14 from DTU whenever the model parameters or the input data are updated by the scientific consortium. Some CPPs that are used in the current approach were not originally available in USEtox®. In these cases, DTU supplemented the missing substances or substance data based on available public databases. Bayer applies the data as received by the DTU.
3. The crop protection inventory data from Agrowin are then combined with PestLCI and USEtox® results to conduct the global crop protection impact assessment based on method outlined by the DTU using the first analyzed 2018 inventory data.

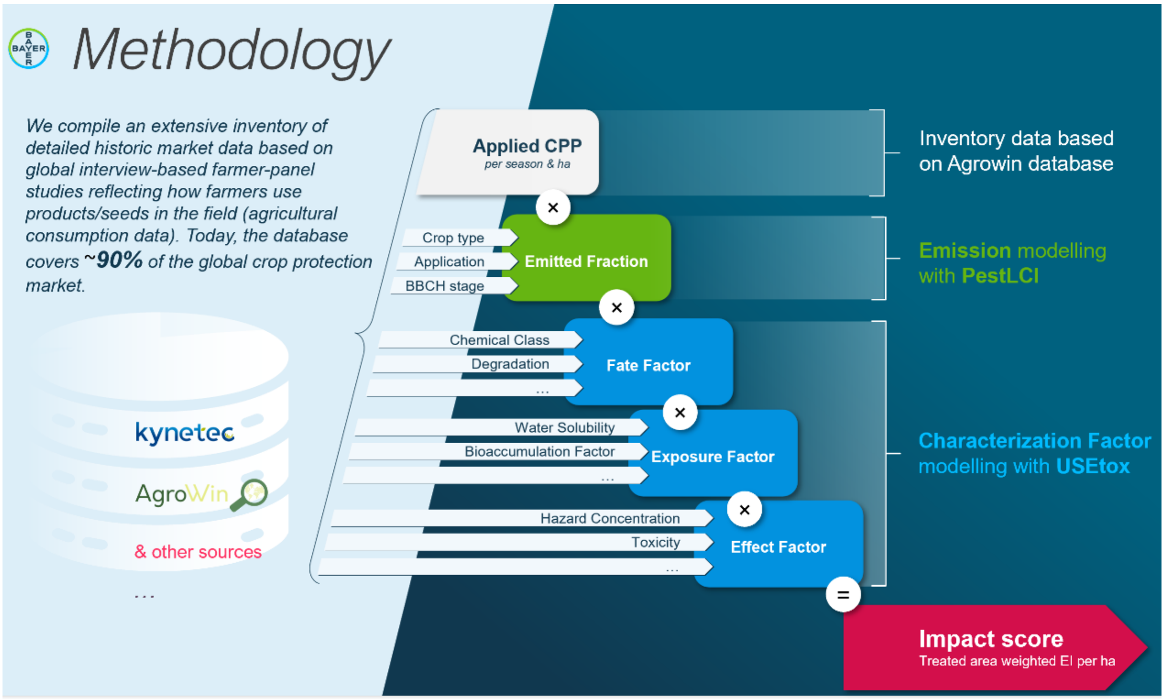

Figure 3: An overview of the methodology used for the calculation of Impact Score

In the next chapters, we provide more details on the compilation of inventory data, emission modelling, impact assessment, and interpretation.

3.1. Compilation of inventory data

The data inventory includes relevant input data from each application scenario (e.g. amount applied per ha as reference flow) as well as data from widely used state-of-the-art consensus models for environmental evaluation (using LCA) of agricultural CPPs as well as for quantifying freshwater ecotoxicity from chemical emissions.

Substance characteristics like environmental degradation half-lives, solubility, and ecotoxicological data are necessary for product registration and can be pulled from public databases such as the Pesticides Properties DataBase (PPDB), the Bio-Pesticides Database and FooDB. Climate, field and soil data inputs are based on pre-defined regional data sets of the PestLCI and USEtox® models. The climate, field and soil data are set for default (sub)continental and global systems in the USEtox® model (incl. land area with the fraction of freshwater, natural and agricultural soil, sea area, the temperature, wind speed, rain rate, freshwater depth, fraction of freshwater discharge from the continental to the global system, fractions of the rain rate that run off and respectively infiltrate the soil, soil erosion and irrigation). USEtox® also includes urban landscape data containing the urban area and the fractions of non-paved and paved area, and in addition for 8 continental landscapes and 16 sub-continental landscapes. Amongst others, the windspeed has been calculated based on GEOSChem wind speeds from IMPACT World and rain rates are based on GIS computation from IMPACT World. Further information of the model climate, soil and field data can be found in Rosenbaum et al. (2008) and Kounina et al. (2014). A consistent set made up respectively of emission fraction and mass balance equations are at the core of the two models and were applied by DTU as further described in Gentil-Sergent et al. (2020) (for PestLCI) and Rosenbaum et al. (2008) (for USEtox®).

3.2. Compilation of inventory data on global crop protection product consumption based the ‘Agrowin’ database

Bayer complements the aforementioned inventory data parameters with the Agrowin database and software, which delivers application data for crop protection products. Agrowin is a database-software by Lexagri (2021) which generates a complete view of the entire crop protection market by harmonizing multiple data sources. This software is used within Bayer to access a detailed historic consumption market data overview (starting 1996) and reflects how farmers use products/seeds in the field. Overall, the database covers 90% of global crop protection products market value. Focusing on Bayer, the database covered about 85-95% of the Bayer market value in the past, depending on the year. The data in Agrowin represents so-called consumption data, in other words: what have farmers planted and applied on their fields as opposed to sales data (what has been sold by crop protection manufacturers into the market).

The gap between consumption data and reported data from crop protection manufacturers can be attributed to several factors such as intercompany sales, channel inventories, royalties and crop year gap. Figure 4 below illustrates the different factors that cause an unquantifiable gap between reported data and consumption data. Bayer relies on Agrowin for consumption data.

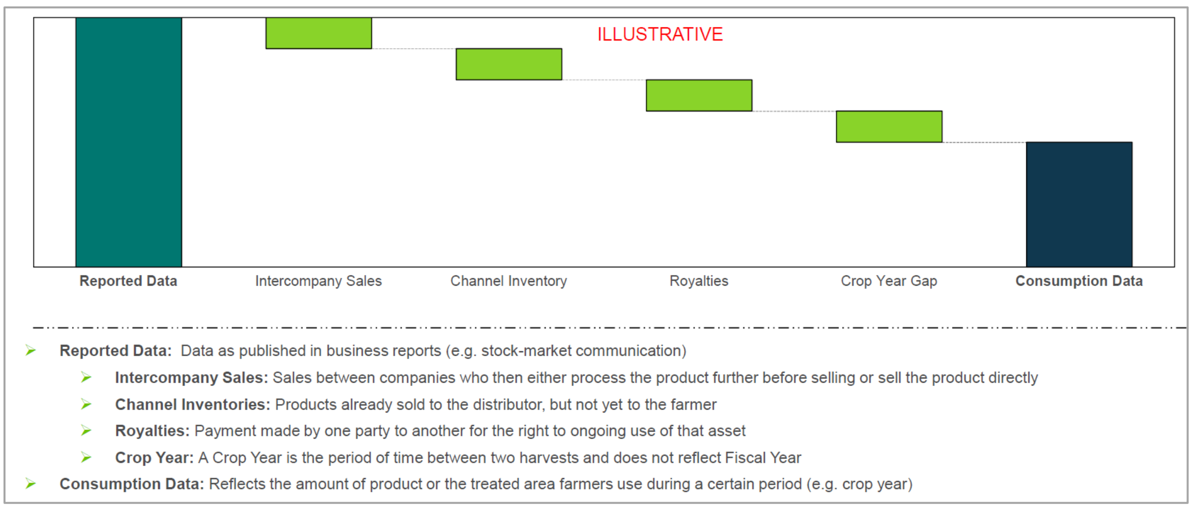

Figure 4: Gap between reported data and consumption data in global data sets on crop protection use[5]

The Agrowin database is built on two sets of data: farmer-panel data and non-farmer-panel data. Farmer-panel data are first-hand information from farmers through interviews after crop seasons. Collecting such information is based on interviewing global panels of farmers on how farmers use products in the field. These farmer-panel data are externally sourced from agricultural market research companies (e.g., Kynetec, SPARK, Kleffman Group etc.) which conduct global interview-based farmer-panel studies for monitoring market trends. At the end of a crop cultivation season, farmers are interviewed and asked about which crop protection products and practices they applied. For example, farmers are asked:

- Which crop protection products they used?

[5] The figure is only illustrative and does not specifically represent the result of an analysis or data collection. It is shown to bring clarity to the reader on the differences in the consumption data and companies reported sales data and why these differences could arise.

- How many hectares they treated (treated area)?
- How many kilograms of a product they used (volume applied)?
- At which crop growth stage they applied a product?
- Which application methods they applied?
- What was the reason for application? (Pest, Disease, etc.)

Farmer-panel data are freely available to purchase, and the data are typically licensed to the purchaser for a specific use case. In each crop cultivation season, the purchasers of farmer-panel data decide if and to which extent interview farmer-panel data need to be collected depending on the commercial relevance of a market. This means that the comprehensiveness and frequency of data collection is higher in relatively big and commercially relevant markets such as the US-corn market (typically farmer-panel data are collected once per year). In other markets with a lower commercial relevance, the frequency of farmer-panel data collection can be lower and irregular (e.g. only every 2-3 years in the Belgium-potato market). Once market research companies such as Kynetec have collected the farmer interview panel data, these data are automatically moved to the company Lexagri which compiles and harmonizes these farmer-panel data about the use of crop protection products and seeds in their Agrowin database. That means Lexagri does not conduct interviews with farmer-panels itself, but only compiles and harmonizes the data and moves the data from the original sources (e.g., Kynetec panel data) to Agrowin.

Farmer-panels are not conducted in every country for many reasons such as low commercial relevance in the market. Bayer does not buy all available farmer-panel data for cost reasons. Countries where farmer-panel data are used in Agrowin are shown in Figure 5. Non farmer-panel data are based on different sources such as industry sales statistics published by governments, sales statistics made available from market research companies, or in some countries, Bayer´s own assumptions. Non farmer-panel data are typically made available as sales data which are then translated to consumption data. Overall, the hierarchy of data is based on 1) using farmer-panel data, 2) using industry statistics, and 3) using expert market knowledge of dedicated market analysis and business intelligence colleagues (internal estimates). .

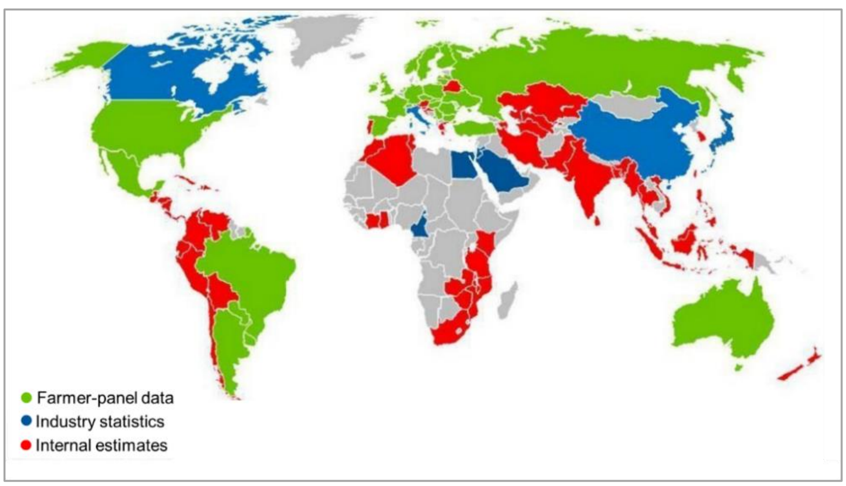

Figure 5: Agrowin country-specific data sources overview (2016 status)

3.2.1 Data quality

Farmer-panel data are Bayer preferred option to use in the Agrowin database, however, farmer-panels use different methodologies (e.g. for sampling) and approaches (e.g. mathematical approaches to project sample data to overall market). Therefore, the quality of the farmer-panel data still needs to be continuously verified for each data set as Bayer strives for quality accuracy of 95%.

The quality accuracy of 95% relates to the stratification of the interview sampling. The number of interviews and the distribution throughout the country is very important for the quality of the study. When defining the stratification method, different criteria such as soil, climate, farmer age, farmer education, etc. need to be considered. In general, stratified sampling is a method of sampling from a population which can be partitioned into subpopulations. In statistical surveys when subpopulations within an overall population vary, it could be advantageous to sample each subpopulation (stratum) independently. Stratification is the process of dividing members of the population into homogeneous subgroups before sampling. The strata should define a partition of the population. That means, it should be collectively exhaustive and mutually exclusive. Every element in the population must be assigned to only one stratum. The objective is to improve the accuracy of the sample by reducing sampling error. Stratification gives a smaller error in estimation and greater accuracy than the simple random sampling method.

Farmer-panel data quality is assured by selecting representative farmers as interview participants. A representative selection and distribution of farmers in a farmer-panel is mainly based on the following criteria: Age of the farmer, educational level of the farmer, and spatial distribution of soil types cultivated within a country. For example: a panel on the German-Wheat market is based on approximately 3000 interviews. Data quality also depends on the education, training, and experience of the interviewers. For example, interviewers need to adequately utilize showcards in interviews to ensure that farmers with a low education level understand interview questions. See section 4.4 for information on data limitations and how they are addressed.

Bayer has defined quality standards for farmer-panel providers with more than 30 criteria to ensure the farmer-panel data quality (see Appendix 7.3). For example, criteria like age and educational level of the farmer, climate, and spatial distribution of soil type within a country are used to ensure a representative selection and distribution of farmers in the sample of interview participants. Bayer acknowledges that data quality also depends on the education, training, and experience of the interviewers.

Once data are collected, incorporated, and harmonized in Agrowin through excel files which include multiple cross-checks, data are confirmed by country planners with the help of a check file to review. This is an important step as the system reflects the countries' official view on their respective market. Farmer panel data may be completed by non-farmer-panel data. Its quality depends strongly on internal education level and expertise of the country planner and business intelligence manager as they decide on method for data collection. Data then often needs to be transferred from sales information to consumption data. Bayer is also aware that inputs from excel files have potential for human errors. However, internal data checks and corrections are mainly related to prices or product allocation to reflect the correct distributor to a given product. The product usage itself (including dose rates and other usage attributes) is usually not changed from the original source.

3.3. Impact assessment based on active ingredients emissions and freshwater ecotoxicity impact calculation

3.3.1 Emission modelling with PestLCI

To estimate emission fractions for CPPs applied to agricultural fields for each application scenario, PestLCI Consensus version 1.0 was used as implemented in the web-based tool[6]. This tool builds on a mass-balance model developed initially by Birkved and Hauschild (2006) and further advanced by Dijkman et al. (2012) and by Gentil (2020) and Gentil et al. (2021).

PestLCI Consensus provides 'primary emission distribution fractions' (i.e., active ingredient mass reaching the environment as emissions within minutes after application following primary partitioning) for the compartments air, field crop surface, field soil surface, and off-field surfaces. Primary emission fractions are mainly influenced by growth stage and morphology of treated field crops defining the fraction of applied mass that is intercepted by crop surfaces, and by the drift deposition function for a given crop protection product application method defining the fraction reaching off-field surfaces. Primary emission fractions have been applied for each application scenario and can then be transferred into the USEtox® model. The primary distribution processes considered in PestLCI Consensus are presented in Figure 6 below, and are further detailed in Dijkman et al. (2012), Gentil (2020),Gentil et al. (2021) and (Nemecek, et al., 2022).

PestLCI Consensus furthermore provides 'secondary emission fractions' (i.e. CPP mass reaching the environment within a given timeframe, typically 1 day) for the compartments air, field crop surface, field crop leaf uptake, field soil, groundwater below field, and off-field surfaces, also considering degradation in field crop and soil. Secondary emission fractions are likewise a function of crop characteristics and application method, but depend on additional aspects, such as climate and field characteristics, application month, and active ingredient physicochemical properties. Secondary distribution was excluded from the environmental impact assessment because the level of detail required to model secondary distribution processes are not readily available in the present screening-level assessment, which would introduce large additional uncertainties related to collecting and defining e.g., field-level characteristics at the global scale.

[6] Available at https://pestlciweb.man.dtu.dk

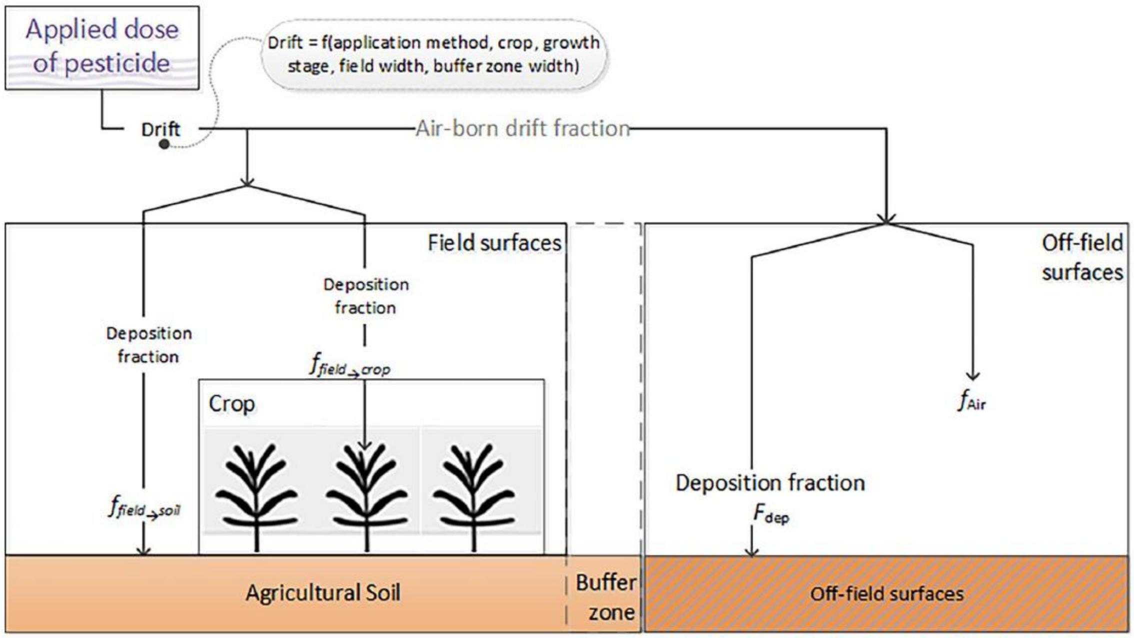

Figure 6: PestLCI Consensus primary emission distribution processes and compartments for the example of aerial application of CPPs, which first enter the "air" compartment and from there further distribute to other compartments. Figure taken from (Nemecek, et al., 2022).

When using the PestLCI model, the following main assumptions were established: Only primary emission distribution was calculated for the present study as all long-term processes (such as leaching, degradation) are covered in USEtox® and because currently, the uncertainty related to some of the processes included in the secondary distributions are higher than the rather small additional accuracy gained for screening-level assessments. Initial distributions cover initial processes within a few minutes after crop protection product application. Four relevant compartments for initial primary distribution are described below:

- Air: Initial primary distribution to air consists of the fraction remaining airborne (f_{air}) during crop protection product application. This fraction is a fixed value, depending on the primary drift of the application method and the drift reduction.
- Off-field surfaces: Initial fraction to off-field surfaces (f_{dep}) are emissions to off-field agricultural soil, natural soil or surface water that arise as a consequence of wind drift deposition during crop protection product application.
- Field crop leaf surfaces: Initial fraction to field crop leaf surface ($f_{field \to crop}$) is the fraction of crop protection product deposited on crop leaves when applying the crop protection product.
- Field soil surface: initial primary distribution on soil ($f_{field \to soil}$) is the fraction of crop protection product deposited on soil when applying the crop protection product. The fraction deposited on soil is calculated as the remainder of all CPP involved in the initial (primary) distribution: i.e. it is the remaining fraction of crop protection product that is (a) not volatilized during application, (b) not deposited off-field due to wind drift, and (c) not intercepted by the leaves in the selected growth stage of the crop.

Primary emission fractions are derived based on distributing applied CPP mass according to mass balance principles. As a starting point, within few minutes after CPP application, a mass fraction of CPP is deposited to off-field surfaces (f_{dep}). It is derived from drift deposition functions specific to each application method. Drift deposition functions were collected for various crop-application method combinations and implemented into PestLCI (see Gentil-Sergent et al. (2021)). Another mass fraction goes to the air by wind drift (f_{air}) as a default fraction per application method and crop, and the remaining mass fraction reaches the field surface via direct deposition (f_{field}), which is typically the intended target area for applied CPPs. With that, the governing emission equations reads according to Gentil-Sergent et al. (2021):

$$1 = f_{\text{air}} + f_{\text{dep}} + f_{\text{field}}$$

Equation 1

The fraction reaching the field surface area (f_{field}) is partially deposited on crop leaves ($f_{\text{field}\rightarrow\text{crop}}$) according to crop intercepted mass fraction $f_{\text{intercept,crop}}$ and calculated as:

$$f_{\text{field}\rightarrow\text{crop}} = f_{\text{field}} \times f_{\text{intercept,crop}}$$

Equation 2

Then, the fraction left on the field after crop interception ($f_{\text{field}\rightarrow\text{soil}}$) will reach field soil surfaces and is calculated as:

$$f_{\text{field}\rightarrow\text{soil}} = f_{\text{field}} \times (1 - f_{\text{intercept,crop}})$$

Equation 3

3.3.2 PestLCI input data

To run the PestLCI Consensus model, some input data are mandatory, and some are optional. For the primary emissions, the mandatory data are crop type, applied CPP fraction intercepted by field crop surfaces, and application method. The optional input data are drift reduction methods during application, presence (or absence) of a buffer zone, width of the buffer zone and field width perpendicular to the wind direction. The following model inputs have been used in this study relevant for primary emissions:

- Crop type derived from associating reported crop to PestLCI crop type (indirect influence; in particular, it influences the available options for the next two parameters)
- Fraction of applied CPP intercepted by field crop surface area, derived from reported BBCH range
- Application methods

Due to the lack of data, the following model inputs relevant for primary emissions have not been used in this study:

- Buffer zone (in the present screening-level assessment, buffer zones were not considered)
- Drift reduction methods have only been used in a limited number of application scenarios where information on the applied drift reduction method has been available. If no such information was available in the Agrowin data set, drift reduction is not included.

Other model inputs, such as crop protection product characteristics relevant for secondary emissions, climate, month of applications and soil, have no influence in the calculation of primary emissions, and are hence not relevant for application scenarios. The listed main model inputs influencing primary emissions are described in the below sub-sections.

3.3.2.1 Crop types in PestLCI

There are 16 representative crop classes available in the PestLCI Consensus model that were selected from more than 172 crops based on the FAO and Central Product Classification (CPC) Version 2.1. The crop type Agrowin data that Bayer provided to DTU were assigned by DTU to one of these 16 available crop classes, which are listed in Table 4 below. For example, the Pooideae crop class are subfamily of the grass family Poaceae which in turn includes cereals such as wheat, barley, oat, rye, and pasture grasses. Panicoideae is also a subfamily of the grasses, and it comprises agricultural crops such as sugarcane, maize (or corn), and sorghum. The selected crop type in PestLCI will define the range of available application methods and with that will influence the selection of the available off-field drift deposition functions that are relevant.

Table 4: Crop classes implemented in the PestLCI Consensus model

ID	Crop class		ID	Crop class
1	Pooideae		**9**	Fruits tropical
2	Panicoideae		**10**	Fruits temperate
3	Paddy rice		**11**	Citrus fruits
4	Pulses		**12**	Grapes/vines
5	Roots, tubers and bulbs		**13**	Berries
6	Oil-bearing crops		**14**	Nuts
7	Vegetables leafy		**15**	Oil-bearing trees
8	Vegetables fruit		**16**	Other permanent crops

3.3.2.2 Fractions of applied CPP intercepted by crop surface area in PestLCI

In the following section, different underlying cases for deriving fractions intercepted by crop surfaces from crop growth stages are described along with the various challenges for the different cases, including difficulties to allocate specific crops to crop classes for which interception fractions are available.

For application scenario calculations, foliar interception fractions were assigned to the different crop growth stage (i.e. “BBCH”) ranges and then applied to each related scenario. For that, Bayer crops were mapped to crops from Linders et al. (2000), where crop and growth phase-specific (BBCH) interception fractions have been proposed for different crops/crop classes using the growth stages with BBCH-scale (Meier, 2018). Where a direct match was possible, Bayer crops were mapped to their respective crop or crop family (e.g. Apple was directly linked to ‘Pomme Fruit’ or Apricots to ‘Stone fruit’).

When this was not possible, the crop with the closest looking leaves and maximum soil coverage from Linders et al. (2000) was chosen as a proxy. For instance, Amaranth was approximated with cereals and burdock root with sugar beets. If neither a direct link nor an approximation was possible, assigning an interception fraction was done based on the BBCH alone. Here, for each BBCH indicated, the smallest interception fraction of all crops/crop classes in Linders et al. (2000) that corresponds to this BBCH was assumed. For example, the Bayer crop ‘Agave’ remained unclassified into any given crop class and was associated with a crop growth stage (BBCH) of 10 at the time of crop protection product application. There is a total of 27 crops in Linders et al. (2000) (e.g. Bulbs, Beans, Carrots) which have a BBCH code of 10. The smallest related interception fraction is 0.1 for Onions, indicating a very early crop stage for these crops that leads to only a small fraction intercepted by the crops. This interception fraction was used for Agave at a BBCH of 10 and any other Bayer crop that remained unclassified and had an entry (application scenario) associated with a BBCH of 10. The main BBCH codes (not a linear numerical scale but numeric codes between '00' and '99' assigned to different crop life cycle stages) are described in Meier (2018). Crop interception fractions, instead, range from 0 (no crop interception) to 1 (100% crop interception) as described in Linders et al. (2000).

After Bayer crops had been mapped to the respective crop/crop class, the reported BBCH at time of crop protection product application was compared with the BBCH ranges for a given crop/crop class from Linders et al. (2000) to extract the related interception fraction. For example, the Bayer crop 'Barley-spring' had one application scenario associated with a BBCH of 70 (A7090H-POST-FLOWERING-AUT-CER). For the crop class 'Cereals' a BBCH of 70 means booting/senescence (BBCH range 40-99) and corresponds to an interception fraction of 0.9 (Linders, Mensink, Stephenson, Wauchope, & Racke, 2000). If Bayer's (or the farmer's) reported BBCH for any given crop exceeded the largest BBCH value available for the corresponding crop/crop class, the maximum available interception fraction for that crop/ crop class was taken.

Finally, if the reported BBCH did not fall into any of the BCCH ranges indicated for a given crop/crop class, the closest lower BBCH range was taken as reference point. For example, Broccoli is sprayed at a BBCH of 21 (crop growth stage: S2129-SIDE-SHOTS-SPR-LEG). The related crop 'Cabbage' has interception fraction values indicated for the BBCH ranges 10-19 and 40-49. The closest lower BBCH range to 21 is thus 10-19 with an interception fraction of 0.25.

Two additional assumptions were made in the derivation of the fraction intercepted for different crops and application scenarios. Any Bayer crop allocated to "bare-soil" (e.g. NON-CROP-LAND) was assigned an interception fraction value of zero as no crop coverage is assumed in these scenarios. There are some entries for crop (e.g., "Warehouses", "Grain: stored", "Glass-house/Greenhouse", etc.) and application method ("Stored-Goods-Treatment") that are considered out of scope, because the treatments do not occur on the field. In this case, no BBCH or interception fraction was assigned to the respective crop and application scenario. Hence, these scenarios have been excluded from the analysis that is restricted to scenarios implying emissions from CPP applications to agricultural fields.

3.3.2.3 Application methods in PestLCI

From the 31 application methods available in the PestLCI Consensus, 12 representative application methods were selected and manually associated with the data provided by Bayer. These representative application methods are listed in Table 5 below. For each application method, DTU used a fixed value for primary emission fractions to air[7].

Table 5: Crop protection product application methods and primary emission fraction to air as available in PestLCI

ID	Application method	Primary emission to air (%)
5	Boom sprayer - conventional nozzle – other crops	10
6	Boom sprayer - conventional nozzle - roots/tubers	10
13	Air blast sprayer - early stages (leafless)	20
14	Air blast sprayer - late stages (in leaf)	8
17	Air blast sprayer - grapes/vines	12.5

[7] An overview is also given at https://pestlciweb.man.dtu.dk/images/Application_Method_CropV3.png.

18	Air blast sprayer - other crops	10
19	Hand operated sprayer - crops that are < 50 cm	6
20	Hand operated sprayer - crops that are > 50 cm	10
22	Aerial application (N/A, EPPO)	25
23	Soil incorporation (N/A, N/A)	0
24	Recycling tunnel - air induction flat spray nozzles	1.25*
28	Air-assisted sprayer side by side - flat fan nozzles	7.5*

*Emission reduction included

3.3.2.4 Drift reduction in PestLCI

Additional drift reduction was not included in application scenario calculations. This means that drift reduction was only taken into account if already included in the application method (indicated with '*' in Table 5) as reported by Agrowin data.

3.3.2.5 Consideration of buffer zone in PestLCI

No buffer zone was assumed for the current calculations of primary emissions due to lack of data in Agrowin. A buffer zone is the distance between the point of direct CPP application and the nearest downwind boundary of a sensitive habitat. In CPP application, it is required to maintain a distance between the site of spray application and environmentally sensitive areas. The current calculations with regard to the effect of possible mitigation measures on emissions into different environmental compartments therefore represent a worst case.

3.3.3 Linking PestLCI with USEtox®: Emission compartment allocation

Emission results from PestLCI Consensus are associated with specific environmental compartments. These compartments do not match the emission compartments in the impact assessment model, USEtox®. Hence, the different compartments in both models were assigned in a way to allow combining both emission results and ecotoxicity impact results. Figure 7 below illustrates how application scenario emission compartments from the primary emission distribution in PestLCI Consensus are matched to the emission compartments of USEtox® (boxes relevant to the application scenarios are the initial distribution fractions within PestLCI Consensus (upper left) and USEtox® (right).

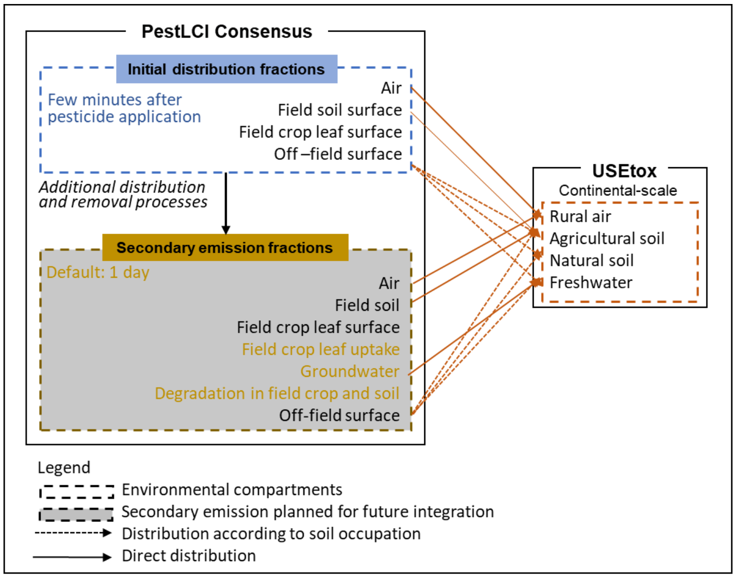

Figure 7: Coupling of different state-of-the-art models for assessing emissions and toxicity related impacts in LCIA

When doing the compartment allocation from PestLCI to USEtox®, the below main assumptions were established:

3.3.3.1 Segmentation/mapping of related emissions

Air emissions were assigned to continental rural air in USEtox®, field soil emissions were assigned to continental agricultural soil in USEtox®, and field crop surface emissions were not assigned to any emission compartment in USEtox®. The latter introduces the assumption that these emissions do not contribute to ecotoxicity impacts, which will, however, be negligible, since only marginal parts of what reaches field crops might in some cases volatilize back into air, while another part could reach the soil via e.g. wash-off or flow through the crop compartments. However, the largest fraction by far either ends up inside the crop as residues or degrades. Introducing these aspects presents an additional complexity which are not meaningful considering the scope of ecotoxicity (Fantke, Charles, de Alencastro, Friedrich , & Jolliet, 2011).

3.3.3.2 Off-field surface emission fractions

Finally, emission fractions reaching off-field surface areas were distributed according to the percentages of surface areas represented by freshwater, agricultural soil, and natural soil for the different country parameterizations in USEtox® (Following USEtox version 2.13 update from the previous continental level parametrization to country level parameterization). The off-field surface area fractions (percentages) used for the different country parameterizations are based on FAO (2020) data and are shown in Appendix 7.1.

3.3.4 Ecotoxicity impact modelling with USEtox®

The overall scope of the assessment is currently limited to freshwater ecotoxicity impacts, which was considered the only scientifically mature indicator at the time of USEtox® release in 2008 (Rosenbaum, Bachmann, Gold, & Huijbregts, 2008)[8]. In a current global guidance effort under UN Environment, this

[8] Further developments of those models are in progress, in order to extend to other environmental compartments, but are not yet finished nor have reached any consensus at the date of production of the present report.

recommendation has been revisited, and additional indicators (i.e., soil terrestrial ecotoxicity) are currently being evaluated for possible inclusion into a future update of USEtox® (Fantke, et al., 2018a). Since its release, USEtox® has been widely used by LCA practitioners. The European Commission recommends it as a reference model to characterize human toxicity and freshwater aquatic ecotoxicity impacts from life cycle chemical emissions for the International Reference Life Cycle Data System Handbook and the Product Environmental Footprint context (Saouter, et al., 2020). Despite the consensus on USEtox®, stakeholders still debate appropriate methods for characterizing ecotoxicity in life cycle impact assessment (LCIA). Since the release of USEtox® in 2008, practitioners and stakeholders have requested an extension of ecotoxicity characterization beyond freshwater environments. Several efforts have explored the possibility of including other compartments and have resulted in emerging models supporting the assessment of fate, exposure, and ecotoxicological effects for marine, terrestrial, pollinators, and birds' toxicity. Despite the clear recommendations to continue with efforts of integrating these topics (and other topics such as adding characterization factors for metal/inorganic/biological/natural active substances; adding groundwater, sediment and plant compartments) into LCIA, the respective models and their underlying data are yet to become mature enough for inclusion into LCIA (Crenna, Sala, Polce, & Collina, 2017; Fantke, et al., 2018a; Gentil, Fantke, Mottes, & Basset-Mens, 2019).

Therefore, for this report, only freshwater ecotoxicity impacts have been considered since this is the best understood biosphere and a major share of emissions will end up in freshwater (Henderson, et al., 2011). A full description of the environmental mechanism for freshwater ecotoxicity impacts is provided in Henderson et al. (2011). Bayer plans to enlarge the scope by integrating the impacts on terrestrial organisms like earthworms or pollinators in the near future, when the models are integrated into the scientific consensus versions.

To estimate ecotoxicity impacts per unit emission into a given environmental compartment for CPPs applied to agricultural fields, the USEtox® model version 2.13 was used as available at https://usetox.org/. This tool is a global scientific consensus model (Hauschild, et al., 2008; Rosenbaum, Bachmann, Gold, & Huijbregts, 2008) developed under the auspices of and formally endorsed by the UNEP-SETAC Life Cycle Initiative (Westh, et al., 2015). USEtox® calculates characterization factors for freshwater ecotoxicity by combining a multimedia box model and an impact assessment model. Further explanation are as follows:

"Assessing ecotoxicological effects of a chemical emitted into the environment implies the analysis of a cause-effect chain that links chemical emissions to impacts on freshwater ecosystems through four assessment steps: environmental fate, (freshwater ecosystem) exposure, (freshwater ecotoxicological) effects, and damages on freshwater ecosystem quality" (Fantke, et al., 2017a).

"USEtox® follows the whole impact pathway from a chemical emission to the final impact on humans and ecosystems. This includes modelling the environmental distribution and fate, human and ecosystem population exposure, and toxicity-related effects associated with the exposure." (Fantke, et al., 2017a). For ecotoxicity impacts, USEtox® currently only includes freshwater ecosystems, since data and processes are available and best understood for freshwater ecosystems as compared to e.g. marine and terrestrial soil ecosystems in an LCIA context, of which the latter are currently difficult to characterize (see Hendersen et al. (2011)).

Combining fate, exposure and effects yields characterization factors (CFs) for ecotoxicity. These freshwater ecotoxicity characterization factors are expressed in "Potentially Affected Fraction" (PAF) of freshwater species, integrated over exposure water volume and chemical residence time in water per unit mass emitted. These characterization factors provide information on the sensitivity of different tested species to different concentration levels of the dissolved substance in freshwater (ecotoxicity effect). For example, most species start being affected within a specific range of the concentration level, whereas the most sensitive species are affected at lower level of concentration. These combined effect concentrations are used to express the potential impact on species for which toxicity data are available.

These CFs serve as characterization results at the midpoint global level in LCA. They can be combined with a damage factor translating ecotoxicity impacts into damages on freshwater species , to arrive at a damage (endpoint) level in LCA. However, damage factors are not applied in the present study, which only provides results at midpoint level in line with the goal and scope of the present assessment. This report only focuses on the characterization factor for aquatic ecotoxicity impacts at midpoint level providing an estimate of the potentially affected fraction of species (PAF). This report does not cover the CF at endpoint level which would be associated with the potentially disappeared fraction of species (PDF) integrated over time and volume per unit mass of a chemical emitted. Further details about the general LCA midpoint-damage characterization framework are given in Hauschild and Huijbregts (2015). Uncertainty in all steps is explicitly taken into account in USEtox®, allowing for a comparative assessment of the potential environmental impacts of chemicals to provide insights on “best in class” products in product comparisons regarding the environmental performance of products in terms of ecotoxicity related to chemical emissions.

The main steps in characterizing the impact pathway for freshwater ecotoxicity in USEtox® 2.14 are illustrated in Figure 8, with further details provided elsewhere (Rosenbaum, Bachmann, Gold, & Huijbregts, 2008; Henderson, et al., 2011; Fantke, et al., 2018b).

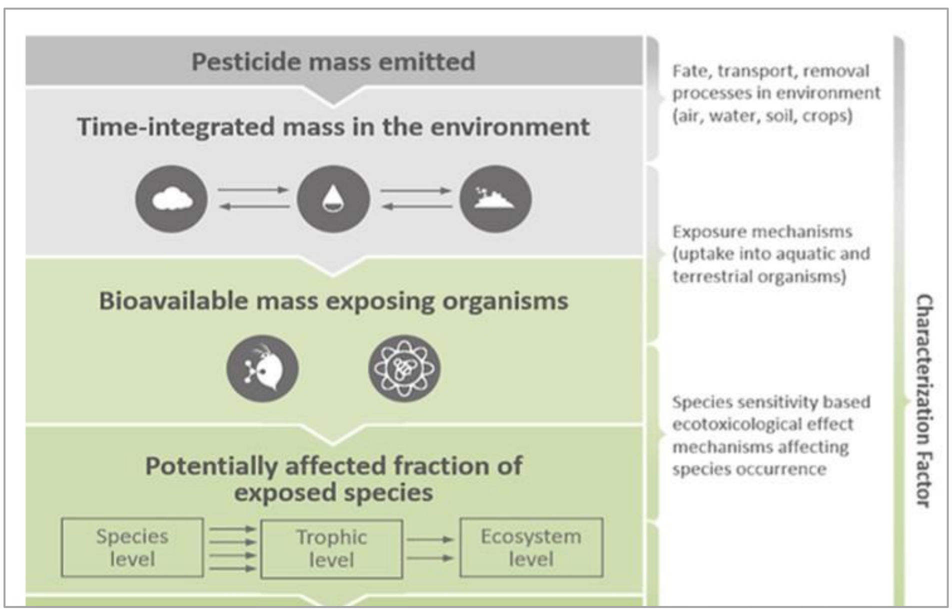

Figure 8: Impact pathway for freshwater ecotoxicity impacts in USEtox® 2.14 (Fantke, et al., 2018b)

The freshwater ecotoxicity characterization factor, CF [PAF m³ d/kg emitted], representing the potentially affected fraction (PAF) of species integrated over the considered freshwater compartment volume and time per kg of chemical emitted to an environmental compartment, is derived as follows:

$$CF = FF \times XF \times EF$$

Equation 4

where FF [kg in freshwater/(kg emitted/d)] is the fate factor relating the chemical mass in the freshwater compartment to the chemical mass emitted per day into the same or another environmental compartment. However, since CPPs are not emitted continuously but in pulses, the fate factors are interpreted as [kg in compartment integrated over time/kg emitted], i.e. the time-component in the fate factor is the integral over time for a given pulse input. XF [kg bioavailable/kg in freshwater] is the ecosystem exposure factor representing the bioavailability of chemicals to organisms in the freshwater compartments considered for ecotoxicity, EF [PAF m³ freshwater/kg bioavailable] is the ecotoxicity effect factor relating the potential of the bioavailable fraction of a chemical to cause toxic effects to an exposed ecosystem expressed as potentially affected fraction of species in the exposed ecosystem integrated over the considered freshwater volume to the bioavailable chemical mass in freshwater. When the emission compartment is different from the compartment of the exposed ecosystem, the fate factor is interpreted as product of the residence time of a chemical in the receiving exposure compartment, FFi_2 [day], and the overall time-integrated chemical mass fraction transferred from the emission compartment i_1 to the exposure compartment i_2, $f_{i2\leftarrow i1}$ [kg in compartment integrated over time/kg emitted], i.e. $FF = f_{i2\leftarrow i1} \times FFi_2$. For better interpretation, the CF for aquatic ecotoxicity impacts at midpoint level (potential ecotoxicity) provides an estimate of the potentially affected fraction of species (PAF) integrated over time and volume per unit mass of a chemical emitted. Describing the full units of all factors is important to understand these factors. More specifically, fate factor units can only be reduced to “day” where emission and receiving compartment are the same, whereas for cases where emission and receiving compartment are not the same, fate factors denote mass received for a given emission rate in the source compartment. Exposure factors are dimensionless but refer effectively to a chemical mass fraction. Finally, effect factors are interpreted as inverse of a chemical water concentration leading to a certain fraction of species that shows a potential effect. Further details are found elsewhere (Rosenbaum, Bachmann, Gold, & Huijbregts, 2008; Henderson, et al., 2011; Fantke, et al., 2017a).

One of the main assumptions in USEtox® is that solutions are provided for steady-state conditions for environmental fate processes, which assumes constant, continuous emission inputs into the different environmental compartments. However, this assumption is mostly relevant for industrial chemicals emitted continuously over time, where emission pattern might vary e.g. with season. For CPPs, this assumption is not relevant as fate factors in this case are interpreted as time-integrated mass due to a given CPP amount applied at a given point in time (see Rosenbaum et al. (2007)). With that, this assumption does not influence the accuracy of results for CPPs applied to agricultural fields. Another assumption is that all environmental compartments are homogeneously mixed, assuming that regardless of where within the same continent an emission occurs, it will yield the same ecotoxicity impact magnitude and compartmental distribution. Emissions to different continental regions will however be different as a function of differences in compartment properties (e.g. volume). This assumption is in line with box model principles that are commonly applied in screening level assessment within and outside LCA (MacLeod, Scheringer, McKone, & Hungerbuhler, 2010). With that, the nested compartment model USEtox® is most applicable to situations where emission locations are unknown, to estimate the relative magnitude of toxicity potency across various chemicals and emission scenarios, as compared to estimating local and absolute risks, for which more sophisticated and localized models have to be applied. In the context of Bayer’s application scenarios, it is mainly applicable to screen many scenarios for dominating combinations of crop, country and active ingredient, as well as of active ingredient within a given crop-country combination.

3.3.5 USEtox® input data

The most important inputs that drive ecotoxicity characterization results are physicochemical substance data. An overview of required inputs in USEtox® are provided in Table 6 below.

Table 6: Chemical input data in USEtox® for organic substances or metal ions that are relevant for application scenario calculations.

Parameter	Unit	Substances	
		Organics	Metals
Chemical abstract service registry number CAS RN		X	X
Chemical common name		X	X
Molar weight MW	g/mol	X	X
pKa chemical class		X	
pKa base reaction pKa.gain		X	
pKa acid reaction pKa.loss		X	
Partitioning coefficient between n-octanol and water Kow	l/l	X	
Partitioning coefficient between organic carbon and water Koc	l/kg	X	
Henry's law constant (at 25°C) K_H	$Pa \cdot m^3/mol$	X	
Vapor pressure (at 25°C) Pvap	Pa	X	X
Solubility (at 25°C) Sol	mg/l	X	
Partitioning coefficient between dissolved organic carbon and water Kdoc	l/kg		X
Partitioning coefficient between suspended solids and water Kp_{SS}	l/kg		X
Partitioning coefficient between sediment particles and water Kp_{Sd}	l/kg		X
Partitioning coefficient between soil particles and water Kp_{Sl}	l/kg		X
Degradation half-life in air to derive degradation rate constant HLair	d	X	
Degradation half-life in water to derive degradation rate constant HLwater	d	X	
Degradation half-life in sediment to derive degradation rate constant HLsediment	d	X	
Degradation half-life in soil to derive degradation rate constant HLsoil	d	X	

Dissipation half-life in above-ground plant tissues to derive dissipation rate constant HLplant	d	X	
Bioaccumulation factor in plant roots BAFroot	kgveg/kgsoil	X	X
Bioaccumulation factor in plant leaves BAFleaf	kgveg/kgsoil	X	X
Bioaccumulation factor in fish BAFfish	l/kgfish	X	X
Species-specific EC50 (effect concentrations at which 50% of individuals for a single species show an effect) combined to derive hazard concentration HC50 as the concentration at which 50% of the exposed species exceed their EC50. HC50 itself is never reported in underlying databases, but instead calculated from the various available EC50 data across species per chemical.	Mg/l	X	X

The substance data describe the physical-chemical characteristics, degradation rates, toxicity, ecotoxicity, bioaccumulation factors, and biotransfer factors of a substance. The bioaccumulation, biotransfer and ecotoxicity are three different substance data that are used to understand the behavior of a chemical in relation to biological organisms. Biotransfer is the process by which a chemical substance is absorbed from one organism by another mostly through ingestion. The biotransfer factors from USEtox® into meat and milk are not relevant for freshwater ecotoxicity impact pathway of USEtox® and have thus not been considered. Bioaccumulation is the overtime accumulation of a chemical in an organism (e.g., Fish) while ecotoxicity is the potential adverse effects that a chemical substance causes to an aquatic organism.

The degradation rate constants are used to determine the environmental fate of the substance or active ingredient. Majorly this consists of the substance transformation processes which includes substance degradation in air, water, sediments, and soil. The Partition coefficient is used to describe how a chemical solute is distributed between two immiscible solvents. They are used as a measure of a solute's hydrophobicity and a proxy for its membrane permeability. Hydrophobicity is the physical property of a molecule that is seemingly repelled from a mass of water (known as a hydrophobic). Partition coefficients (sometimes referred to as partition ratios) are widely used in environmental science to relate the concentration of a chemical solute in one phase to that in a second phase between which equilibrium applies or is approached. The solutes include organic and inorganic substances and the phases of interest include air, water, soils, sediments, and aerosols.

Ecotoxicity test results are reported as Effect Concentrations ECx, where the effect may be mortality, immobilization, reproduction or other endpoints and ‘x’ refers to the fraction of the tested organisms or organism groups showing the effect. EC50 results are determined from statistical evaluation of the concentration-effect values in experiments. The middle of the derived concentration effect curve is considered to be more robust than lower ends. Therefore, EC50 values are used for determining the ecotoxicological effect factor to minimize uncertainties in the effect factor.

After the EC50 test results from different species are collated, the distribution of the test results for the chemical (or active ingredient) across different test organisms is shown in the Species Sensitivity Distribution (SSD) curve (Postshuma, Suter II, & Traas, 2002). SSDs represent the potentially affected fraction of species for which toxicity data are available, which can differ across assessed chemicals. A SSD of chronic EC50s depicts the fraction of species with available toxicity data that are affected above their chronic EC50 value as a function of the bioavailable concentration (X) of the chemical. The SSD-midpoint has been named the HC50, which is the Hazardous Concentration for 50% of the species. This USEtox® HC50-value of the chemical indicates the concentration corresponding to 50% of the species being exposed above their EC50 value. In a series of chemicals, it holds that the lower the HC50-value of a chemical, the higher the relative ecotoxicity of a compound. This principle is the basis for quantifying expected aquatic ecosystem impacts in USEtox®. The SSD-based approach is to date the most reliable way to assess toxicity of chemicals across species. However, it is currently difficult to use SSDs to directly reflect damages on ecosystem quality, for which further research is required to e.g. consider the influence of chemical stressors on interactions among species within the same ecosystem.

A selection is made from the available ecotoxicity data, which may represent acute or chronic exposures. To reveal the possible chronic effects of a substance on freshwater species, preference is given to results from chronic or sub-chronic tests at the EC50-level in the LCIA step (Jolliet, et al., 2006; Larsen & Hauschild, 2007). The motives for this are, amongst others, the statistical robustness of deriving the 50%-response level, and – not the least – the ecological interpretation of the EC50-endpoint in terms of impacts that are meaningful and can be observed in field-exposed ecosystems. Chronic EC50 exposure data were given priority. However, when chronic data is not available, acute EC50-data are used to derive the chronic-equivalent EC50 per species using a generic acute-to-chronic ratio (ACR) of 2 (Rosenbaum, Bachmann, Gold, & Huijbregts, 2008).

Among the listed substance parameters in Table 6, degradation rate constants, ecotoxicity effect data, and partitioning coefficients (mainly Kaw, and Kow via its influence on Koc) are the factors that are most influential on variability of characterization results across substances. Based on the available information for each parameter, different sources have been used to derive a value for each parameter per substance in order to calculate characterization results.

The different sources have been used in the following hierarchy:

- First priority – USEtox®: Whenever data were available for a given substance in the official USEtox® substances databases (Rosenbaum, Bachmann, Gold, & Huijbregts, 2008) this source was used.
- Second priority – Solutions: For ecotoxicity effect information only, results from the Solutions project (Posthuma, van Gils, van de Meent, & de Zwart, 2019) were applied whenever USEtox® data were not available.
- Third priority – PPDB: Whenever USEtox® data were not available for any given substance parameter nor data from the Solutions project for effect information, data from the Pesticide Property Database (Footprint, 2020) have been applied.
- Fourth priority – CompTox: Whenever no other source provided data for a given parameter, substance data from the U.S. Environmental Protection Agency's CompTox Chemistry Dashboard database (Williams, et al., 2017) were applied, based on the OPERA prediction models suite (Mansouri, Williams, Grulke, & Judson, 2018).

Based on the available substance property data and the general applicability of USEtox® to characterize organic substances and metal ions, a total of 892 substances could be characterized. Among these, there are 801 organic substances, 47 additional organic compounds that contain a metal ion, but are treated as organic substances, and 39 metal-based compounds that were treated based on their containing metal ions and 5 organometals that were treated based on their containing metal ions. 65 organic compounds and 3 organic compounds containing a metal ion could not be characterized due to missing relevant substance data. All other substances that were not characterized in USEtox® belong to chemical groups for which USEtox® is not applicable, including biological agents, complex mixtures, inorganic compounds (other than metal ions), and metal-based compounds for which the relevant metal ion is not included in USEtox®. Since results of both organic and metal-based substances are expressed in the same metrics, they can be aggregated and discussed together. However, results from both substance groups should first be discussed separately to understand major contributors within each group. Aggregating both groups can additionally help to understand how much each substance group contributes to overall results.

An overview of the substances included and excluded from USEtox® calculations for application scenarios are provided in Figure 9 below.

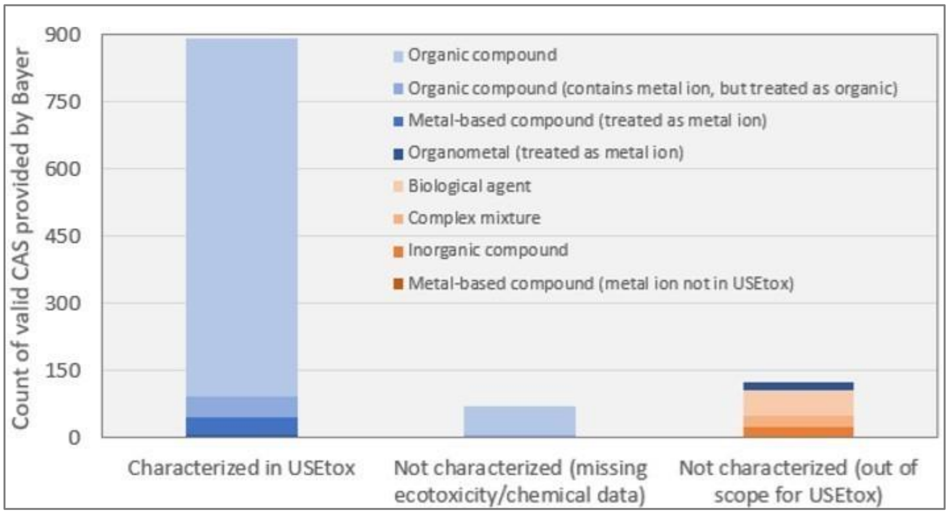

Figure 9: Distribution of substances included and excluded from USEtox® calculations

The 'not characterized' compounds are substances for which minimum input data requirements could not be fulfilled after considering all the four substance property data input sources (i.e. USEtox®, Solutions, PPDB, and CompTox database) or substances which currently cannot be characterized by USEtox®

3.4 From application scenarios to global EI

When PestLCI and USEtox® are combined into one model, the output is a CP EI score per application scenario. Figure 10 below shows the overall approach followed to assess the environmental score of each application scenario. Results of both models have been evaluated in various other studies, with uncertainty ranges provided that are dominated by effect factors in USEtox®, and overall ranging from 1 to 3 orders of magnitude for ecotoxicity impacts (see e.g. Dijkman et al. (2012), Rosenbaum et al., (2008)).

As described above, the PestLCI Consensus model was used for evaluating emissions of agricultural CPPs. Output of the PestLCI Consensus model are emission fractions (i.e. emitted mass into a given environmental compartment per mass applied for a given scenario). For application scenario calculations, emission fractions considering initial partitioning and drift within minutes after crop protection product application have been adopted, are referred to as primary distribution fractions.

For quantifying ecotoxicity impacts from chemical emissions, the USEtox® model, version 2.13, was then used. These results have been adopted for application scenario calculations, following the recommended procedure for deriving characterization factors in USEtox® as described in the official USEtox® documentation (Fantke, et al., 2017a). USEtox® is based on models that have for each process and parameter been extensively evaluated, peer-reviewed and widely applied in scientific and practical application studies. USEtox® itself is the most widely applied, evaluated and accepted LCIA toxicity characterization model in LCA (see e.g. the >1000 peer-reviewed articles, reports, and books referencing Rosenbaum et al., (2008).

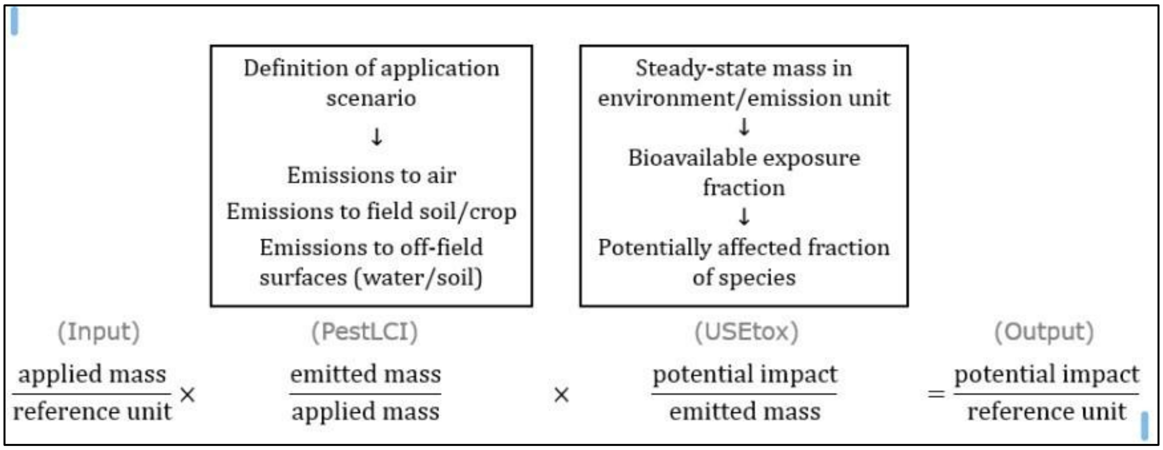

Figure 10: Overall approach followed to assess the EI of each application scenario[9]. Emission and potential impact results are compartment specific as shown in Figure 7.

As outlined in section 1, Bayer considers the combined modelling output of emissions according to PestLCI and characterization factor according to USEtox® as crop protection potential environmental impact (EI).

3.4.1 Agrowin CP application scenario data processed in PestLCI / USEtox® modelling approach

Information for 500,873 crop protection product application scenarios (for the whole CP market) for the year 2018 have been provided to DTU by Bayer as a starting point for calculating related potential environmental impact. As described earlier in section 2.3, a scenario refers to a unique combination of the following variables: country, crop, crop growth stage, application method, product, indication, distributor, active ingredient, and dose. Each scenario represents an active ingredient contained in a crop protection product applied in a given crop and country, with a given treated area per active ingredient, and a given volume per active ingredient.

As products are repeatedly used on crops and in different countries, scenarios cover 96 distinct countries, 55 crop groups, 1082 active ingredients, and 108 distinct application methods. The data set covers both active ingredients and crop protection products sold by Bayer and the rest of the crop protection market. For Bayer (without the rest of the CP market competitors), the study using 2018 data relies on a data set covering 54,204 crop protection application scenarios, 82 countries, 55 crop groups, 86 distinct application methods, 340 active ingredients and 2,291 crop protection products. Certain scenarios had to be excluded from the study. The reasons are outlined below in section 3.4.2.

[9] Note: the reference unit can vary depending on the objective; here it refers to one hectare.

Table 7: CP 2018 Inventory data description prior to exclusion

CPP 2018 Inventory data description	Whole CP Market	Bayer Market Only
Total number of scenarios	500,873	54,204
Distinct number of Countries	96	82
Distinct number of Crop groups	55	55
Distinct number of application methods (including assumptions)	108	86
Distinct number of crop protection products	34,258	2,291
Distinct number of active ingredients	1082	340

3.4.2 Exclusions of CP application scenarios

Out of the assessed crop protection product application scenarios in the 2018 dataset, 54,185 scenarios (10.8% of all scenarios) have been excluded from the analysis. The main reasons for excluding scenarios or not providing impact results are as follows:

- ~1000 data points excluded due to negative or null reported area treated and/or mass applied. In Agrowin, this can happen when the data on treated area or mass applied are either not available or when farmers have given back a certain amount of product before using it.
- ~2000 data points excluded due to application method or crop stage not valid/not in PestLCI Consensus
- >50,000 data points excluded due to missing Chemical Abstracts Service (CAS) number[10], not characterizable in USEtox® or missing chemical/ecotoxicity data to derive characterization factors or ecotoxicity.

The excluded scenarios refer to the entire 2018 data set covering the whole CP market. For Bayer specific product related application scenarios only 2,813 application scenarios (5.2% of the Bayer application scenarios) had to be excluded. 2,273 out of 2,813 application scenarios (80%) were excluded due to USEtox® limitations. The remaining 20% were mainly due to limitations of PestLCI and to a minor degree due to data issues from Agrowin. Therefore, most application scenarios exclusions were due to current limitations of the USEtox® model. See Figure 9 for the overview of the substances included and excluded from USEtox® calculations for application scenarios.

For the reasons outlined above, the application scenario exclusions for Bayer can be translated into excluded active ingredients and crop protection products as follows:

- Regarding the entire data set covering Bayer and other manufacturers: From 1082 active ingredients, 892 active ingredients could be characterized in USEtox® and are therefore part of the study.

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[10] The CAS number is a unique identifier assigned to every chemical substance described in open scientific literature (link: CAS registry description Archived 25 July 2008 at the Wayback Machine, by Chemical Abstracts Service)

- Regarding Bayer: 54 crop groups are part of the Bayer assessment. The crop group "environmental markets" was excluded. "Environmental markets" contains crop protection uses on e.g. turf or forest. BCS's EIR target refers only to field applications.
- Regarding Bayer: From 340 active ingredients, 270 active ingredients could be characterized in USEtox®. Most of the excluded active ingredients relate to BCS's biological portfolio.
- Regarding Bayer: From 2,291 crop protection products, 2,056 are part of the study.

For Bayer, most of the excluded active ingredients are Bayer biological portfolio. Therefore, BCS's CP EI based on the current study might be conservative[11].

Despite these exclusions, Bayer and DTU argue that this is the largest high-quality CP application data set ever used to our knowledge. If there is no data in certain cases (mostly CP application methods and application timing), Bayer fills the gaps (transparently) based on reasonable market intelligence assumptions because official statistics such as FAO do not offer such comprehensive, harmonized, and high-quality application data sets (See Figure 15 for a list of available data sources).

The majority of the excluded scenarios relate to 139 (out of 1082) substances not commonly included in assessment models or chemical and ecotoxicity databases (e.g. microorganisms). With that, these chemicals are likely not leading to a relevant contribution to overall global impacts at a screening-level, whereas they might become relevant in refined, more local assessments.

The system of exclusion including reasons for exclusion detailed here and applied on the 2018 data set have been applied across the received Agrowin dataset used in setting the baseline and continuous performance tracking. The exclusions for Bayer stated above refer to all Bayer CPP contained in Agrowin. As stated in section 3.2 and 4.4 Agrowin covers 85-95% of Bayer CPP sales depending on the year.

3.4.3 Combining application scenarios with the models to derive EI scores

The following general approach has been applied to assess the potential environmental impact of each application scenario.

The results from the combination of emission and ecotoxicity impact characterization factor (impact score - PAF m3 d / Kg applied) have been combined with applied dose (kg applied) and hectare treated (ha) to arrive at the potential Environmental Impact.

- Mass applied of crop protection product has been combined with area treated to derive an applied dose [kg applied/ha treated] for each scenario.
- An area split for the emission fraction reaching off-field surfaces has been assigned to each combination based on mapping of the reported country available in USEtox® 2.14. Namely, a certain fraction of the off-field area is assigned to USEtox'® freshwater, agricultural soil and natural soil compartments. The off-field surface area fractions (percentages) used for the different country parameterizations are based on FAO (2020) data. See Appendix 7.1 for the different countries' percentages.
- For each emission compartment defined in the PestLCI Consensus model, application-scenario-specific emission results from the PestLCI Consensus model have been derived based on mapping reported crops to crop types, reported crop stages to crop surface

[11] Conservative because a worst-case assumption is always made when necessary data were not available (For example, in the case of application method or crop growth stage). Also, because biologicals as "improvement levers" are not reflected yet and we do not consider mitigation measures. Both, biologicals and mitigation measures, would likely decrease Bayer CP EI.

interception area fractions for field crops, and reported application methods to drift functions for a pre-defined set of application methods available in PestLCI Consensus. Details on the mapping and assumptions made to derive emission results are presented in sections 3.3.1.

- For each emission compartment defined in the USEtox® model, active-ingredient-specific ecotoxicity impact results from the USEtox® model have been derived for a global average model setup (default model settings), based on implementing all reported active ingredients into the substance databases of USEtox® that can be characterized and that have all required physicochemical property data available and accessible. Details on the substance input data collection and assumptions made to derive ecotoxicity impact results are presented in section 3.3.4.
- Emission results (kg emitted into a given emission compartment defined in the PestLCI Consensus model per kg applied for a given application scenario) have been combined with ecotoxicity impact characterization results (PAF m³ d/kg emitted into an emission compartment defined in the USEtox® model), based on matching emission compartments between both models following the approach described in Fantke (2019) and in Gentil et al. (2020), as well as based on assigning the area split for off-field surfaces to respective emission compartments in the USEtox® model, as shown in Figure 7.
- The results from the combination of emission and ecotoxicity impact characterization factor (impact score - PAF m3 d / Kg applied) have further been combined with applied dose (kg applied) and hectare treated (ha) to arrive at the potential Environmental Impact. See Table 8 below for the detailed mathematical calculation and Figure 12 below for further description of the results.

The descriptions above are shown in a simplified version in Figure 11

Table 8, and Figure 12 below.

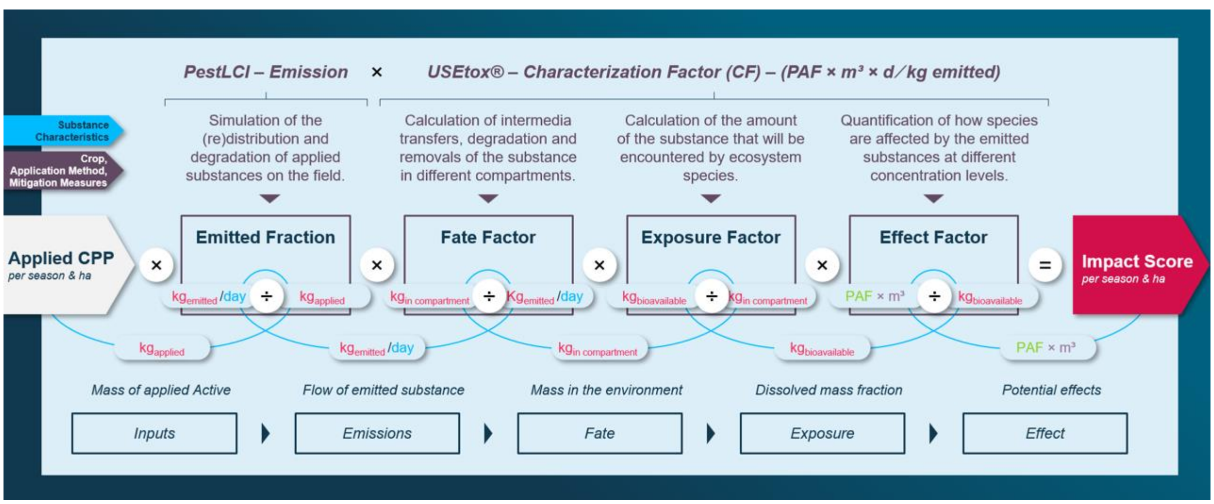


Figure 11: Framework representation considering both PestLCI and USEtox® inputs

Table 8: Stepwise calculation of EI scores for an individual application scenario

EI / Quantity	= Mass of emission x Characterization factor $= \frac{\cancel{Kg\ emitted}}{Kg\ applied} \times \frac{PAF\ m^3\ d}{\cancel{Kg\ emitted}}$ = PAF m^3 d / Kg applied	The combination of emissions from PestLCI and characterization factors from USEtox® yields potential ecotoxicity impacts per kg applied in a given application scenario (PAF m^3 d/kg applied). Bayer calls this value **EI/quantity**.
EI / ha	= (EI/ Quantity) x (Applied dose) $= \frac{PAF\ m^3\ d}{\cancel{Kg\ applied}} \times \frac{\cancel{Kg\ applied}}{treated\ hectares}$ = PAF m^3 d / hectare	Further, the EI/quantity score in a given application scenario is multiplied with the applied dose (kg applied/ha treated) to arrive at 'impact per ha treated' [PAF m^3 d/ha treated]. Bayer calls this value **EI/ha**].
EI / Scenario [labelled as 'EI' by Bayer]	= (EI / ha) x (Treated hectares/ Country) $= \frac{PAF\ m^3\ d}{\cancel{treated\ hectares}} \times \frac{\cancel{treated\ hectares}}{Country}$ = PAF m^3 d / Country	Finally, the EI/ha score is multiplied with treated area [ha/country] to arrive at a 'cumulative impact per scenario' in a given country [PAF m^3 d/country. Bayer calls this value **EI**].

Note. The crossed-out elements show how the different parameters cancel out each other in the stepwise calculation of EI scores for each individual application scenario.

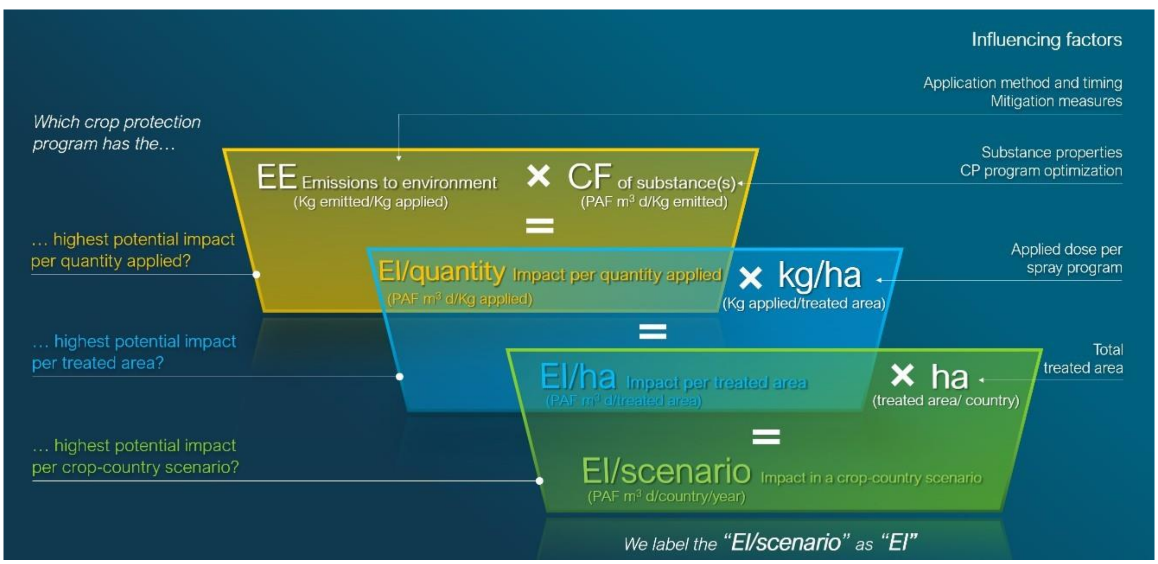


Figure 12: Definition of key measurement factors within the CP EI derivation methodology

3.4.4 Aggregating EI scores

Aggregation of EI across application scenarios will enable calculation of cumulative impacts at different aggregation levels. In general, the aggregation can be described as follows. For each application scenario (see again section 2.3. for all elements of an individual scenario), the potential environmental impact scores are computed. The following equation shows that the aggregation is based on the sum of the total EI scores across the scenarios of interest (e.g., at the level of a crop, country, indication, application method etc. or even combinations of these).

$$EI = \sum (EI/kg)_i \cdot dose_i \cdot ha_i$$

Equation 5

Where *(i)* indexes the scenarios for the CP application (consisting of the scenario elements described in section 2.3). Thus, in a scenario, $(EI/kg)_i$ is the potential environmental impact per quantity of applied active ingredient, with a specific $dose_i$, on a certain number of treated hectares (ha_i). For example, we can sum the EI for:

- all active ingredients used to treat cabbage crops (i.e., at the aggregation level of a single crop).
- all vegetables cultivated in Vietnam (i.e., at the aggregation level of a crop-country-combination).
- all active ingredients used in all crop classes cultivated in Vietnam (i.e., at the aggregation level of a country).
- various other potential aggregation levels, such as crop, country, active ingredient, indication, crop growth stage, application method, etc. (and any combinations of these).

4 Interpretation

4.1 CP EIR baseline and performance tracking

AgrowinAs described above, each application scenario has its own potential environmental impact score, which is dependent on, inter alia, substance characteristics of the active ingredients contained in the crop protection products applied on field, dose rates of active ingredient per ha, application method, application timing, the crop and country where the product has been applied. There are many aggregation methods of the different metrics available. Bayer is currently working with a ***'treated-area-weighted EI/ha'*** as the measure of potential environmental impact. The treated-area-weighted EI/ha represents how efficiently, from an environmental impact perspective, the crop protection portfolio is meeting the needs of the growers. i.e. the focus is to help growers achieve the desired goal of protecting crops with lower environmental impact even in a situation of increased pest or disease pressure which can lead to increasing growers treated area. The lower the treated-area EI/ha, the better, while still meeting the growers need. It is calculated as the ratio of the cumulative potential environmental impact and the total treated area:

$$'\boldsymbol{Treated\ area\ weighted\ EI/ha}' = \frac{EI}{ha} = \frac{\sum (EI/kg)_i \cdot dose_i \cdot ha_i}{\sum ha_i} = \frac{\sum EI_i}{\sum ha_i}$$

Equation 6

If the treated area is not used to scale the cumulative potential environmental impact, some increases in the metric could be encountered due to a greater need for crop protection by growers even if the leveraged products show a lower individual potential environmental impact. In addition, weighing for treated area across the entire Bayer CP portfolio ensures that both CP intensive crops, such as fruits, with relatively small treated areas and CP extensive crops, such as soybeans, with large treated areas, are adequately reflected in the Bayer impact assessment.

Towards achieving a 30% reduction of CP EI by 2030, Bayer established a baseline using a 5-year-average (2014 - 2018). A 5-year-average (2014 – 2018) baseline is used to account for the specificities of agriculture, such as inter-annual variability, seasonality or dependence on climatic conditions. Bayer has calculated the final baseline based on the 5-year-average (2014 – 2018) using the formulae below.

$$\text{Baseline calculation Formulae} = \frac{sum\ of\ all\ Bayer\ EI\ from\ 2014\ to\ 2018}{sum\ of\ all\ Bayer\ Treated\ Area\ (ha) from\ 2014\ to\ 2018}$$

Equation 7

The baseline consists of all global Bayer crop protection applications in the open field as reported in Agrowin which can be characterized by PestLCI and USEtox®.

Bayer will regularly track progress against the baseline towards the 30% reduction in environmental impact by 2030 (see Figure 13 below).

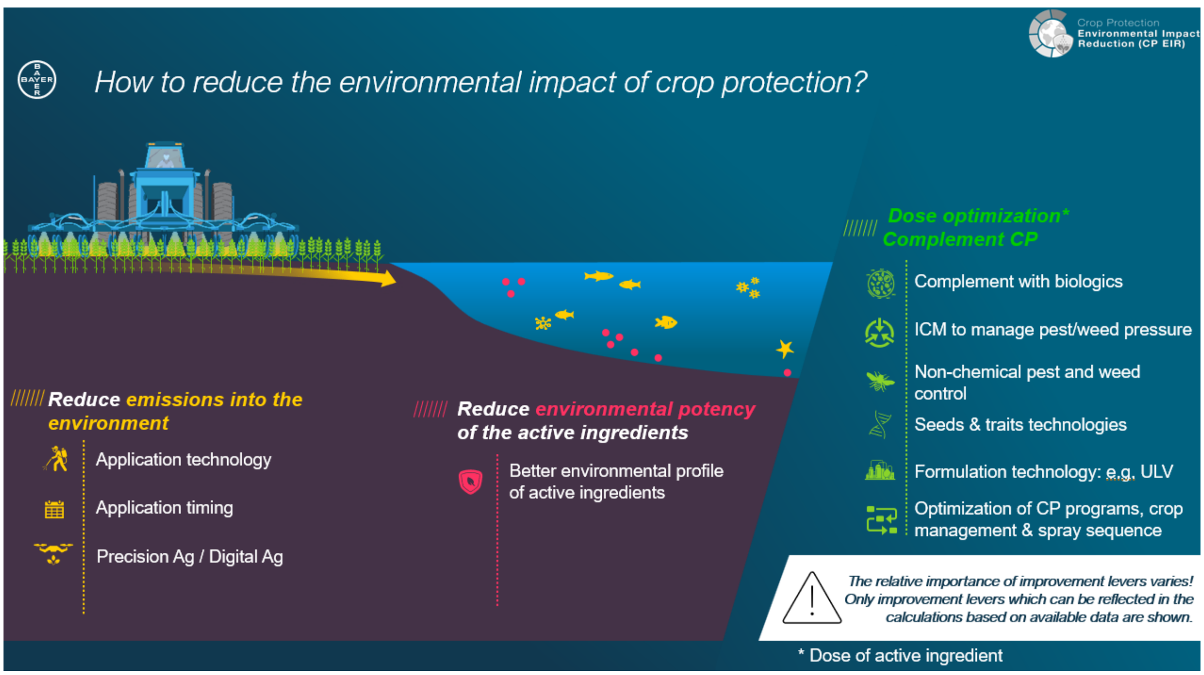


Figure 13: Overview of available Bayer potential CPP levers and their role within the EI scope[12].

Future scenarios will be calculated by using the same calculation approach as for the baseline. The underlying market research input data will be provided annually by the data provider 'Lexagri' via the 'Agrowin' database which covers 90% of the global crop protection market. Therefore, the envisioned scope of the data will be the same as for the baseline data. That encompasses data on: CP applications per crop and country; CP applications differentiated per trait system (for some countries where data

[12] ICM – Integrated Crop Management, ULV – Ultra-low volume

are available); application method; dose; total ha treated per product; and application timing (crop growth stage).

Based on these annual input data updates, the EI calculation will be done automatically in an established database (see Figure 14 for the structure of the database) based on the same PestLCI and USEtox® modelling framework that are used for the 2018 data set described in this report.. Bayer utilizes the PestLCI and USEtox® models and its associated input data as received by DTU. Finally, the calculated impact scores of the future scenarios will be compared against the baseline impact to track progress against the 30% objective.

The performance tracking will be done using a 5-year rolling treated-area-weighted global environmental impact per ha. For example, in the performance tracking period 2017 to 2021, the Environmental Impact (EI) score is calculated using the below formulae after which it is compared with the baseline result.

$$\frac{sum\ of\ all\ Bayer\ EI\ from\ 2017\ to\ 2021}{sum\ of\ all\ Bayer\ Treated\ Area\ (ha) from\ 2017\ to\ 2021}$$

Equation 8

Bayer will report its global relative progress against the baseline. Illustrative example: “Based on the data collected between 2017-2021, we have reduced the treated-area-weighted environmental impact per hectare of our global crop protection portfolio by X% against the 2014-2018 baseline.”

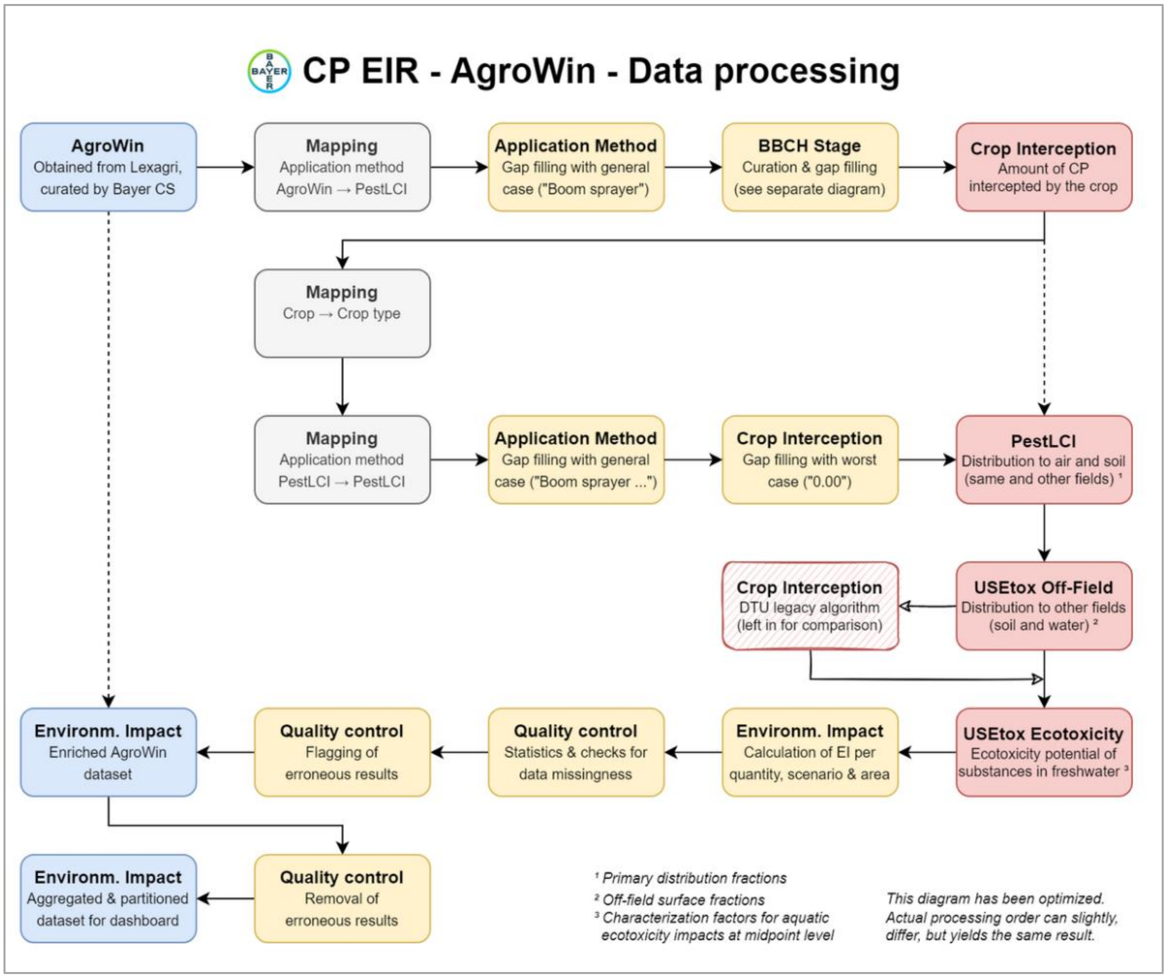


Figure 14: The interconnectivity between different input data embedded in the database for the derivation of EI score.

If additional input data become available in the future, Bayer will evaluate with the Technical University of Denmark how to best integrate these data. Such potential data might encompass: Environmental mitigation measures as practically applied on field; Seeds & Traits specific collected CP application data in additional countries; Field information (if we choose to measure at field-level) such as field size, slope, off-field surfaces, drainage depth, etc.; Agronomic practices relevant to CP program/doses such as tillage, cover crops, crop rotation (see Figure 15)...

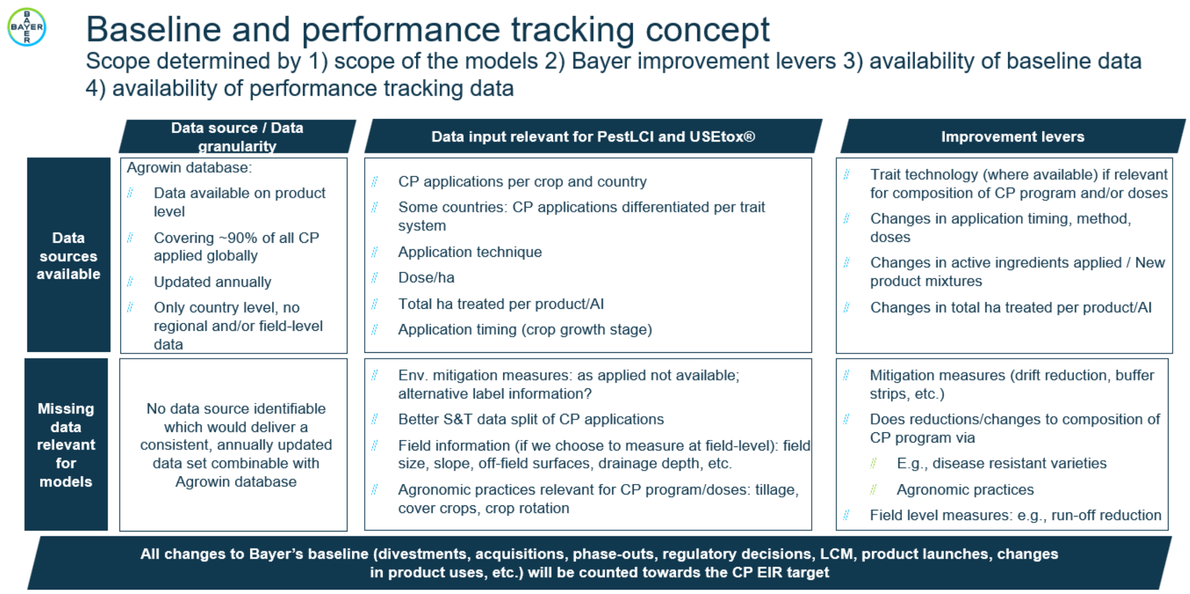


Figure 15: Outline of the Bayer EIR baseline and the performance tracking concept.

4.2 Sensitivity analysis: USEtox®

A full sensitivity analysis, starting from the environmental impact scores, covering both PestLCI, USEtox® and the respective data input parameters, is not yet available from the scientific consortium. Also, if there are updates to the underlying data requirements for PestLCI and USEtox®, e.g., the inclusion of climate data where relevant, an updated sensitivity analysis would be assessed once available from the consortium. As the most dominant factor in environmental impact scores is often the substance specific characterization factor from USEtox®, a sensitivity analysis for USEtox® is provided in this study.

An additional sensitivity study was also done for understanding how varying input parameters in USEtox® influence ecotoxicity impact characterization results. In this sensitivity approach, Bayer used the existing USEtox® ecotoxicity characterization model, except that data inputs are specified as probability distributions as opposed to point estimates. Input data distributions are sampled independently 10,000 times, and the values were used as input to USEtox® to calculate fate, eco-exposure, and ecotoxicity effect factors, and resulting stochastic characterization factors plotted as frequency distributions along with descriptive statistics based on Monte Carlo simulations for all sample distribution combinations. To evaluate the relative influence of input parameter variability on calculated characterization factors, we compare Spearman's rank correlation indices for all inputs. This approach has been applied and is further detailed in a previous study on a pharmaceutical tested in USEtox® (Wender, Prado, Fantke, Ravikumar, & Seager, 2018). Input data for fate, eco-exposure and ecotoxicity effect modelling that have been varied are presented in Table 9 below. As an initial default, Bayer assumed uncertainty ranges having independent uniform distributions for all input parameters, spanning one order of magnitude (a factor of 10) above and below the point estimate. Deviations from these assumptions would change some aspects of the simulated distributions of characterization factors, but the overall grouping of more influential input parameters may not change.

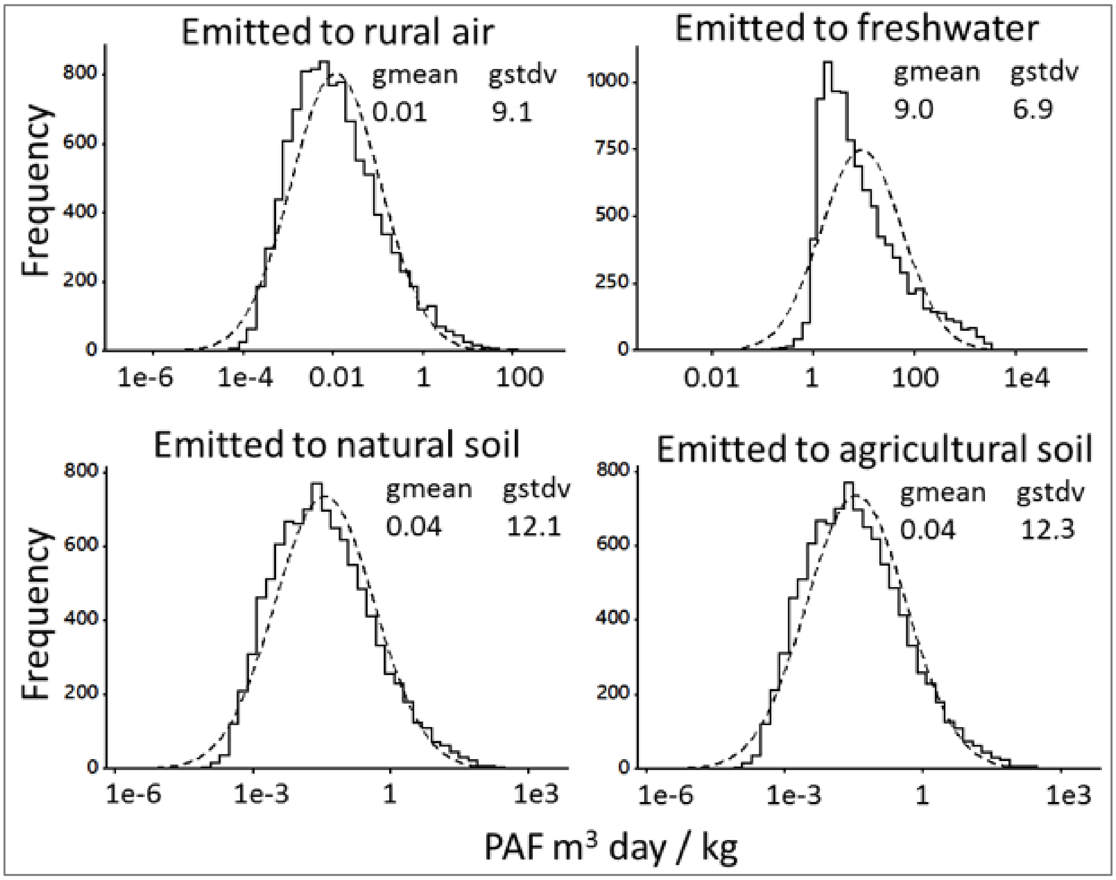
Table 9: Fate, eco-exposure and ecotoxicity effect relevant input data for USEtox® and their modelled variance for the neutral test substance methamidophos (CAS RN: 10265-92-6)[13].

Parameter	Description	Units	Point value(s)	Uncertainty range	Reference
MW	Molecular weight	g/mol	141.1	141.1	Chemical formula
Kow	Octanol-water partitioning coefficient	l/l	0.16	0.016—1.6	EPISuite, experimental value
Koc	Soil organic carbon-water partitioning coefficient	l/kg	5.01	0.501—50.1	EPISuite, experimental value
Kh	Henry's law constant	Pa m3/mol	8.8×10^{-5}	8.8×10^{-6}—8.8×10^{-4}	EPISuite, HenryWin
Pvap	Vapour pressure	Pa	4.7×10^{-3}	$4.7\text{x}10^{-4}$—0.047	EPISuite, experimental value
Solubility	Solubility in water	mg/l	1×10^{6}	1×10^{5}—1×10^{7}	EPISuite, experimental value
kdeg, air	Degradation rate constant in air	1/s	2.5×10^{-5}	2.5×10^{-6}—2.5×10^{-4}	EPISuite, AopWin
kdeg, water	Degradation rate constant in water	1/s	5.3×10^{-7}	5.3×10^{-8}—5.3×10^{-6}	EPISuite, BioWin
kdeg, soil	Degradation rate constant in soil	1/s	2×10^{-6}	2×10^{-7}—2×10^{-5}	PPDB, field DT50 based
kdeg, sediment	Degradation rate constant in sediment	1/s	5.9×10^{-8}	5.9×10^{-9}—5.9×10^{-7}	EPISuite, BioWin
BAF fish	Bioaccumulation factor in fish	l/kg	0.9	0.09—9	EPISuite, BCFBAF upper trophic
HC50	Freshwater aquatic hazard concentration	mg/l	0.94	0.094—9.4	USEtox®, precalculated

Results of the sensitivity analysis of USEtox® input parameter variations are shown in Figure 16 below for different emission compartments relevant for CPP emissions, with related Spearman Rank

[13] The sensitivity analysis results shown for a single substance are purely illustrative. Sensitivity has been tested in various publications across a variety of substances, yielding a typical ranking of input parameters influencing model output (see e.g. Fantke et al. 2012, https://doi.org/10.1021/es301509u). The presented results are in line with this general ranking of parameters.

Correlation results shown for the most influential input parameters per emission scenario given in Figure 17.



Solid lines on the graph *denote frequency distributions from 10,000 Monte Carlo runs* while d*ashed lines represent normal distributions that were fitted to the underlying log-transformed data.*

Figure 16: Stochastic freshwater aquatic ecotoxicity characterization factors (PAF m³ d/kg emitted) for methamidophos (CAS RN: 10265-92-6) emitted to continental rural air, freshwater, agricultural and natural soil.

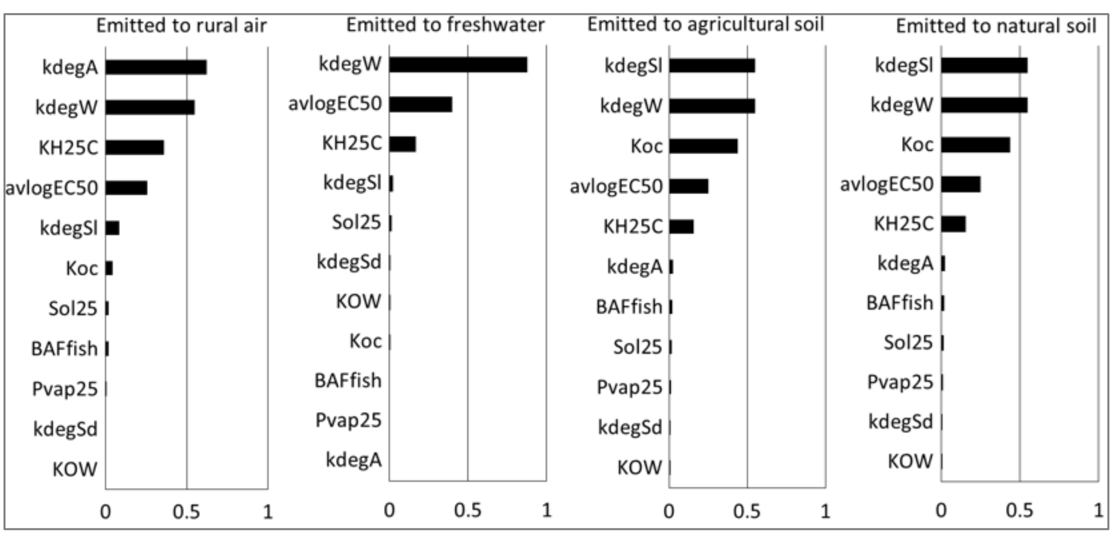


Figure 17: Spearman Rank Correlation for model input variables with the largest magnitude of influence on characterization factor variability across four emission scenarios in USEtox®.

Spearman Rank Correlation identified that USEtox® ecotoxicity characterization factor results for methamidophos (CAS RN: 10265-92-6) are mainly influenced by degradation half-lives across compartments, followed by ecotoxicity effect information, and partitioning coefficients (mainly Kaw and Koc for this moderately volatile and rather polar (i.e. not very lipophilic) chemical). Kow would typically become more relevant for more lipophilic chemicals (i.e. log Kow > 3). From this sensitivity analysis, we identified degradation and ecotoxicity information as main aspects that require careful consideration in refined scenarios, and where data quality for these aspects should be improved across substances. Moreover, as different input parameters affect both fate and exposure factor, while only the ecotoxicity information affects the effect factor, the ecotoxicity information gains additional importance in terms of influencing variability of characterization factors, which consist of the simple product of fate, exposure and effect factors (i.e. characterization factors are equally sensitive towards these three intermediate factors). Moreso, on the influence of input parameter dependency on the results interpretation of the sensitivity analysis, the most influential parameters in Figure 17 above are truly independent of other parameters in the input dataset, and with that the interpretation of the applied statistical approach is not biased. While some parameters are really co-dependent (e.g. mostly Koc and BAF with Kow, and KH25C with Sol25 and Pvap25), they are not driving sensitivity of model results for most scenarios.

4.3 Qualitative discussion of uncertainty

Dubus et al. (2003) have extensively discussed numerous sources of uncertainty in CPP emission modeling including **uncertainty in primary data** (from the spatial and temporal variability of environmental variables, from sampling procedures and measurement errors in the field, and from analysis in the laboratory), **uncertainty in the derivation of model input parameters** (when a modeler might decide to (a) leave the parameters at their default values, (b) make an educated guess using expert judgement, (c) extract values from existing databases or (d) derive the values from empirical functions presented in the literature; each procedure may introduce uncertainty into the modelling, depending on the sensitivity of the model), and **other factors** (such as multiplicity of physical, chemical and biological factors affecting the fate of CPPs; the inability of a model to represent reality accurately even when adequate model inputs are being used; subjectivity introduced by the modeler; linguistic imprecision; inappropriate use of concepts implemented in the models; human error through unstable or biased experimental procedures, interpretation, typing error or the simple variation between people; upscaling of models to a scale larger than that for which they were developed) might affect the representativeness of the results.

“Various sensitivity studies have demonstrated that the combined use of the PestLCI and USEtox® models lead to a reasonable impact assessment. Nevertheless, users are advised to exercise caution when interpreting the results, since, despite their detailed simulation, both methods still exhibit uncertainties” (Gentil, et al., 2020). Also, the applied models are calibrated using past environmental data, which might need to be adapted considering possibly relevant changes in environmental conditions, such as changes in average air temperature.

The results of both models have been evaluated in various other studies, with uncertainty ranges provided that are dominated by effect factors in USEtox®, and overall ranging from 1 to 3 orders of magnitude for ecotoxicity impacts (see e.g. Dijkman et al. (2012), Rosenbaum et al. (2008)).” However, due to its aggregated and relative nature, the CP EIR target percent reduction will be less uncertain.

In addition, in terms of the inventory data on global crop protection product consumption taken from the ‘Agrowin’ dataset, we argue that Agrowin provides the most extensive and rigorously collected data set currently available that covers agricultural CP consumption data (i.e., consumption data on what has been truly applied on the field). Other existing databases on CPPs use statistics which are not consumption data but mostly sales data. For example, the FAOSTAT CPP use database by the Food and Agriculture Organization (FAO) of the United Nations covers CPPs sales in most countries**.** In some countries FAO data includes non-agricultural uses such as home and garden use. Furthermore, the FAO CPP definition varies in some countries. Thus, by using the Agrowin dataset which is based on actual CPP consumption data (not sales data), we worked to ensure the representativeness of the primary data as much as possible.

A full uncertainty assessment might be needed, and this will be added once available from the scientific consortium. Based on analysis we argue that there are no significant factors that would limit the interpretation of the findings of this study.

4.4 Main limitations and how they are addressed

The main limitations in this assessment are associated with the Agrowin inventory data, emission modeling with PestLCI, and impact assessment using USEtox®.

Regarding limitations of the Agrowin inventory data on agricultural CP consumption data, the frequency and comprehensiveness of the available farmer-panel interview data varies, because it depends on the commercial relevance of a market, the accessibility to farmers for farmer-panel interviews and other factors. In big and commercially relevant markets, farmer-panel data is typically available on a yearly basis. In other markets with a lower commercial relevance, the frequency of farmer-panel data collection can be lower and irregular (e.g. only every 2-3 years in the Belgium-potato market). Even if farmer-panel data is available in a given crop and country, Bayer might decide to not purchase a farmer-panel study on a certain market at all because the commercial relevance of that market is too low. In those cases, Bayer intends to fill the data from other sources. For such countries and markets where no farmer-panel data are available, data gaps are filled by using national statistics (e.g., import and export data). If there are no national statistics, dedicated Bayer market analysis and business intelligence colleagues fill the data gaps based on their expert knowledge of the respective markets (e.g., based on sales information). Even taking those limitations into account, the current Agrowin data set covers about 85-95% of the Bayer specific crop protection market value and ~90% of all crop protection applied globally (coverage varies from year to year). For the target delivery, Bayer relies as well on its crop protection sales planning which covers all CP Bayer sales (as opposed to application data in Agrowin). Bayer therefore does not exclude any known CP sales from the analysis of mitigation measures and target delivery. In addition, all substances which can be characterized by USEtox® are part of Bayer analysis.

Regarding limitations in the emission modeling via PestLCI, no buffer zone was assumed in the calculation of primary emissions as a result of lack of data in the Agrowin inventory data set. Also, secondary distribution was excluded from the environmental impact assessment, because the level of detail required to model secondary distribution processes are not readily available in the present screening-level assessment[14], which would introduce large additional uncertainties related to collecting and defining e.g. field-level characteristics at the global scale. Another limitation related to PestLCI is that for rice, no distinction was made between paddy and upland rice as we assume only emissions to compartments available in PestLCI. PestLCI currently does not consider paddy water as a separate compartment. A complex dynamic between dry and wet surfaces for paddy rice and similar crops will require further improvements of field emission distributions in PestLCI.

14 low-resolution assessments as applied via the combination of PestLCI and USEtox to allow for a global coverage

Regarding limitations of the impact assessment via USEtox®, for this report, only freshwater ecotoxicity impacts have been considered, since it represents the current scope of USEtox®. To address this issue, Bayer is collaborating with DTU, Technical University of Munich and The Ohio State University to integrate the impacts on pollinators in the near future into the assessment. The academic consortium under the auspices of UNEP-SETAC GLAM working group is working on other impact categories such as soil organisms. This will ideally follow similar consensus-building principles as they are underlying USEtox® (Hauschild, et al., 2008). Once the additional impact categories are available in the scientific consensus version of the models, Bayer is planning to incorporate the updated versions.

In addition, USEtox® is a lumped systems course-dimension-scale model. This means that it includes compartments to represent various components of the environment, but that there are limited explicit vertical or horizontal dimensions in these compartments. The model has embedded urban, regional, and global environments but does not have detailed spatial resolution. Regarding the use of SSDs in deriving the effect factor, SSDs in all assessments are built from species for which toxicity effect test information is available. These species do not necessarily reflect any actual real-world ecosystems as most test data are derived from standard laboratory tests. With that, SSDs have a limited ability to reflect actual ecosystem effects but are suitable to highlight differences in toxicity pressure of different chemicals across species. Nonetheless, previous studies report an observed association between SSD-predicted and observed biodiversity impacts (Posthuma & De Zwart, 2012).

Overall, both underlying models of the present analysis, namely PestLCI Consensus and USEtox®, have undergone model evaluations via previous studies. PestLCI results have been compared to results from more sophisticated risk assessment models (Dijkman, Birkved, & Hauschild, 2012), showing overall consistency between the compared models and explaining main differences along considered or omitted processes in each model. USEtox®, in contrast, was originally built based on a systematic model comparison of models that had been evaluated individually before USEtox® was developed. The overall model comparison leading to USEtox® is described in Hauschild et al. (2008), while an example model that was included in the model comparison leading to USEtox®, SimpleBox, was for instance evaluated for specific chemicals against other models as well as against measurements (Hollander, et al., 2007). Hence, no additional model evaluation was included in the present study. All methodological aspects that are not yet described elsewhere in this report will be published in separate scientific articles, subject to international scientific peer review.

5. Future updates to this report

This report is limited to describing the methodology and overall impact assessment calculation process. The methodological report will be further updated if there are changes of model boundaries and scope, changes of the metric, changes in calculation methodology of the models and if there are model advancement such as the inclusion of pollinators and soil organisms.

Further information related to the performance tracking, quantitative progress reporting and how the Crop Science division of Bayer is delivering against its target will be continuously reported in the Crop Protection Environmental Impact Reduction (CP EIR) section of the Bayer sustainability report and Crop Science division of Bayer sustainability progress report which are released annually.

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7. Appendix

7.1 Percentages of surface areas represented by freshwater, agricultural soil, and natural soil for continental level parameterizations in USEtox® based on FAO (2020) data*

* These fractions are only relevant for the marginal emission fraction that reaches off-field areas.

Country	Agricultural Soil	Natural Soil	Freshwater
Afghanistan	59%	41%	0%
Albania	43%	56%	1%
Algeria	17%	83%	0%
American Samoa	20%	80%	0%
Andorra	40%	60%	0%
Angola	46%	54%	0%
Anguilla	0%	100%	0%
Antigua & Barbuda	20%	80%	0%
Argentina	40%	59%	2%
Armenia	59%	37%	4%
Aruba	11%	89%	0%
Australia	46%	53%	1%
Austria	32%	66%	2%
Azerbaijan	58%	37%	5%
The Bahamas	1%	60%	39%
Bahrain	11%	89%	0%
Bangladesh	76%	11%	13%
Barbados	23%	77%	0%
Belarus	41%	57%	2%
Belgium	45%	54%	1%
Belize	8%	92%	1%
Benin	35%	63%	2%
Bermuda	6%	94%	0%
Bhutan	13%	86%	1%

Bolivia	35%	64%	1%
Bonaire, Sint Eustatius and Saba	0%	100%	0%
Bosnia & Herzegovina	43%	57%	0%
Botswana	46%	52%	3%
Brazil	28%	70%	2%
British Virgin Is.	47%	53%	0%
Brunei	3%	88%	9%
Bulgaria	46%	51%	2%
Burkina Faso	44%	55%	0%
Burundi	79%	12%	8%
Cape Verde	20%	80%	0%
Cambodia	33%	65%	3%
Cameroon	21%	79%	1%
Canada	6%	83%	10%
Cayman Is.	11%	79%	10%
Central African Republic	8%	92%	0%
Chad	40%	58%	2%
Channel Islands	43%	57%	0%
Chile	21%	77%	2%
China, Hong Kong SAR	4%	90%	6%
China, Macao SAR	0%	100%	0%
China, mainland	56%	42%	2%
China, Taiwan Province of	22%	76%	2%
Colombia	43%	54%	3%
Comoros	70%	30%	0%
Congo	31%	69%	0%
Cook Islands	6%	94%	0%
Costa Rica	34%	65%	0%
Cote d'Ivoire	67%	32%	1%
Croatia	27%	72%	1%
Cuba	62%	32%	6%
Curaçao	0%	100%	0%
Cyprus	15%	85%	0%
Czech Republic	46%	52%	2%
North Korea	22%	78%	0%

Congo, DRC	15%	82%	3%
Denmark	66%	27%	7%
Djibouti	73%	26%	0%
Dominica	33%	67%	0%
Dominican Republic	50%	49%	1%
Ecuador	22%	75%	3%
Egypt	4%	95%	1%
El Salvador	58%	41%	2%
Equatorial Guinea	7%	93%	0%
Eritrea	63%	37%	0%
Estonia	23%	71%	6%
Swaziland	71%	28%	1%
Ethiopia	34%	65%	1%
Falkland Is.	93%	7%	0%
Faroe Is.	70%	27%	2%
Fiji	17%	83%	0%
Finland	7%	81%	11%
France	52%	48%	0%
French Guiana	0%	99%	1%
French Polynesia	14%	86%	0%
Gabon	9%	88%	4%
The Gambia	60%	29%	12%
Georgia	34%	65%	0%
Germany	47%	50%	2%
Ghana	55%	40%	5%
Gibraltar	0%	100%	0%
Greece	46%	52%	2%
Greenland	1%	99%	0%
Grenada	24%	76%	0%
Guadeloupe	31%	69%	1%
Guam	30%	70%	0%
Guatemala	36%	62%	2%
Guinea	59%	41%	0%
Guinea-Bissau	29%	43%	28%
Guyana	6%	84%	9%

Haiti	67%	33%	1%
Holy See	0%	100%	0%
Honduras	31%	68%	1%
Hungary	54%	44%	2%
Iceland	19%	79%	2%
India	60%	29%	11%
Indonesia	33%	65%	2%
Iran	29%	64%	7%
Iraq	21%	78%	0%
Ireland	65%	32%	2%
Isle of Man	70%	30%	0%
Israel	30%	68%	2%
Italy	44%	54%	2%
Jamaica	41%	58%	1%
Japan	12%	84%	4%
Jordan	12%	88%	1%
Kazakhstan	79%	20%	1%
Kenya	49%	49%	2%
Kiribati	42%	58%	0%
Kuwait	8%	92%	0%
Kyrgyzstan	54%	42%	4%
Laos	9%	89%	3%
Latvia	32%	65%	4%
Lebanon	65%	32%	2%
Lesotho	86%	14%	0%
Liberia	20%	64%	16%
Libya	9%	91%	0%
Liechtenstein	33%	67%	0%
Lithuania	47%	49%	4%
Luxembourg	51%	48%	1%
Madagascar	70%	29%	1%
Malawi	60%	14%	26%
Malaysia	26%	73%	1%
Maldives	21%	79%	0%
Mali	34%	65%	2%

Malta	32%	68%	0%
Marshall Is.	48%	52%	0%
Martinique	30%	64%	7%
Mauritania	38%	62%	0%
Mauritius	42%	57%	0%
Mayotte	53%	47%	0%
Mexico	50%	49%	1%
Micronesia	31%	69%	0%
Monaco	0%	100%	0%
Mongolia	72%	27%	0%
Montenegro	19%	78%	3%
Montserrat	30%	70%	0%
Morocco	68%	32%	0%
Mozambique	53%	46%	2%
Myanmar	20%	76%	4%
Namibia	47%	53%	0%
Nauru	20%	80%	0%
Nepal	29%	69%	3%
Netherlands	54%	35%	11%
New Caledonia	10%	88%	2%
New Zealand	39%	60%	2%
Nicaragua	42%	50%	8%
Niger	37%	63%	0%
Nigeria	76%	22%	1%
Niue	19%	81%	0%
Norfolk I.	25%	75%	0%
Macedonia	50%	48%	2%
Northern Mariana Is.	1%	99%	0%
Norway	3%	92%	6%
Oman	5%	95%	0%
Pakistan	48%	49%	3%
Palau	9%	91%	0%
Gaza Strip	74%	26%	0%
West Bank	74%	26%	0%
Panama	29%	69%	2%

Papua New Guinea	3%	95%	2%
Paraguay	42%	55%	2%
Peru	19%	80%	0%
Philippines	43%	57%	1%
Pitcairn	0%	100%	0%
Poland	47%	51%	2%
Portugal	42%	57%	1%
Puerto Rico	19%	81%	0%
Qatar	6%	94%	0%
South Korea	17%	81%	3%
Moldova	69%	28%	3%
Reunion	19%	81%	0%
Romania	59%	37%	4%
Russia	13%	82%	4%
Rwanda	73%	20%	7%
Saint Barthélemy	0%	100%	0%
Saint Helena, Ascension and Tristan da Cunha	31%	69%	0%
St. Kitts & Nevis	23%	77%	0%
St. Lucia	16%	82%	2%
St. Pierre & Miquelon	9%	87%	4%
St. Vincent & the Grenadines	18%	82%	0%
Saint-Martin (French part)	0%	100%	0%
Samoa	18%	82%	0%
San Marino	38%	62%	0%
Sao Tome & Principe	46%	54%	0%
Saudi Arabia	81%	19%	0%
Senegal	46%	52%	2%
Serbia	40%	59%	1%
Seychelles	3%	97%	0%
Sierra Leone	55%	45%	0%
Singapore	1%	98%	1%
Sint Maarten (Dutch part)	0%	100%	0%
Slovakia	39%	59%	2%
Slovenia	30%	69%	1%
Solomon Is.	4%	93%	3%

Somalia	70%	28%	2%
South Africa	79%	20%	0%
South Sudan	45%	55%	0%
Spain	52%	46%	1%
Sri Lanka	45%	48%	6%
Sudan	37%	62%	1%
Suriname	1%	94%	5%
Sweden	7%	83%	10%
Switzerland	38%	57%	4%
Syria	76%	23%	1%
Tajikistan	35%	63%	2%
Thailand	45%	55%	0%
Timor-Leste	23%	77%	0%
Togo	70%	25%	4%
Tokelau	60%	40%	0%
Tonga	49%	47%	4%
Trinidad & Tobago	11%	89%	0%
Tunisia	63%	32%	5%
Turkey	49%	49%	2%
Turkmenistan	72%	24%	4%
Turks & Caicos Is.	1%	99%	0%
Tuvalu	60%	40%	0%
Uganda	72%	8%	20%
Ukraine	71%	25%	4%
United Arab Emirates	5%	94%	0%
United Kingdom	71%	28%	1%
Tanzania	45%	48%	7%
United States	44%	48%	7%
Virgin Is.	9%	91%	0%
Uruguay	80%	19%	1%
Uzbekistan	58%	40%	2%
Vanuatu	15%	85%	0%
Venezuela	24%	72%	3%
Vietnam	39%	55%	6%
Wallis and Futuna Islands	43%	57%	0%

Western Sahara	19%	81%	0%
Yemen	44%	56%	0%
Zambia	32%	67%	1%
Zimbabwe	42%	57%	1%
Central America Caribbean	21%	74%	5%
Global	38%	59%	3%

7.2 External sources in Agrowin 2019 (all other crop-country combinations are based on non farmer-panel data)

Market	Country	Source	Crop Main Group	Data purchased
CP	Argentina	Kleffmann	Corn/Maize	X
CP	Argentina	Kleffmann	Soybeans	X
CP	Argentina	Kleffmann	Cereals	X
CP	Belgium	Kynetec	Cereals	X
CP	Belgium	Kynetec	Corn/Maize	X
CP	Belgium	Kynetec	Potatoes	X
CP	Belgium	Kynetec	Fruits	X
CP	Belgium	Kynetec	Leeks	X
CP	Brazil	Spark	Corn/Maize	X
CP	Brazil	Spark	Cotton	X
CP	Brazil	Spark	Coffee	X
CP	Brazil	Spark	Soybeans	X
CP	Brazil	Kleffmann	Cotton	X
CP	Brazil	Kleffmann	Corn/Maize	X
CP	Brazil	Kleffmann	Soybeans	X
CP	Bulgaria	Kleffmann	Cereals	X
CP	Bulgaria	Kleffmann	Corn/Maize	X
CP	Bulgaria	Kleffmann	Oilseed-Rape/Canola	X
CP	Canada	Agdata		X
CP	China	Kleffmann	Corn/Maize	X
CP	China	Kleffmann	Rice	X
CP	China	Arn/Shanghai	All Available Crops	X

CP	Czech Rep.	Kleffmann	Cereals	X
CP	Czech Rep.	Kleffmann	Corn/Maize	X
CP	Czech Rep.	Kleffmann	Oilseed-Rape/Canola	X
CP	Czech Rep.	Kleffmann	Potatoes	X
CP	Czech Rep.	Kleffmann	Beets	X
CP	Czech Rep.	Kleffmann	Grapes	X
CP	Denmark	Kleffmann	Cereals	X
CP	Finland	Kleffmann	Cereals	X
CP	France	Adquation-France	Beets	X
CP	France	Adquation-France	Cereals	X
CP	France	Adquation-France	Corn/Maize	X
CP	France	Adquation-France	Oilseed-Rape/Canola	X
CP	France	Adquation-France	Forage Crops	X
CP	France	Adquation-France	Sorghum & Millet	X
CP	France	Adquation-France	Sunflower	X
CP	France	Adquation-France	Soybeans	X
CP	France	Adquation-France	Potatoes	X
CP	France	Adquation-France	Top Fruits	X
CP	Germany	Kleffmann	Beets	X
CP	Germany	Kleffmann	Cereals	X
CP	Germany	Kleffmann	Corn/Maize	X
CP	Germany	Kleffmann	Oilseed-Rape/Canola	X
CP	Germany	Kleffmann	Forage Crops	X
CP	Germany	Kleffmann	Oilseeds: Other	X
CP	Germany	Kleffmann	Potatoes	X
CP	Germany	Kleffmann	Fruits	X
CP	Germany	Kleffmann	Asparagus	X
CP	Germany	Kleffmann	Grapes	X
CP	Germany	Kleffmann	Strawberry	X
CP	Hungary	Kleffmann	Beets	X
CP	Hungary	Kleffmann	Cereals	X
CP	Hungary	Kleffmann	Corn/Maize	X
CP	Hungary	Kleffmann	Oilseed-Rape/Canola	X
CP	Hungary	Kleffmann	Sunflower	X
CP	Hungary	Kleffmann	Vegetables & Flowers	X

CP	Hungary	Kleffmann	Fruits	X
CP	Hungary	Kleffmann	Grapes	X
CP	Indonesia	Kleffmann	Corn/Maize	X
CP	Kazakhstan	Kleffmann	Cereals	X
CP	Kazakhstan	Kleffmann	Cotton	X
CP	Kazakhstan	Kleffmann	Flax/Linseed	X
CP	Kazakhstan	Kleffmann	Sunflower	X
CP	Kazakhstan	Kleffmann	Rice	X
CP	Kazakhstan	Kleffmann	Vegetables & Flowers	X
CP	Kazakhstan	Kleffmann	Fruits	X
CP	Kazakhstan	Kleffmann	Lentil	X
CP	Kazakhstan	Kleffmann	Potatoes	X
CP	Latvia	Kleffmann	Cereals	X
CP	Latvia	Kleffmann	Oilseed-Rape/Canola	X
CP	Lithuania	Kleffmann	Cereals	X
CP	Lithuania	Kleffmann	Oilseed-Rape/Canola	X
CP	Mexico	Kleffmann	Corn/Maize	X
CP	Mexico	Kleffmann	Potatoes	X
CP	Mexico	Kleffmann	Tomatoes	X
CP	Netherlands	Branches&Trends	Arable Crops	X
CP	Netherlands	Branches&Trends	Flower Bulbs	X
CP	Netherlands	Branches&Trends	Cauliflower	X
CP	Netherlands	Branches&Trends	Broccoli	X
CP	Netherlands	Branches&Trends	Fruits	X
CP	Paraguay	Kleffmann	Cereals	X
CP	Philippines	Kleffmann	Corn/Maize	X
CP	Philippines	Kleffmann	Rice	X
CP	Poland	Kleffmann	Beets	X
CP	Poland	Kleffmann	Cereals	X
CP	Poland	Kleffmann	Corn/Maize	X
CP	Poland	Kleffmann	Oilseed-Rape/Canola	X
CP	Poland	Kleffmann	Potatoes	X
CP	Poland	Kleffmann	Fruits	X
CP	Poland	Kleffmann	Berries	X
CP	Poland	Kleffmann	Vegetables & Flowers	X

CP	Romania	Kleffmann	Cereals	X
CP	Romania	Kleffmann	Corn/Maize	X
CP	Romania	Kleffmann	Oilseed-Rape/Canola	X
CP	Romania	Kleffmann	Sunflower	X
CP	Romania	Kleffmann	Potatoes	X
CP	Romania	Kleffmann	Soybeans	X
CP	Romania	Kleffmann	Fruits	X
CP	Romania	Kleffmann	Vegetables & Flowers	X
CP	Romania	Kleffmann	Grapes	X
CP	Russian Fed.	Kleffmann	Cereals	X
CP	Russian Fed.	Kleffmann	Corn/Maize	X
CP	Russian Fed.	Kleffmann	Oilseed-Rape/Canola	X
CP	Russian Fed.	Kleffmann	Sorghum & Millet	X
CP	Russian Fed.	Kleffmann	Sunflower	X
CP	Russian Fed.	Kleffmann	Soybeans	X
CP	Russian Fed.	Kleffmann	Fruits	X
CP	Russian Fed.	Kleffmann	Potatoes	X
CP	Russian Fed.	Kleffmann	Beets	X
CP	Russian Fed.	Kleffmann	Vegetables & Flowers	X
CP	Russian Fed.	Kleffmann	Grapes	X
CP	Slovakia	Kleffmann	Cereals	X
CP	Slovakia	Kleffmann	Corn/Maize	X
CP	Slovakia	Kleffmann	Sunflower	X
CP	Slovakia	Kleffmann	Oilseed-Rape/Canola	X
CP	Slovakia	Kleffmann	Potatoes	X
CP	Slovakia	Kleffmann	Beets	X
CP	Slovakia	Kleffmann	Grapes	X
CP	Sweden	Kleffmann	Cereals	X
CP	Thailand	Kleffmann	Corn/Maize	X
CP	Turkey	Kleffmann	Cereals	X
CP	U.Kingdom(Uk)	Kynetec-Seed-Dressing	Beets	X
CP	U.Kingdom(Uk)	Kynetec-Seed-Dressing	Cereals	X
CP	U.Kingdom(Uk)	Kynetec-Seed-Dressing	Corn/Maize	X

CP	U.Kingdom(Uk)	Kynetec-Seed-Dressing	Oilseed-Rape/Canola	X
CP	U.Kingdom(Uk)	Kynetec-Seed-Dressing	Flax/Linseed	X
CP	U.Kingdom(Uk)	Kynetec-Seed-Dressing	Forage Crops	X
CP	U.Kingdom(Uk)	Kynetec-Seed-Dressing	Oilseeds: Other	X
CP	U.Kingdom(Uk)	Kynetec-Seed-Dressing	Potatoes	X
CP	U.Kingdom(Uk)	Kynetec	Beets	X
CP	U.Kingdom(Uk)	Kynetec	Cereals	X
CP	U.Kingdom(Uk)	Kynetec	Corn/Maize	X
CP	U.Kingdom(Uk)	Kynetec	Oilseed-Rape/Canola	X
CP	U.Kingdom(Uk)	Kynetec	Fallow-Land/Set-Asid	X
CP	U.Kingdom(Uk)	Kynetec	Flax/Linseed	X
CP	U.Kingdom(Uk)	Kynetec	Forage Crops	X
CP	U.Kingdom(Uk)	Kynetec	Oilseeds: Other	X
CP	U.Kingdom(Uk)	Kynetec	Potatoes	X
CP	Ukraine	Kleffmann	Beets	X
CP	Ukraine	Kleffmann	Cereals	X
CP	Ukraine	Kleffmann	Corn/Maize	X
CP	Ukraine	Kleffmann	Oilseed-Rape/Canola	X
CP	Ukraine	Kleffmann	Sorghum & Millet	X
CP	Ukraine	Kleffmann	Sunflower	X
CP	Ukraine	Kleffmann	Fruits	X
CP	Ukraine	Kleffmann	Grapes	X
CP	Ukraine	Kleffmann	Vegetables & Flowers	X
CP	Ukraine	Kleffmann	Potatoes	X
CP	Ukraine	Kleffmann	Soybeans	X
CP	Uruguay	Kleffmann	Soybeans	X
CP	Usa	Kynetec	Corn/Maize	X
CP	Usa	Kynetec	Soybeans	X
CP	Usa	Kynetec	Cotton	X
CP	Usa	Kynetec	Specialty Crops	X
CP	Usa	Kynetec	Other Row Crops	X
CP	Vietnam	Kleffmann	Corn/Maize	X

CP	Vietnam	Kleffmann	Rice	X

7.3 Checklist quality standards for farmer-Panel Providers

Checklist Panel Quality Standards for Panel Providers

- 1 -

Checklist Panel Quality Standards						
			Documentation		Control	
	Recom-mended	Must	Internal	To client	Carried out?	Results OK?
1. Information about agricultural universe						
1.1. Country:		X		X		
1.2. Definition of the covered region, sub-regions relevant to the evaluation		X		X		
1.3. Statistics about:						
• Cultivated areas by crops		X		X		
• Farm structures according to country specific farm sizes for crops, according to the regions (smallest unit: farm size specific to the crop for a crop in a region)		X		X		
1.4. Special features (e.g. peculiar significance of small or large farms)		X		X		
1.5. Data source: publisher and date / period for all statistics used in 1.3 / for the extrapolation		X		X		

- 2 -

Checklist Panel Quality Standards						
			Documentation		Control	
	Recom-mended	Must	Internal	To client	Carried out?	Results OK?
2. Description of sampling						
2.1. Targeted sample according to farm sizes per crop and region						
• Representative for the total cultivated area of the respective crop		X		X		
• Coverage: at least 90% of the respective cultivated crop area		X		X		
• Coverage: at least 50% of the farmers of the respective crop		X		X		
• At least 30 interviews per cell		X		X		
• Consideration of “cut offs” = farm size classes, grown/cultivated crop areas		X		X		
• Safety level = 95% at an error probability of 5%		X		X		
• Information regarding deviations for percentages / extrapolation data (confidence intervals) for market share levels of 5/10/20%:		X		X		
▪ for each crop per country		X		X		
▪ for each crop per region		X		X		
▪ for each farm size class per crop / country		X		X		
▪ for each farm size class per crop / region		X		X		
2.2. Actual sample (criteria the same as for targeted sample)		X		X		
2.3. Description of the stratification method (distribution of the interviews with regard to cultivated areas, crops and regions)		X	X			

- 3 -

Checklist Panel Quality Standards						
			Documentation		Control	
	Recom-mended	Must	Internal	To client	Carried out?	Results OK?
2.4. Survey periods						
a) Conducted waves in the same crop (time/date)		X	X			
b) Number of interviews in the individual waves (for panel approach = number of the constant panel farms / mortality rate)		X	X			
2.5. Changes to sampling compared to the previous years						
• Panel: panel mortality in percent		X	X			
• Changes to the number of interviews in the individual cells		X	X			

- 4 -

Checklist Panel Quality Standards

	Recom-mended	Must	Documentation: Internal	Documentation: To client	Control: Carried out?	Control: Results OK?
3. Description of the recruiting method						
3.1. Survey methods				X		
• Panel approach						
• Ad-hoc survey						
3.2. Methods of data collection				X		
• Farm by farm						
• Crop by crop						
• Field by field						
3.3. Interview technique				X		
• Face to face = … % of the interviews						
• CATI = … % of the interviews						
• Online = … % of the interviews						
• Self-completion = … % of the interviews						
3.4. Selection method				X		
• Random						
• Quotas						
• Cluster sampling						
• Others						

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Checklist Panel Quality Standards

	Recom-mended	Must	Documentation: Internal	Documentation: To client	Control: Carried out?	Control: Results OK?
4. Questionnaire						
4.1. Contents / structure of questionnaire						
4.1.1. Screening questions to control target group		X		X		
4.1.2. Logic checks in the questionnaire	X		X			
4.1.3. Main part plant protection measures:						
• Recording the cultivated area per crop		X		X		
• Recording the number of crops per field and year (rotations)		X		X		
• Definition of the treated area (information should refer to the effectively treated area, including band/row and partial treatment/patches, and even if a part of land is used several times per year for one crop).		X		X		
• Recording of the non-treated area in the crop (to estimate potentials)		X		X		
• Recording of products, mixtures, spraying sequences, reasons for use…		X		X		
• Net area		X		X		
• Super-developed area (= area treated with product)		X		X		
• Tractor-treated area (= treated basic area, number of tractor crossings)		X		X		
• Dose rate in l/ha or l/100l water or litres per water (concentration)		X		X		
• Dose rate in the cultivation of grapes, fruit, hops, etc. :		X		X		
- Dose rate per ha.		X		X		
- Dose rate per 100l of spray mixture + applied volume of water or volume of water and concentration of the spray mixture		X		X		
• Dose rate for seed dressings:		X		X		
- Seed sowing rate, sowing amount per ha. For corn / rapeseed, also quantity of seed units per ha.		X		X		

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Checklist Panel Quality Standards						
			Documentation		Control	
	Recom-mended	Must	Internal	To client	Carried out?	Results OK?
- Dose rate of seed dressing per 100kg seeds		X		X		
• Assignment of twin packs / combi packs or products with additives/ adjuvants and their use (together/separately)		X		X		
• Aims of control (most important pests/weeds/grass weeds/ diseases) per product used		X		X		
4.2. Show cards						
4.2.1. Development stages (with BBCH code and standard name as a graphic)		X		X		
4.2.2. Lists of pests/weeds/grass weeds/diseases (the 15 most important of each)						
• Colloquial nomenclature		X		X		
• Latin nomenclature		X		X		
4.2.3. Product lists per crop						
• If the market has generic products		X		X		
• If the market has no generic products		X		X		
4.3. Price records						
• Wherever possible, based on submitted invoices (ratio of prices from invoices: ...%)	X			X		
• Record as price per kg/l		X		X		
• Including or excluding VAT		X		X		
• Discounts and discount amount		X		X		
4.4. Providing of questionnaire including show cards in English and the national language		X		X		
4.5. Final approval of the questionnaire by the client before start of field work		X		X		

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Checklist Panel Quality Standards						
			Documentation		Control	
	Recom-mended	Must	Internal	To client	Carried out?	Results OK?
5. Interviewers						
5.1. Number and distribution of the interviewers over the regions		X	X			
5.2. Information on the qualifications of the interviewer (e.g. education, background, experience, mastery of regional dialects...)		X	X			
5.3. The training methods used						
• Training documentation		X	X			
• Supervision		X	X			

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Checklist Panel Quality Standards

			Documentation		Control	
	Recom-mended	Must	Internal	To client	Carried out?	Results OK?
6. Weighting and extrapolation processes						
6.1. Method, general		X		X		
• Weighting by farms						
• Weighting by areas						
6.2. Weighting process		X		X		
• Stage (single-stage, multi-stage)						
• Definition of the weighting cells (crops/regions/farm size classes)						
6.3. Weighting factors						
• Number of interviews per weighting cell (minimum = 30)		X		X		
• Size of the weighting factors (specification = no more than 100)		X		X		
6.3. Evaluation of the confidence intervals (at an error probability of 5%, 95% safety level)						
For market share levels of 5/10/20%:						
• for each crop and country		X		X		
• for each crop and region		X		X		
• for each crop and farm size class		X		X		
• for each region/crop/farm size (so far as it is relevant)		X		X		

Checklist Panel Quality Standards

			Documentation		Control	
	Recom-mended	Must	Internal	To client	Carried out?	Results OK?
7. Evaluation / Reporting						
7.1. Quality controls before the evaluation						
7.1.1. Method and ratio of controlled interviews (at least 10%, yet not only about problem farms) and controlled interviewers		X	X			
7.1.2. Information regarding the identification method for illogical data (two-stage data check: first of all plausibility, then logical consistency)		X	X			
7.1.3. Recording of the controls		X	X			
7.1.4. Recording of the initiatives to participate due to possible influence on the data quality		X	X			
7.1.5. Problem report (design of the questionnaire, illogical entries, rejects, callbacks due to problems in interview,…)		X	X			

Checklist Panel Quality Standards						
			Documentation		Control	
	Recom-mended	Must	Internal	To client	Carried out?	Results OK?
7.2. Basic results						
7.2.1. per country, defined region, crop and pesticide segments: • areas • market shares • dose rates • tons • turnovers for total market, product and ingredient		X		X		
7.2.2. per country, crop and pesticide segment: • tank mixtures • spraying sequences		X		X		
7.3. Specifics						
7.3.1. Identification of twin packs applied together or separately		X		X		
7.3.2. Identification of the aims of control in Latin nomenclature		X		X		
7.3.3. Identification of the application times according to the BBCH code		X		X		
7.3.4. Orientation towards the data format by Kleffmann		X	X			

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Checklist Panel Quality Standards						
			Documentation		Control	
	Recom-mended	Must	Internal	To client	Carried out?	Results OK?
7.4. Data transfer and submission						
• Data delivery within 4-6 weeks after the last interview is done		X		X		
• Forwarding of the data simultaneously to local clients and Agrobase		X		X		

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