Disclaimer: This report is part of a project that has received funding by the European Union's Horizon 2020 research and innovation program under grant agreement number 862568.

Global Health Risk Assessment Toolbox

Deliverable number: 5.1
Due date: 31.08.2025 (month 60)
Dissemination level: public
Lead beneficiary: WU
Deliverable type: report
Version: 1.0

Disclaimer: This report is part of a project that has received funding by the European Union's Horizon 2020 research and innovation program under grant agreement number 862568.

PROJECT INFORMATION	
Project Title	Sustainable Plant Protection Transition; A global health approach
Project Acronym	SPRINT
Call Identifier	H2020-SFS-2019-2; Sustainable Food Security
Grant Agreement no.	862568
Starting Date	01-09-2020
End Date	28-02-2026
Project duration	66 months
Website address	www.sprint-h2020.eu
Project coordinator	Wageningen University, NL
Overall Project coordinator	Prof. Dr. V. Geissen (Violette.geissen@wur.nl, +31317485144)
Scientific Project Manager	Dr. V. Felix da Garca Silva (Vera.felixdagracasilva@wur.nl)
REPORT INFORMATION	
Report Title	D5.1: Global Health Risk Assessment Toolbox
Principle Author(s)	Jakub Hofman (MU), Anke Huss (UU), Joost Vlaming (FAO),Lingtong Gai (WU), Rozita Soltani Tehrani (WU), Paula da Silva Tourinho (MU), Vera da Graca Silva (WU), Artur Radomyski (MU), Daniel Figueiredo (UU), Farshad Soheilifard (DTU), Arash Derakhshan (UU), Shiva Sabzevari (MU), Daniele Mandrioli (RAM), Simona Panzacchi (RAM)
Principle Author e-mail	sprint@wur.nl
Deliverable Number	5.1
Work Package	5
WP Leader	Jakub Hofman (MU), Anke Huss (UU)
Nature	Report
Dissemination	PUBLIC. Toolbox launch Webinar 13-2-2026
Editor(s)	Violette Geissen (WU), Vera Silva (WU), Paul Scheepers (SRU)
Report publish date	15-02-2026 (month 66)

Disclaimer: This report is part of a project that has received funding by the European Union's Horizon 2020 research and innovation program under grant agreement number 862568.

Table of Contents

Abbreviations ... 3

Summary ... 3

Introduction ... 4

Platform ... 8

Case Study Site Results ... 8

Concentration Maps ... 14

Pesticide concentrations in soil and surface water ... 15

Pesticide concentrations in air ... 21

European Level ... 26

Ecological Risks ... 28

Description ... 28

Methodology ... 28

Application ... 29

Limitation ... 29

Dietary Exposure Assessment ... 30

Human dietary exposure ... 30

Farm animal dietary exposure ... 32

Health Impact ... 34

Toxicity/Ecotoxicity ... 50

Human and Animal Toxicity results ... 50

Ecotoxicity results ... 53

Models ... 55

Impact & Future Use ... 57

References ... 59

Abbreviations

ADI: Acceptable Daily Intake;

AOEL: Acceptable Operator Exposure Level;

AS: Active substances;

CAS: Chemical Abstracts Service;

CSS: Case study site;

DT_{50}: half-life for degradation or dissipation;

EFSA: The European Food Safety Authority;

EPAH: Environment, plant, animal and human;

GeMUP: Generelised mapped usage patterns;

LC_{50}: median lethal concentration;

LOQ: Limit of quantification;

NOEC: No observed effect concentration;

PEC: Predicted environmental concentration;

PPP :Plant Protection Product ;

RQ: risk quotient;

wHQ: weighted Hazard Quotient;

ΣRQ: cumulative risk quotient.

Summary

Deliverable 5.1 describes the Global Health Risk Assessment Toolbox (hereinafter the Toolbox) for risk and impact assessment of pesticides. The Toolbox integrates the results of multiple SPRINT work-packages and other available data on the occurrence, environmental fate, exposure, and impacts of pesticides regarding ecosystem, plant, animal and human (EPAH) health at the local, regional, national and European level. The toolbox is envisioned to support the governance, regulation, and policy- and decision-making for the transition towards a sustainable use of pesticides. Most tools will be useful for the pesticide post-registration phase, however, new approaches for the registration phase are as well included. The Toolbox consists of six interlinked tools. An overview of the different tools and a detailed description of each tool is presented in D5.1: i) Results of the Case Study Sites (CSS): Pesticide concentrations in environment, animals and humans based on the monitoring campaign in 11 case study and the resulting risk quotients for the aquatic and terrestrial ecosystem. ii) Upscaling: Calculating concentrations of 4 selected pesticides in soil and surface water bodies at regional and national scale based on national application datasets. Calculating concentrations of multiple pesticides in soil, surface water and air at European scale based on an extended dataset. Based on these calculations ecological risk quotients for single pesticides are calculated on regional and national scale. iii) Dietary exposure of farm animals and humans is calculated based on EFSA data on pesticide residues in food. iv) New developed ecotoxicological and toxicological SPRINT approaches are presented in the tool Toxicity/ecotoxicity.

Introduction

The overall aim of SPRINT project, along with the proposal of the transition pathways, is to develop, test, validate and deliver a Global Health Risk Assessment Toolbox (hereinafter the Toolbox) for risk and impact assessment of pesticides. Therefore, the framework of the Toolbox was developed to integrate the results of multiple SPRINT work-packages and deliverables (e.g., D2.3[1], D4.1[2], D4.2[3], D4.4[4], D4.5[5]), and other available data on the occurrence, environmental fate, exposure, and impacts of pesticides with regard to

[1] Inventory of PPP distribution and accumulation in EPAH, including gender-mediated differences
[2] Ecotoxicological assessment of PPPs' mixtures on terrestrial non-target species
[3] Ecotoxicological assessment of PPPs' mixtures on aquatic non-target species
[4] Assessment of the effects of PPPs' mixtures on animal health.
[5] Assessment of the effects of PPPs' mixtures on human health.

All SPRINT Deliverables available at https://sprint-h2020.eu/index.php/resources/project-milestones:

ecosystem, plant, animal and human (EPAH) health at the local, regional, national and European level. When possible gender specific analyses are presented. The toolbox is envisioned to support the governance, regulation, and policy- and decision-making for the transition towards a sustainable use of pesticides. Most tools will be useful for the pesticide post-registration phase, however, new approaches for the registration phase are as well included. We believe that especially maps of predicted pesticide application input, environmental distribution, exposure and risks of pesticides will be a valuable contribution to discussions regarding pesticide use reduction and the transition towards a more sustainable agriculture in Europe. However, the Toolbox users can also be other scientists, students, industry, farmers, wide public and other stakeholders.

The Toolbox - available at https://sprint-toolbox.eirene.eu/ - consists of six interlinked tools as shown in the **Figure 1.** An overview of the different tools and a detailed description of each tool is presented in the following chapters:

Results of the Case Study Sites (CSS): This tool visualizes the monitoring plan of the project as well as presents the results of all the pesticide residues detected in each Case Study Site (CSS) and environmental, human and animal compartments in an aggregated way.

Concentration maps/Upscaling: Within this section, the SPRINT project brings maps of estimated soil, water, and air concentrations of pesticides with different resolutions (field-resolution maps, national maps, pan-European maps).

Ecological Risk Maps: This tool helps identify areas where pesticides may be putting ecosystems under pressure. The maps serve as a demonstration of what the tool can do, allowing users to view the risk of pesticides (individually or combined) in soil and water for individual fields and river segments modelled in districts of Czechia.

Dietary exposure This tool brings two data-driven tools designed to estimate potential dietary exposure to pesticides for both humans (via food consumption) and farm animals (via feed intake), using harmonized datasets, scientifically validated methods, and transparent assumptions.

Health impact: This tool demonstrates Health Impact Assessment (HIA), which predicts health effects of policies or products before implementation. HIA is applied to pesticides, combining exposure such as from biomonitoring data, with dose–response outcomes and prevalence of disease in a population. For the selected example glyphosate, HIA quantifies potential health impact in populations, which is why it is seen as very valuable to policy makers.

Toxicity/Ecotoxicity: The tools in this section provide an overview of the main outcomes from the toxicity and ecotoxicity tests conducted within the SPRINT project. They allow users to explore and compare toxicity and ecotoxicity results, understand methodological approaches, and assess how mixtures of concern may impact both human (toxicity) and environmental (ecotoxicity) health.

Model Library: interactive database designed to provide an overview of the fate models used within the SPRINT case study sites, as well as other relevant fate modelling tools that were screened along the way. It serves as a central reference point for researchers,

policymakers, industry, and regulatory bodies interested in understanding and comparing environmental models applied in pesticide fate and exposure assessments

In this deliverable we highlight the main characteristics and functionalities of each tool. Stakeholder feedback was used before the public launch (on 13 February 2026; see the event recording at https://www.youtube.com/@sprinth2020) to improve the toolbox functionality. Important to highlight also that the tools, as they currently stand, are provided for research and informational purposes only. The underlying models, assumptions, data sources, and methodologies are experimental and might have not yet been peer-reviewed or independently validated. Outputs may be incomplete, uncertain, or inaccurate and should be interpreted with caution. The tools do not provide regulatory, medical, legal, toxicological, or professional risk assessment advice. For the time being, it must not be used as a substitute for expert judgment, regulatory review, or established risk-assessment frameworks, nor relied upon for decision-making related to human health, environmental protection, occupational safety, product registration, compliance, or policy. Use of these tools for unlawful, harmful, misleading, or unethical purposes—including but not limited to regulatory circumvention, misrepresentation of risk, or inappropriate application to real-world pesticide use decisions—is strictly prohibited. The tool is provided "as is," without warranties of any kind, express or implied, including but not limited to accuracy, fitness for a particular purpose, or non-infringement.

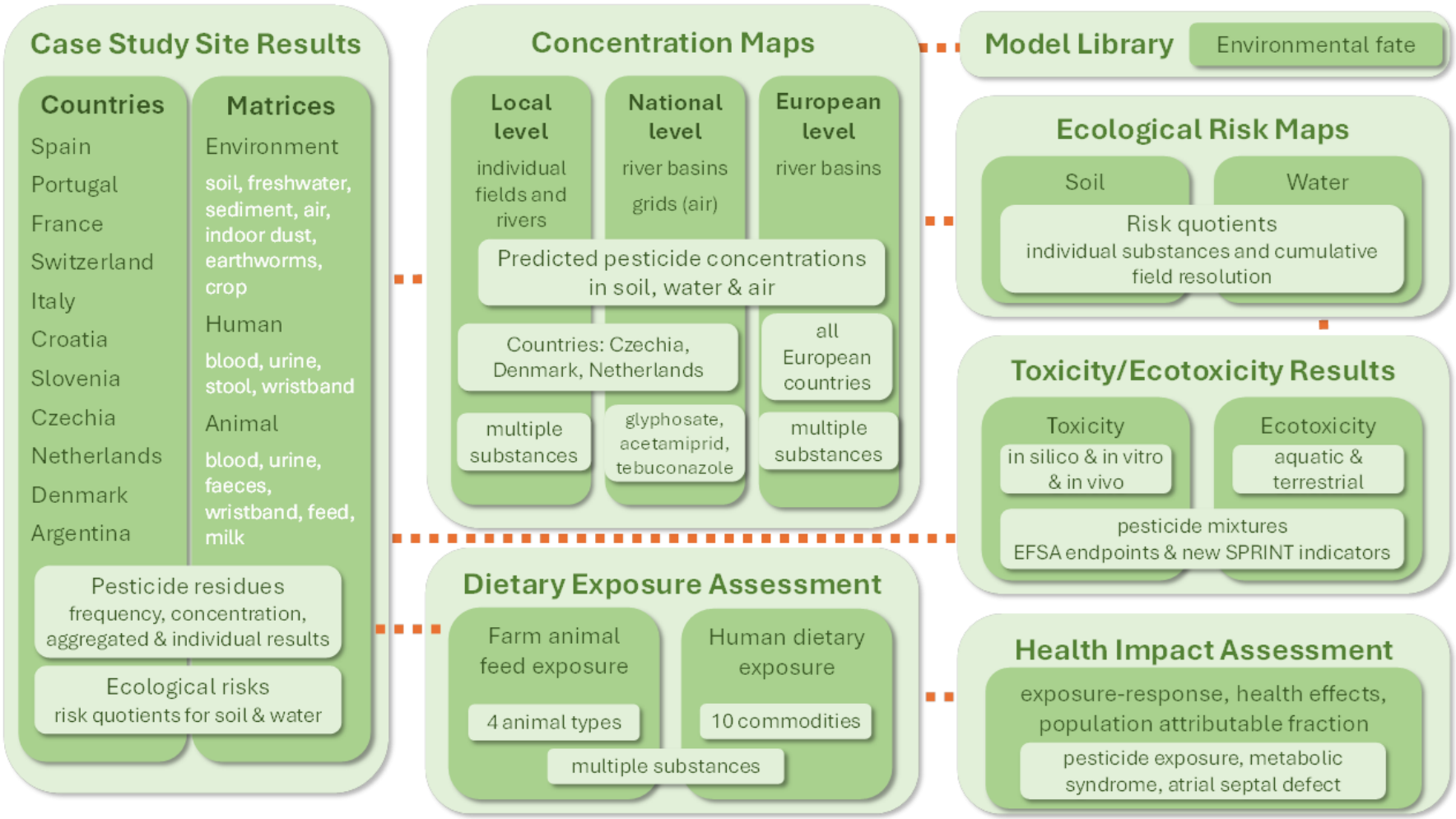

Figure 1: the toolbox tool scheme; orange dashed lines denotate direct data flows between tools

Platform

The SPRINT Toolbox development website runs on the Open Source Joomla! Content Management System (CMS) (https://www.joomla.org/), Most tools and results on the website are presented in as interlinked texts and images.

Custom scripts are used to present the results for some of the tools. These are:

- Concentration maps:
  - Field resolution maps: embedded Shiny application (https://shiny.posit.co/)
  - National - Soil & Water: embedded Shiny application
  - National - Air: embedded Leaflet (GIS) maps (https://leafletjs.com/)
  - Pan-European: script loading data into an embedded Leaflet GIS map
- Ecological risk maps: embedded Shiny application
- Dietary Exposure
  - Human exposure: script loading data into an embedded Leaflet GIS map
  - Farm Animal Exposure: embedded Shiny application
- Model Library: embedded database

Once out of development phase the Toolbox website will be turned into a static website and migrated to its permanent url: https://sprint-toolbox.eirene.eu/

Case Study Site Results

Description

The knowledge about the distribution of pesticides across different environments, plants, animals, and humans (EPAH) is limited in Europe and in general. The SPRINT project aims to deliver an overview of the pesticide residue levels analyzed in EPAH matrices in the project case study sites (CSS) (Silva et al., 2021).

A cross-sectional sampling campaign was conducted during the growing season of 2021 in the 11 case study sites (Spain, Portugal, France, Switzerland, Italy, Croatia, Slovenia, Czechia, Netherlands, Denmark, and Argentina) covering 13 EPAH matrices (soil, water, sediment, crop, earthworm, indoor dust, outdoor air, urine, wristband, faeces, feed, milk and blood) following the SPRINT monitoring plan (Silva et al., 2021). The results have been presented in the project deliverables 2.3[6] and 2.4[7]. Most of the results have been already published in individual and overarching papers[8]. The *SPRINT Toolbox – Case Study Site Results Tool* presents the results of the pesticide residues detected the different matrices, while ensuring data are stored and described according to FAIR principles (with standardized metadata for accessibility and reusability) and compliant with GDPR (through anonymization and secure handling of any personal data). Moreover, ecological risks for

[6] https://www.sprint-h2020.eu/index.php/my-sprint/project-documents/deliverables-and-reports/270-sprint-d2-3-m18/file
[7] https://www.sprint-h2020.eu/index.php/my-sprint/project-documents/deliverables-and-reports/405-d2-4-inventory-on-epah-health-status-in-css/file
[8] https://www.sprint-h2020.eu/index.php/resources/publications

the aquatic and terrestrial ecosystem are calculated based on field pesticide findings. By presenting the data in an interactive and visual format, we aim to provide the complex analytical results in a more accessible and engaging way. The tool can be explored through the left menu, where users can select between different sections. The "CSS Matrices" section allows users to browse results by matrices grouped under Environment, Human, and Animal, while the "CSS Countries" section presents results by country/case study site. The "CSS Ecological Risks" section provides information on ecological risk assessment for soil and water. Users can navigate between these sections to visualize and compare results from different perspectives.

Methodology

This tool utilizes all the pesticide analytical results to visualize country and matrix specific results. All the figures are created after the raw data (i.e. tables with pesticide residues concentrations from analytical laboratories) being processed using R programming version R-4.4.1, taking into account the readability in terms of both graphic complexity and colour-blind accessibility of the figures. This tool also estimated ecological risks by calculating risk quotients, defined as the concentration of each pesticide residue in soil or water divided by the NOEC (No Observed Effect Concentration) values for earthworms (soil) or fish (water). Cumulative risk quotients were calculated at sample level, by adding up the risk quotients of individual pesticides present in the sample.

In general, four major plotting methods were used in this tool:

- Heatmaps: The concentrations of individual pesticides in environmental (Figure 2), animal and human samples are presented by heatmaps, where each heatmap presents the median concentration of the compound for a specific category, regarding matrix and farming type (conventional/organic), approved/not-approved status, pesticide type (herbicide/insecticide/fungicide/transformation product/synergist). Heatmaps have the advantage to show patterns *across matrices* and allow a quick visual on high(er) vs. low(er) values. Heatmaps were also employed to visualize the risk quotients of individual pesticides in each sample and classify them based on established thresholds as NOECs.

Figure 2. Example heatmap: Median concentrations of pesticides in environmental matrices in Spain. Color legend: the darker the purple squares are, the higher the pesticide concentration is. Light orange means 'tested & not detected (<LOD)'. The thresholds classes associated with color scheme are automatically generated from values distribution. Lightest blue squares indicate compounds not above zero but above respective limit of detection and below 250 ug/kg //ng/sample // ug/L, depending on the matrix under evaluation. CF=conventional farm OF=organic farm

- Strip plots: used at matrix level. The total pesticide concentration (i.e. sum of levels of all pesticides in the sample) and cumulative risk quotients within a specific country are shown by the strip plot, which offers a visual benchmark by comparing results across samples (Figure 3).

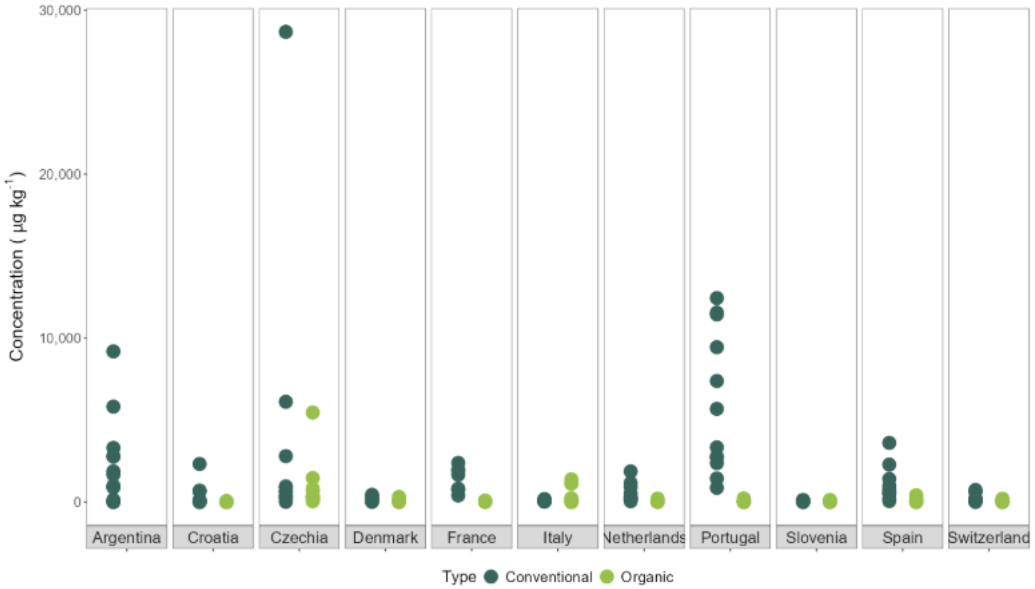

Figure 3. Example strip plot: Total pesticide concentration in soil.

- Pie charts: used also at matrix level but to represent the number of pesticides detected *i*. the pie charts (Figure 4), clustered by crop type, illustrate the proportional composition of the whole sample collections. The pie chart provides a quick overview of the dominant or minor (samples with a lower amount of compounds) segments of the pool of samples within and among factors.

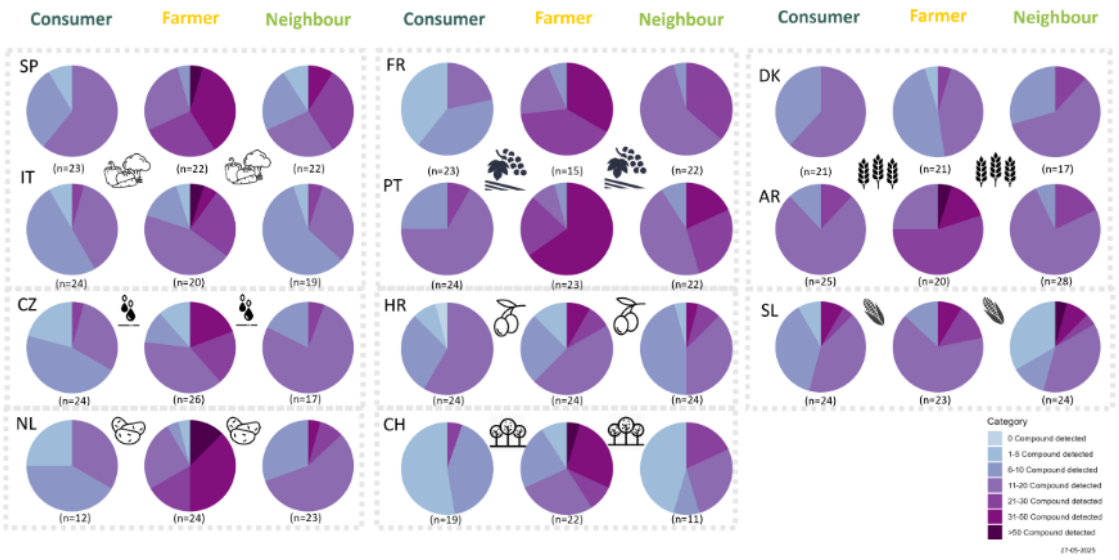

Figure 4. Example pie chart: Number of pesticides found per human wristband sample (%) stratified by consumer, farmer, and neighbour categorization in different CSS.

- Bar charts: They illustrate the *variation among individual samples*, which represent the total concentration and the total number of pesticide detections. Ecological risk is illustrated using stacked bar charts that compare countries and farming types based on mean and median pesticide risk quotients and the percentage of samples classified as risky (above or below the threshold).(Figure 5).

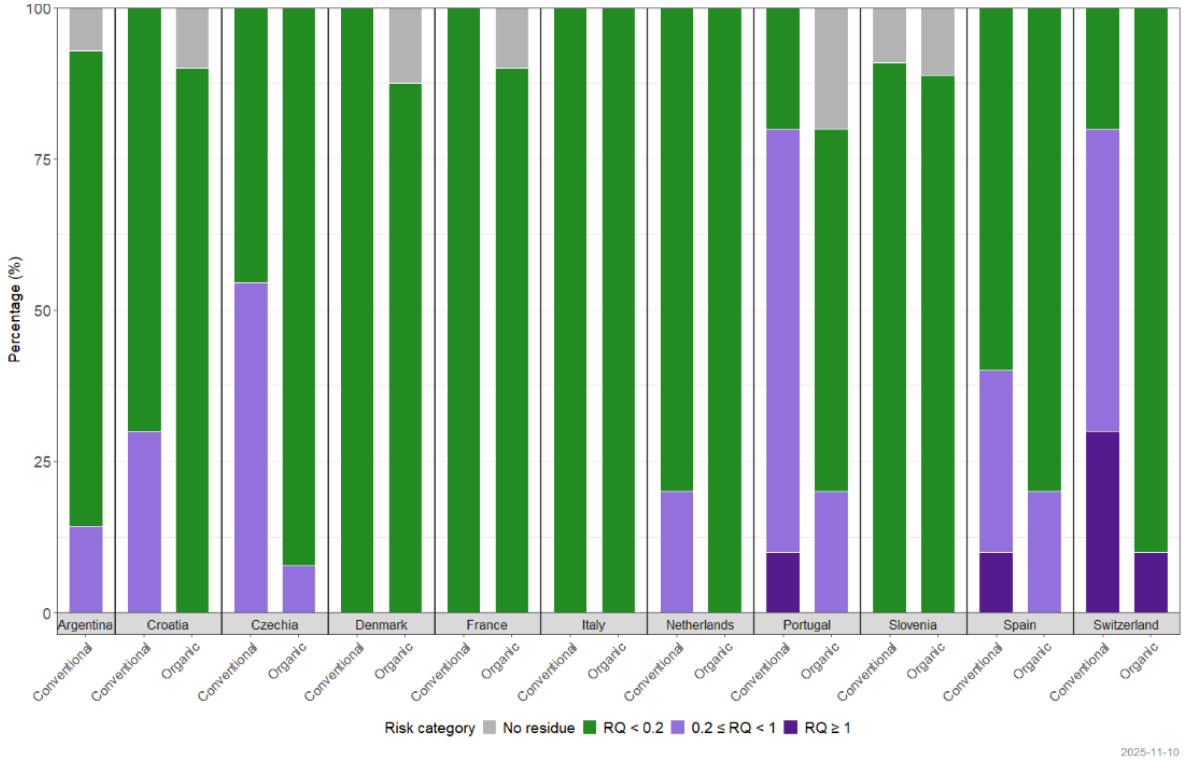

Figure 5. Example bar chart: Percentage of soil samples by risk category per country.

The webpage of the tool is designed with three ways to visualise: "CSS" entry, "Matrix" entry, and "Ecological risk" entry. Through the "CSS" entry, users are able to read the basic information about the CSS such as sampled crop, main characteristics of sampling design and sampling numbers, followed by a heatmap figure presenting the overall pesticide levels in human, environmental and animal matrices in this specific CSS. Through the "Matrix" entry, information about the sampling strategies is presented for each matrix, followed by the figures comparing total pesticide concentrations and the number of pesticides detected across different CSS. For both entries, by clicking on the figure, visitors can access the next level pages, which present the CSS x Matrix result in more details.

The CSS x Matrix pages breakdown provides information such as detection frequency, approval status of the compound according to the European status as of 01/01/2021 - i.e. start of SPRINT sampling campaign.

Through the "Ecological risk" entry, the calculation of the risk quotients and the definition of threshold values are explained in the Introduction tab. In the Results tab, the first figures compare the total risk quotient in soil and water across different CSS, followed by figures

showing the distribution of risk categories in the samples across CSS. These interactive figures allow the users to explore more detailed information on the contribution of individual pesticides to total risk. Results cover the mean and median risk quotient per CSS and farm type.

Application

This tool provides insights into the pesticide residues across matrices and CSS allowing

- comparison and communication for both further scientific research and policy decisions relating to pesticides management,
- informing the wide public about the facts of pesticides' presence in our surroundings.

Comparing pesticide residue levels between conventional and organic farm management with each CSS will help better assess the impact of different cropping and pesticide application practices, while ecological risks will help translate these residue levels into potential effects on soil and water organisms.

The presence of banned compounds in all the matrices of interest highlights the long-lasting impacts of pesticides, which should be accounted for in both risk assessment (as baseline contamination), and field management strategies.

The heatmap figures can provide insights into the distribution of pesticide residues across the different ecosystem, animal and human matrices.

The overall result also underscores the occurrence of mixtures in all sampled matrices rather than single compound in the entire ecosystem, especially by the pie chart on the sample composition (See Figures 2-4.).

Limitation

A limitation of the tool used is that it is not calibrated to specific pesticide application schemes and treats pesticide samples independently . Although we have multiple layers of information, the integration into ecosystem with other animal and human health indicators (like biomarkers and microbiome, not covered in the toolbox) is limited. Whereas RQ in ecological risk assessment can easily be assessed, human health risk depends on many not yet known factors , reason why it was not addressed here.

Direct interpretation of pesticide findings A is not appliable due to often lack of reference values/thresholds, and comparisons with literature is limited due to different sampling times, and analytical details (list of compounds analyzed, limit of detection, etc). In addition, the source of compounds with dual use applications cannot be clearly distinguished, which introduces additional uncertainty in source attribution.

The main limitation of the data is related to the fact that only one sampling time (in middle of 2021 growing season) was used, so the results are not dynamic. The pesticide residues occurrence and levels are only related to a snapshot sampling during a growing season in

specific cropping systems and countries. They are representative for these systems during the growing season 2021. Without the invent of all agricultural areas in each CSS region, producing the same or different crops to those sampled, and information on their management, out result could lead to overseeing off-site transport, background contamination and any other uncertainties in the pesticide concentrations. Exploring connectivity is also advised to assess for instance if findings in the sampled water bodies, close to agricultural fields, are representative of the water condition of the watershed.

Our analysis focused on a large screening approach (> 200 pesticide residues) based on expert knowledge. We prioritized comprehensive monitoring to support future risk assessments. Simplifications were made, including treating analytes independently. EU approval status for pesticides on 01 January 2021 was used as a reference

Concentration Maps

By 2030, the Farm to Fork Strategy aims for the 50% reduction in the use and risk of chemical pesticides and in the use of more hazardous pesticides. Under the Sustainable Use Directive (Directive 2009/128/EC), National Action Plans should set "quantitative objectives, targets, measures and timetables to reduce risks and impacts of pesticide use on human health and the environment". For all of these, EU policy-makers and regulators need good data and tools allowing to do informed decisions and to monitor, report, and valuate mitigation strategies. The main current tool, the harmonised risk indicator (Directive 2019/782/EC), is based on the pesticide sales weighted by hazard class, but does not account for geographically explicit usage. Because the risks posed by pesticides depend on where, when and how they are applied, there is a need for approaches that identify exposure and risks from pesticide uses with spatial resolution (showing geographic hotspots for exposure and risk) and across timescales (allowing for the assessment of trends in exposure and risk).

Environmental monitoring and human biomonitoring of pesticide residues require great effort and costs. Modelling approaches (predictions, estimations) can demonstrate pesticide exposure and risk at the large scale, complementing the value of monitoring. The exposure and risk of pesticide at the European scale can be accomplished with modelling approaches that rely on quality harmonised data on pesticide usage and pesticide authorisations at the crop and field level resolution. Currently, such data at appropriate quality are available only for several EU countries (see Chaideftou et al., 2025 a,b).

Within this tool, SPRINT creates maps with the results of modelling of 4 selected pesticide concentrations in soil, water and air with different resolutions (field resolution maps, spatially-aggregated national maps, pan-European maps). Different modelling approaches and input data were used for each environmental compartment and each resolution level. The "concentration maps" do not show any results of real measurements, surveys or monitoring. SPRINT created concentration maps for 4 European countries and the 4 selected pesticides. They display predictions (estimations) modelled using the existing data on pesticide usage (or sales), pesticide application scenarios according to good agriculture praxis in line with pesticide authorizations, and crop maps. These estimations are based on many simplifications and assumptions. Therefore, the resulting maps must be used and interpreted with the highest care considering the provided information on methodology

used for their creation and limitations and uncertainties inherently coupled with each of the map.

The concentration maps created in the SPRINT project can help to identify the spatio-temporal cumulation of pesticide exposures in the environment resulting from the spatio-temporal combination of crops and pesticide applications. Also, the highest-risk pesticide application patterns and cropping systems can be determined from analyses of source data for these maps. Using these maps, policymakers and regulators can more effectively target interventions and prioritize actions for informed pesticide reduction strategies (e.g., targeted reduction, withdrawal or substitution).

Field-resolution local maps and spatially-aggregated national maps

Pesticide concentrations in soil and surface water

Description

Understanding how pesticides impact the environment is critical for sustainable agriculture and ecological protection. Spatio-temporal simulation methods are crucial tools in helping to prevent potential adverse effects on living organisms by providing valuable information about where, how much and when pesticides and their mixtures are present in the environment. Such information can be then utilized to estimate the exposure of non-target organisms in ecosystems (terrestrial and aquatic organisms) and also the exposure of humans. Employing these approaches requires collection of detailed input data on farming practices (crop spatio-temporal distribution, pesticide usage statistics, recommended pesticide indications, their application rates, times, and conditions), climate, soil properties, and hydrology to simulate how pesticides enter the environment and how they interact with their surroundings at scale at which decision to take action may be necessary.

By focusing on *individual fields* as the smallest "target spatial unit" rather than broad regions, spatio-temporal modelling highlights local variability in pesticides' application, their fate, and consequently their occurrence in soil and water systems. The resulting spatio-temporal exposure profiles help pinpoint potential environmental risks, such as hotspots where pesticide concentrations may threaten soil and aquatic ecosystems. These insights support more effective decision-making, aligning with the European Union's sustainability goals under the Farm to Fork strategy.

This tool offers a transformative step toward precision environmental risk assessment, enabling tailored strategies to mitigate the ecological footprint of pesticides while maintaining agricultural productivity.

Methodology

In order to estimate the amount of pesticide that is transported into the surface water by the overland surface runoff it is necessary to determine the proportion of the active

substance (AS) in the application dose (AD), which will reach the ground and will be dissolved in the water phase of the soil. Similarly, it is important to know how much pesticide will be bound to the solid phase of the soil in order to estimate the amount of pesticide transported into the surface water by erosion. The proportion of AD available for runoff and erosion will be influenced by such factors as soil temperature, soil organic carbon content and pH values of the soil.

For consistency the overall structure of the model follows the OECD model (''simplified formula for indirect loadings caused by run-off'') developed to estimate the percentage of the applied amount of a pesticide that is dissolved in runoff water and, thus, can reach a surface water body (Gutsche & Strassemeyer, 2007). The OECD model calculates the dissolved percentage as a product of functions each of which describes the reduction of the maximum available percentage due to one of the following parameters and processes respectively: plant interception, degradation, sorption, depth of surface water runoff, slope and width of functioning buffer strips (Schriever et al., 2007).

At individual field-resolution and river-segment-resolution, the finest resolution datasets were used when available. If not available, less resolute datasets were used, especially for coarser target areas, such as a river basin or a country district. All spatial input data were converted to spatial objects, *SpatVector* and *SpatRast,* using *vect()* and *rast()* function, respectively, from the ***terra*** package (CRAN) in R programming language. Spatial objects were subsequently transformed using *project()* function to the World Geodetic System (WGS84; https://epsg.io/3857), which is a commonly used metric projection system in meters.

All site-specific values of the model parameters representing the desired spatial target unit are derived through spatial operations divided into several steps:

Step 1: Data Preparation and Spatial Framework

Coordinate System: UTM Zone 31N (EPSG:32631 and 32633) with 100m × 100m raster resolution template for data rasterisation.

Individual field polygons: Area (parcel/plot) on which one crop is cultivated and treated with at least one active substance, and which can be identified by a unique ID.

Table 1: Main sources for AS parcel area data in four selected countries

Country	Sources for parcel maps
Czech Republic	Czech Ministry of Agriculture (EAGRI) / EuroCrops
Netherlands	Netherlands Enterprise Agency (RVO) / EuroCrops
Denmark	EuroCrops
Portugal	EuroCrops

Table 2: Data sources used for obtaining country level river basin polygon data.
River network: HydroSHEDS database with discharge and morphological data, as well as datasets obtained from country authorities

Country	Sources for parcel maps
Czech Republic	Geoportál ČÚZK
Netherlands	Publieke Dienstverlening Op de Kaart (PDOK)
Denmark	The HydroSHEDS database
Portugal	The HydroSHEDS database

Table 3: Data sources used for obtaining country level river basin polygon data. River basin boundaries: HydroSHEDS database with delineated basins

Country	Sources for river basin spatial data
Czech Republic	The HydroSHEDS database
Netherlands	
Denmark	
Portugal	

Soil properties: 4 soil properties (organic carbon content, soil bulk density, sand and clay content) maps available from ESDAC portal were used. They have been derived using soil point data from the LUCAS 2009 soil survey (around 20,000 points) for EU-25, using hybrid approaches like regression kriging (Ballabio et al., 2016).

Terrain: Slope derived from digital elevation models. Terrain slope was extracted from The Harmonized World Soil Database. HWSD v2.0 is a 30 arc-second raster database (Fischer et al., 2021) containing a comprehensive global soil inventory that offers detailed insights into soil properties, including their morphology, chemistry, and physical characteristics, with a focus on a 1 km resolution.

Climate: Annual and monthly precipitation statistics (average, min and max) from HYDROSHEDS 1.0 were used at basin level, and at individual field/river level if finer data were not available. The primary source of precipitation values in HYDROSHEDS is WorldClim v1.4 model (Hijmans et al., 2005). Fine resulution rainfall data registered in 2021 from meteorological station in Czechia were used to obtain more granular values.

Agricultural data: GeMUP crop-specific pesticide application data derived at field level from spatial crop data and active substance usage.

Table 4: Main sources for AS usage data in four selected countries

Country	Country sources for AS use and application data
Czech Republic	Czech Ministry of Agriculture (EAGRI)
Netherlands	Statistics Netherlands' database (CBS)
Denmark	Ministry of Environment of Denmark (MST)
Portugal	Statistics Portugal (INE)

Crop interception factors: FOCUS/EFSA standard values by crop type. The original updated FOCUS crops (Olesen & Jensen, 2013).

Step 2: Pesticide Fate Modeling (Schriever 2007 Framework)
We conducted fate modelling to estimate the concentrations of pesticide residues (here named AS) in soil, surface water and air on regional and national scale.

a) Soil Concentration Calculations
Initial soil concentration after pesticide application:

C_soil_initial = (Application_rate / Bulk_density × mixing_depth) × (f_water + f_solid)

Where:

f_water and *f_solid* are fractions in soil water and solid phases calculated using organic carbon-water partitioning coefficients (Koc/Kfoc). Subsequently, time-weighted average (TWA) concentrations are calculated: 56-day TWA, represents short-term exposure scenarios, and 365-day TWA, represents annual average exposure. The model incorporates first-order degradation kinetics using field half-life (DT_{50}) values.

b) Surface Runoff and Water Contamination
Surface runoff loading:

Runoff_load = Area × Application_rate × Interception_factor × f_water_lag × Slope_effect × Runoff_fraction

Stream concentration:

C_stream = Surface_runoff_load / Annual_discharge_volume

c) Spatial Processing Workflow
Parcel-level calculations: Individual agricultural parcels receive pesticide-specific PEC calculations.
River buffer analysis: 100m stream buffers capture pesticide inputs from adjacent agricultural areas.
Basin aggregation: Results are aggregated to river basin level using area-weighted averages.
Multi-resolution output: Both high-resolution raster maps and basin-level vector summaries are produced as individual layers.

d) Chemical Property Integration
Chemical related parameters are extracted from the PPDB database (Lewis et al., 2016). Alternatively, QSAR from the VEGA tool (Benfenati et al., 2013) are used in cases when PPDB doesn't contain required information. The model incorporates following substance-specific parameters from PPDB (Pesticide Properties Database):

Koc/Kfoc: Organic carbon-water partitioning coefficients

DT_{50}: Soil and water degradation half-life values

Local, high-resolution datasets were preferred for obtaining parameter and forcing variables values. Sources for these datasets are diversified coming from governmental bodies like cadastre, statistical and meteorological authorities. Such data are oftentimes publicly available at high temporal and spatial resolutions. However, if not available, global digital datasets were selected. For consistency, HydroATLAS products version was used since it contains actively maintained large number of well-documented datasets and primary products such as HydroSheds 1.0 (Lehner et al., 2008). Products such as the HydroATLAS Version 1.0 (Linke et al., 2019) offers data for 56 variables, partitioned into 281 individual attributes and organized in six categories: hydrology; physiography; climate; land cover & use; soils & geology; and anthropogenic influences.

For detailed description of input data sets, modelled processes and spatial procedures, see Topsoil-River water Pesticide Fate Model Documentation.

Application

The model provides time-dependent and geo-referenced deterministic predicted environmental concentration estimation (geo-PECs) in soil and river water at individual field-resolution and river-segment-resolution, and frequency distribution or combined PEC values at coarser resolution. Temporal profile of calculated PECs includes two simulation scenarios: a) initial values right after AS application (PECmax), b) time averaged values over the defined duration after the application (e.g., 28 days). Subsequently, geo-PECs can be used to derive time-dependent and spatially distributed RQs for relevant terrestrial and aquatic endpoints.

The model can reflect various spatial and temporal characteristics of the considered parameters and application patterns when building site specific environmental scenarios. Consequently, scenarios are scale dependent by applying weighting factors over the parameters within the scenario's target area.

Depending on the map's communication objective of the simulation scenario at the desired target area, different visualization settings are possible. More detailed breakdown of possible levels of map visualization with respect to communication objectives is given in Table 5.

Table 5: Summary table of visualisation options according to communication objective of concentration maps included in the Toolbox. *Local: country specific high resolution data sources; Global: Large scale digital products included in various databases e.g., Hydrosheds , **Tebuconazole, glyphosate and acetamiprid for demonstration included in the toolbox.

Mapping type	**Granularity/target area for modelling**	**Recommended temporal resolution**	**Spatial object type**	**Target area for visualisation**	**# of AS****	**Crops**	**Regulatory variable**	**RQ-relevant temporal window**
Distributed	Field	daily	Vector	Territorial unit	3	All	PEC topsoil	Initial/56/365 (days)
Distributed	River segment	annual	Vector	Territorial unit	3	All	PEC surface water	Annual
Distributed	Field	daily	Raster	Whole country	3	All	PEC topsoil	Initial/56/365 (days)
Distributed	River segments	annual	Raster	Whole country	3	All	PEC surface water	Annual
Lumped	River basin or district	daily	Vector	Whole country	3	All	PEC topsoil	Initial/56/365 (days)
Lumped	River basin or district	annual	Vector	Whole country	3	All	PEC surface water	Annual

Limitation

Main limitations from this tool:

1) Before running the model, crops grown on individual fields were matched with AS usage data reported for individual crops in the larger area (district for CZ or whole country for NL and DK). However, one of the major sources of uncertainty of this approach is the lack of spatially explicit information on pesticide usage, i.e., which particular fields were really treated and/or how much chemical active substance (AS) was actually used on individual fields. Partial help might be found if at least information on what fraction of the area covered by the given crop was actually treated with a given substance (case of CZ).
For NL and DK, the amount of AS used for the given crop in the whole area was equally distributed into all fields with the given crop. Thus, the resulting application rates represent the theoretical (imputed) values that are probably underestimated when compared to application rates allowed according to good agricultural praxis on pesticide labels and data in national register of authorized pesticides. However, total input of the given AS for the given area is realistic as it comes from the aggregated reported pesticide uses. For CZ, the reported pesticide usage was accompanied with treated area information. Therefore, the calculated application rate is more accurate. However, its application to all fields with the given crop brings overestimation of total volume of AS entering the environment. In both cases, it can be highly recommended to cross-check the application rates against the authorized application rates (available in Generalized Application Patterns, Deliverable 5.2).

2) Pesticide application timing is dependent on application zone and actual application timing may vary significantly; therefore, the model should be run for areas where a fixed temporal application scheme is applied.

3) The depth of surface runoff (mm) is specified according to results of Lutz and Maniak (OECD, 1998) (Berenzen et al., 2005), (Probst et al., 2005) for vegetated dry soils, which represent conditions in middle and late vegetation periods.

4) When equilibrium condition for an AS between porewater and soil particles is not respected, e.g. just after a direct application, the modelling results must then be considered with caution. In such a case, exchanges between water and SPM should be described by non-equilibrium kinetics, using sorption and desorption kinetic rate constants.

5) The individual processes that are responsible for degradation in topsoil and water column (e.g. biodegradation, photolysis, hydrolysis) are not distinguished here but they are added into an aggregated loss rate. Degradation is assumed to follow linear first-order kinetics.

Pesticide concentrations in air

Description

The developed model was built to estimate airborne concentrations of pesticides at a national scale. The model is a simplification of OBOmod (Figueiredo et al. 2022). It calculates concentrations in air at varying spatial-resolutions from both the initial spray drift, occurring immediately after application, and the subsequent volatilization of active substances (AS) from treated surfaces. Maps were created for 1x1km and 2.5kmx2.5km depending on the country.

Why is it needed?

The resulting pesticide air concentrations can inform exposure assessments, policy decisions, and risk management strategies, particularly regarding residential proximity to agricultural areas. Examples include:

- Assessing human exposure, especially for people living near agricultural areas,
- Evaluating environmental risks (e.g. impacts on non-target organisms and ecosystems),
- Supporting policy-making, such as designing buffer zones, planning pesticide restrictions, or setting up monitoring campaigns.

By combining realistic input data on land use, pesticide use, meteorology and crop properties, this tool provides spatially resolved concentration maps, helping authorities and stakeholders identify hotspots and trends in pesticide air exposure.

Methodology

The tool integrates a wide range of data sources and combines R statistical scripting with geospatial processing.

Input data

a. Agricultural field polygons (crop, area) from national registries (BRP 2021).
b. Residential buildings and receptor points (BAG in NL).
c. Pesticide application data (Ctgb authorization data, usage data in NL).
d. Meteorological data (hourly KNMI data in NL; yearly averages for CZ; similar datasets for DK).
e. Crop canopy data (seasonal interception and height, FOCUS, FAO datasets).
f. Published pesticide half-lives (Fantke et al., 2014).

Processing

In R, we processed input tables, calculated application events, paired fields with nearest weather stations, generated emission rates, and derived volatilization parameters. Using GIS (QGIS / ArcGIS), we calculated centroids, distances and bearings between fields and residential buildings, created buffers (e.g. 250m zones), and prepared grids (1 km × 1 km or 2.5 km × 2.5 km).

A combination of short-range Gaussian plume equations (RTDrift-style for drift, PEARL-based for volatilization) was then applied in R to compute air concentrations for each simulation scenario.

Output

Concentrations averaged on grids (1 km² for NL and DK, 2.5 km² for CZ) to generate maps and summary statistics. Data at higher spatial resolution is available as download in the toolbox website.

Application

For application of the model and demonstration of its usability with different quality and a availability of input data, we estimated airborne concentrations for three selected pesticides (glyphosate, acetamiprid, and tebuconazole) at a national scale, focusing on the Netherlands, the Czech Republic and Denmark. Given that each country as different input data sources, the used data is listed below.

Table 6: Main data sources used for the model application

Type	The Netherlands	Czech Republic	Denmark
Crop location - sources	Basisregistratie Percelen" (BRP)		
Receptor data	Grid cells	Grid cells	Grid cells
Meteorological conditions	Royal Netherlands Meteorological Institute (KNMI).	https://www.chmi.cz/	DMI.DK
Crop interception factors	FOCUS		
Application (usage) data	The Ctgb authorization data	GenApps	GenApps
Pesticide half-lifes	Fantke et al., 2014		

For each country, simulations were done differently to test the applicability of the model in different contexts. For the Netherlands, given the large number of agricultural fields per square km, concentrations were calculated at a "virtual receptor point" established downwind of the pesticide application at 10m distance from the edge of the field. Simulations were made for the mode (most often occurring) of weather variables, focusing only on situations where spraying could have occurred (see Methodology). Average concentrations were then calculated for a fixed grid of 1kmx1km (See Figure 6). For Czech Republic, given the lower number of fields, simulations were done for each field for 8 predominant wind directions (N, NE, E, SE, S, SW, W, and NW). Meteorological data used was yearly average, instead of the mode. Concentrations were then averaged on a 2,5kmX2.5km grid (see Figure 7). For Denmark, air concentrations were estimated similarly as for Czech Republic. The output is an average value from all fields for each 1kmx1km grid resolution (see Figure 8).

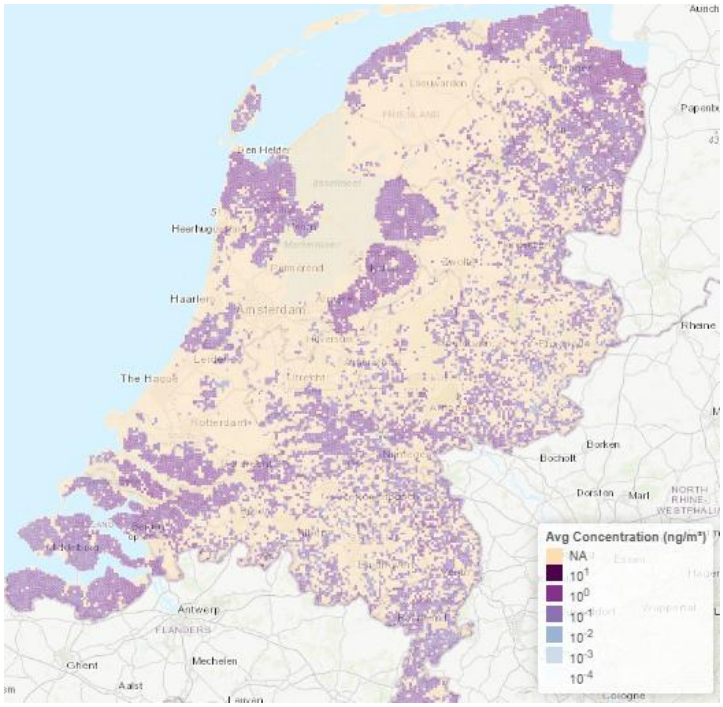

Figure 6 – Predicted year average concentrations of tebuconazole in the Netherlands for 2021. Results averaged per 1km² grid resolution over the country.

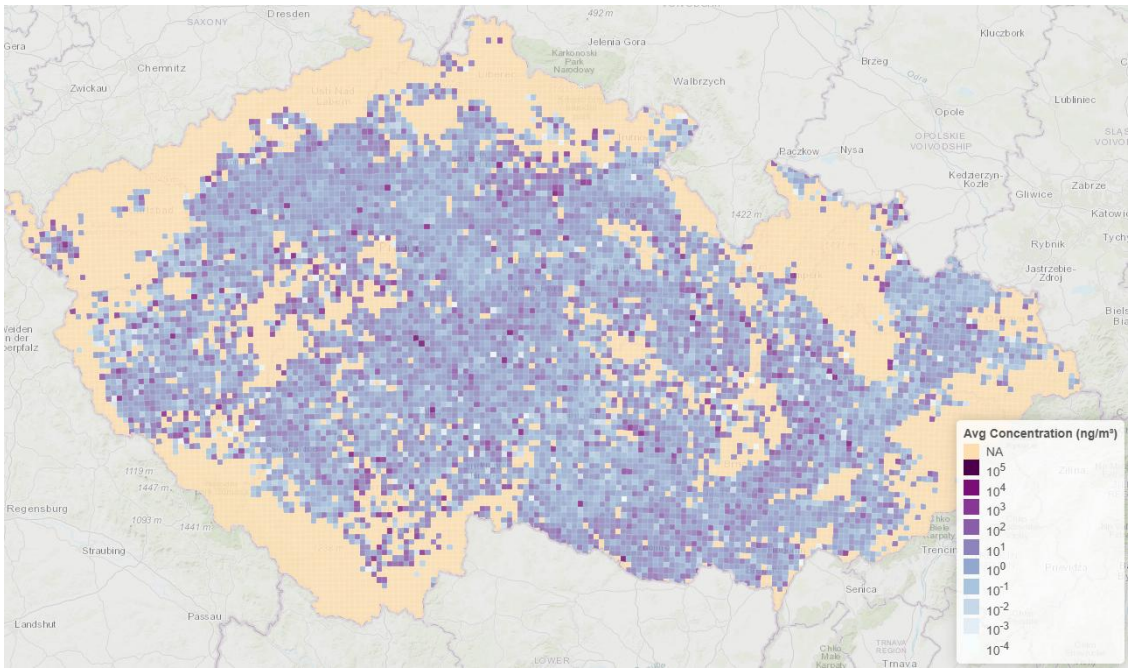

Figure 7 – Predicted year average concentrations of acetamiprid in Czech Republic for 2021. Results averaged per 2.5km² grid resolution over the country.

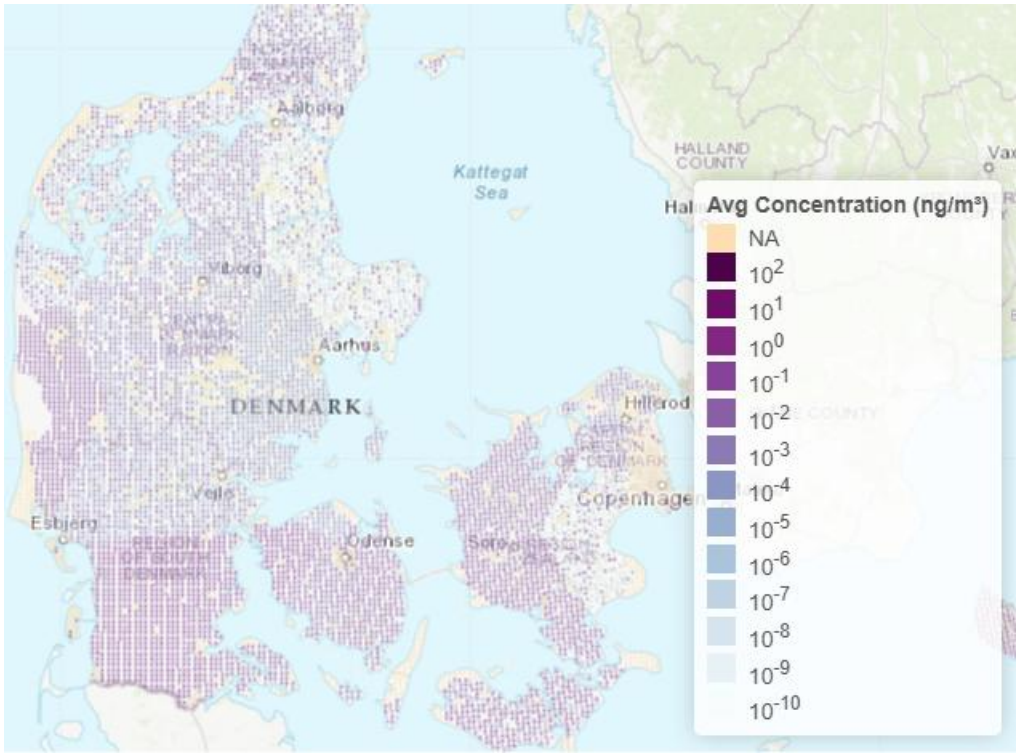

Figure 8 – Predicted year average concentrations of acetamiprid in Denmark for 2021. Results averaged per 1km² grid resolution over the country.

The tool is best suited for screening-level, spatial analyses to identify patterns or prioritize monitoring and further assessments. For example:

- Health exposure specialists might focus on overlaps between residential density layers and high(er) concentration areas.
- Epidemiologists can link long-term pesticide exposure to health outcomes in e.g. retrospective (or ecological) studies. As example, they can overlay concentration maps with health registry data (e.g. incidence of certain cancers, neurological diseases, or birth outcomes) aggregated by postal code or municipality.
- Ecologists might overlay habitat maps with concentration maps to find at-risk natural zones.
- Policymakers could look at exceedance maps (e.g. areas above certain thresholds, if available).

Limitation

Several simplifications and uncertainties should be considered when using the model developed for estimation of pesticide concentrations in air.

Using annual averages or mode for both dosage and meteorology does not capture short-term peaks that could drive acute exposures. Hence, the output data should only be used to understand spatial patterns in chronic (i.e. long-term) exposure assessment.

Only *downward spraying on open fields* was modelled; other techniques like sideways spraying were excluded.

Vegetation effects were incorporated as a uniform factor (0.66) for crops where no interception factor was available. Moreover, e.g. local hedgerows or forest shielding was not captured in the model.

The study did not include re-suspension of deposited particles or secondary drift from wind erosion. Although this work was carried under WP3 of SPRINT and a verification was performed against air measurements, the model was not considered fully validated to be integrated in this tool.

Background levels for pesticides are difficult to ascertain, and it can vary significantly per pesticide.

Future studies could refine these estimates by incorporating dynamic weather patterns, more granular canopy and vegetation barriers, and by extending to additional pesticide types and application techniques. Current efforts along these lines are already being carried out in other national and international projects, such as OBO2 (https://www.rivm.nl/bestrijdingsmiddelen/onderzoek-bestrijdingsmiddelen-en-omwonenden/werkpakket-2) and SOILPROM (https://soilprom.eu/).

European Level

Description

As part of the SPRINT project, European-scale spatially explicit maps were developed to estimate the average environmental concentrations of pesticide active ingredients across different environmental compartments, including agricultural soil, natural soil, freshwater bodies, and the atmosphere. These maps are designed to support EU-level impact assessments on ecosystem and human health.

The maps were generated using real-world pesticide usage data covering the years 2016–2020 and represent spatially explicit modelling outputs. In any sense they don't represent direct field measurements. They integrate pesticide application patterns with environmental emission and fate models, offering annual average concentrations across Europe at high spatial resolution. The result is a powerful tool for understanding the environmental footprint of pesticide use and supporting more sustainable agricultural decision-making.

Methodology

The development of the concentration maps followed a multi-step integrated modelling framework that combines empirical data with mechanistic modelling tools.

Pesticide usage data were acquired for the years 2016-2020 from the commercial GfK Kynetec AgroTrak database (https://kynetec.com), which provides detailed records by country, crop, growth stage, and application method. These data were harmonized and spatialized using global crop production layers derived from the spatial production allocation (SPAM) model (Yu et al., 2020) to generate spatially distributed estimates of pesticide application in each catchment.

To estimate emissions into various environmental compartments, the PestLCI Consensus model (Dijkman et al., 2012; Nemecek et al., 2022) was employed. This model determines initial emissions to air, field soil, crop surfaces, and off-field areas based on application method, crop type, and growth stage at the time of application. These emission fractions serve as direct inputs into the subsequent environmental fate modelling.

The geospatial environmental fate model Pangea (Jolliet et al., 2020; Wannaz et al., 2018a; Wannaz et al., 2018b; Wannaz et al., 2018c) was used to simulate the transport, transformation, and distribution of pesticides across media and spatial scales. Pangea uses a multi-scale grid system based on HydroBASINS catchments (https://www.hydrosheds.org) and GEOS-Chem meteorological data (Bey et al., 2001) and environmental process models to solve mass balance equations at steady state based on IMPACT 2002 and USEtox (Margni et al., 2004; Rosenbaum et al., 2008) (Margni et al., 2004; Pennington et al., 2005; Rosenbaum et al., 2008). Refinement potential, as a basis for building multi-scale grids, was defined based on the ratio of population to freshwater volume and potential ecotoxicity impacts from pesticide use, so that areas with a higher population-to-volume ratio and higher potential ecotoxicity impacts receive higher resolution.

European-scale concentration maps were generated for agricultural and natural terrestrial soils (in µg/kg), freshwater bodies (in µg/L), and air (in ng/m³).

Application

The European-level pesticide concentration maps are designed to enhance transparency and facilitate informed decision-making in pesticide regulation, environmental risk screening, and agricultural sustainability planning.

By visualizing where pesticide residues are most likely to accumulate in the environment, the maps support the identification of geographical "hotspots" of pesticide exposure. This enables policymakers to focus on regulatory and mitigation efforts in areas of greatest concern. The maps also provide a basis for prioritizing ecological and public health risks, as they help to assess where the highest environmental burdens are likely to occur based on actual usage patterns across different crops and countries.

In addition, these maps play a crucial role in monitoring the effectiveness of existing and future pesticide reduction strategies. They contribute to evaluating progress under broader policy frameworks such as the European Green Deal and the Farm to Fork Strategy by translating complex usage and exposure data into interpretable spatial information.

From a strategic perspective, the maps facilitate planning for transitions toward more sustainable farming systems. They can inform decisions on pesticide substitution, promote best practices, and guide investments in alternative pest control methods. Furthermore, by integrating spatial analysis with scientific modelling, the concentration maps enable researchers, environmental agencies, and civil society organizations to better communicate the systemic impacts of pesticides on environmental and human health.

Beyond technical stakeholders, the maps also serve an important role in public engagement. By making pesticide distribution patterns more visible and understandable, they empower citizens, communities, and advocacy groups to take part in the broader conversation about food system sustainability and chemical safety.

Limitation

While these maps represent an important advancement in spatial environmental assessment, they are not without limitations. It is crucial that these maps be interpreted accurately to prevent misuse or overinterpretation.

Pan-European concentration maps are the result of model-based estimations and do not represent direct field measurements of pesticide residues. They are built on a combination of actual pesticide usage data, environmental emission modelling, and geospatial fate and transport simulations. As such, they provide estimates of annual average concentrations, not short-term or peak exposure levels that may occur immediately after pesticide application.

These maps cannot be used to determine whether a particular location is environmentally "safe" or "unsafe" without additional local data and temporal modelling. Instead, they serve

to highlight relative differences between regions, indicating areas of potentially higher or lower environmental concentrations of pesticides.

They are intended to support awareness-raising, strategic planning, and research, and should not be used for direct regulatory decisions or local risk assessments. Moreover, regions with limited data quality or model resolution, such as under-monitored or remote areas, may carry a higher degree of uncertainty in the estimated concentrations.

Ecological Risks

Description

Ecological risk maps help visualize the spatial distribution of pesticide impacts on ecosystem health. The risk quotients (RQ) for an individual AS were calculated as the ratio of its predicted soil or water concentration (PECs, PECw – predicted in the maps of environmental concentrations – see above) to ecotoxicity thresholds (hazard data taken from the databases). When dealing with multiple pesticide residues, which are frequently detected in agricultural soils, the cumulative risk quotient (ΣRQ) for a given area can be assessed by summing the RQs for all single AS, commonly following a concentration-addition approach. These calculated ΣRQ values, representing the severity of risk at various points or grid cells, are then spatially visualized on maps using Geographic Information Systems (GIS) spatial processing. This mapping process allows for the identification of high-risk areas. Ecological risk maps were created for the prioritized AS in the Czech Republic (CZ), covering both terrestrial and aquatic environments.

Methodology

Prioritization of the substances

To select substances for risk maps, pesticides applied in 2021 were ranked based on their usage and chemical/ecotoxicological properties. Usage data were obtained from national sources (ÚKZÚZ, https://ukzuz.gov.cz) for 183 AS. Non-relevant substances (e.g., microbial agents, pheromones, growth regulators, synergists, and inorganic or natural compounds) were excluded.

Chemical and ecotoxicological properties of the pesticides were retrieved from the PPDB database. Chronic NOECs for earthworms (56 days) and fish (21 days) were used when available. If not, acute LC50 values (14 days for earthworms, 96 hours for fish) were divided by 10 as a proxy (Franco et al., 2024). Chemical parameters including DT_{50} in soil, DT_{50} in water, water solubility (at 20 °C), octanol-water partition coefficient, and organic carbon-water partition coefficient were also retrieved. Missing values were supplemented by values taken from EFSA reports.

All data (usage, ecotoxicity, chemical properties) were normalized to a 0–1 scale separately for each country. The normalized values were used to score and rank the AS. The top 95% (based on cumulative scores) was selected for the risk maps. This resulted in 23 substances for terrestrial, and 8 for aquatic environments in CZ.

Risk quotient calculations

Once the substances were selected, the PEC topsoil and PEC surface water were calculated for individual fields and river segments and aggregated over river basins, as outlined in the section 'Pesticide concentrations in soil and surface water' from chapter 'Field-resolution local maps and spatially-aggregated national maps'. A hazard database was prepared for earthworms and fish, using data from PPDB (https://sitem.herts.ac.uk/aeru/ppdb/), EFSA OpenFoodTox database (https://www.efsa.europa.eu/en/microstrategy/openfoodtox), and USEPA ECOTOX database (https://cfpub.epa.gov/ecotox/). The data from the 3 databases were gathered and the lowest NOEC of each pesticide was retained, representing the worst-case scenario. The RQ was calculated as PEC/NOEC. The RQ of all AS in the target spatial units, such as individual fields and river basins, were then summed up to obtain the cumulative risk quotient (∑RQ).

Application

The ecological risk maps can help to identify the most harmful agricultural practices and pesticide uses, based on real pesticide usage, to elucidate the spatio-temporal cumulation of risks resulting from the spatio-temporal combination of crops and pesticide applications, and to indicate the cumulative risks of environmental pesticide mixtures based on typical application series and crop treatment scenarios. They offer a harmonized, data-driven tool to explore how pesticide presence in the environment and toxicity translates into environmental pressure across space. Since these maps were created based on key pesticides selected by their national usage, it can be useful for improving regional pesticide management and establishing priority control lists for more accurate risk mitigation strategies.

For policy makers and regulators, the maps highlight high-risk areas where targeted action, regulation, or mitigation efforts may be most needed. And for the general public, they provide a clear and accessible way to see where ecosystems may be under threat, helping raise awareness and support for environmental protection.

Limitation

Because the calculated risk is based on the concentration mapping (see chapter above), all the limitations for the concentration maps are applicable for the risk maps too. The risk calculated in the maps is not based on the real field survey or monitoring (real measurements) of concentrations or ecological harm. The exposure data (soil and water concentrations) are results of predictions (estimations) modelled using existing data on pesticide usage (or sales), pesticide application scenarios according to good agriculture practices in line with pesticide authorizations, and crop maps. These estimations are based on many simplifications and assumptions, that are propagated also into the risk calculation. Therefore, the resulting maps must be used and interpreted with the highest caution considering the provided information on methodology used for their creation and limitations and uncertainties inherently coupled with each of the map.

On top of these restrictions, there are also other limitations. One major limitation is related to the assessment of the cumulative risk. Our approach relied on concentration-addition,

assuming only additive effects of pesticides. Therefore, synergistic or antagonistic effects are not considered, introducing uncertainties into the results for mixture effects. Another limitation concerns the selection of the toxicity data. Here, we used one model type of organism for soil (earthworms) and water (fish), which may not adequately represent the sensitivity of the broader ecological community. Standard indicator species are not always the most sensitive, potentially underestimating actual toxicity.

Dietary Exposure Assessment

Human dietary exposure

Description

Ensuring food safety is a crucial public health priority, especially given the widespread use of pesticides in agriculture and concerns about their residues in food commodities. Current dietary exposure assessments often rely on simplified or conservative assumptions that may not reflect real-world exposure levels.

The *SPRINT Toolbox – Exposure Assessment - Human Exposure Tool* presents a close-to-reality estimation of the average amount of individual pesticides the European adult population might be exposed to via certain food commodities consumption. The interactive maps highlight variations in pesticide exposure by year, food type, and pesticide, helping identify regions with higher exposure. These insights support safer food policies, inform the public, and promote better farming practices.

Methodology

This tool utilized two datasets: pesticide residue data from EU food monitoring programs (2011–2020) published by EFSA (Carrasco Cabrera and Medina Pastor, 2022; EFSA, 2014), and food consumption data. For the food consumption, data from the raw primary commodity (RPC) model (Dujardin and Kirwan, 2019) were used at the raw primary commodity level. Utilizing the RPC database, ten most frequently consumed primary food commodities across Europe—including onions, tomatoes, carrots, apples, potatoes, sweet peppers, parsley, oranges, strawberries, and lemons—were selected.

It is common in the dietary exposure assessment studies to treat the concentrations lower than the Limit of Quantification (LOQ) by considering lower or upper bound scenarios, depending on the purpose of the study. In this tool, however, our goal was to utilize a realistic approach by imputing the missing values in the AS residue concentration data. Thus, AS with sufficient quantified residue data for individual food commodities, with 90% or less missing values (<LOQ) and at least 15 observations above LOQ, were selected for subsequent imputation. The missing residue data were imputed using a parametric survival regression model (Lubin et al., 2004; M. Figueiredo et al., 2022; Fuhrimann et al., 2022). Eventually, average dietary exposure was calculated by combining average imputed residue concentrations with average food consumption rates for each "AS-food commodity" combination. The results are visualized as country-level exposure maps in the toolbox.

Application

This tool provides the estimation of the amount of selected AS adult population in Europe that is likely exposed to via consumption of selected food commodities (in µg of each AS per kg of body weight per calendar year). The main characteristic of the presented estimation is that, unlike the existing methods that in terms of dealing with missing residue data (below LOQ) follow approaches with scenarios leading to overestimation or underestimation of the dietary exposure (Carrasco Cabrera and Medina Pastor, 2022; Rebouillat et al., 2021), it provides a closer-to-reality approach by imputing the unquantified data instead of considering the lower or upper bound scenarios. The estimated dietary exposure is valuable not only for scientific research, e.g. in epidemiological studies, but also for policymakers for bridging the gap between science and policy. This ensures that pesticide regulations are better aligned with real-world exposure patterns to more effectively protect public health. Additionally, the tool has been designed to be accessible and informative for the general public, and as such may help to raise awareness about food safety.

Limitation

This tool faces two primary limitations: (1) constraints related to the underlying data sources, and (2) challenges associated with imputing missing values.

For the active substance residue concentration data, inconsistencies in analytical methods across countries resulted in different LOQs making it not suitable to be used as a variable for imputation. Additionally, at the country level, there was insufficient data (number of all reports as well as residue concentrations > LOQ) available for individual AS in selected food commodities to support reliable country-specific imputation. As a result, imputation was performed at the European level to cover the shortcomings. Limitations were also present in the utilized food consumption database which we used as provided, particularly due to the modelling already involved in preparation of the RPC database, in the procedure of estimating the intake of raw primary commodities from composite food in the database source (Dujardin and Kirwan, 2019). In addition, the RPC database was missing consumption data for the countries for which adequate residue data was available, such as Portugal, Norway, etc. All these factors influenced the generated dietary exposure estimates.

The input data, specifically active substance residue concentration data, are being released annually. However, there are limitations on updating the maps accordingly. This means the human dietary exposure maps do not tend to be updated for the years after 2020. The interested users can use the scripts and detailed explanations that will be provided in the project's publicly available repositories to process the data and do the calculations for the newly released national data, as long as they follow the same layout and coding system as for the years 2011-2020.

The imputation methodology also contained certain limitations. The precision of the imputation methodology highly depends on the proportion of missing data. Although up to

90% of missing data is claimed to be still enough for the imputation (Madley-Dowd et al., 2019), the lower the missing data is, the more precise the imputed data will be. This high percentage of missing data also limited the predictors we could use for the imputation.

Farm animal dietary exposure

Description

The **Farm-Animal Exposure component** of the toolbox is created to showcase how exposure of livestock/farm-animals to pesticide residues can be quantified through their feed. Closely interconnected with other elements of the SPRINT framework, this tool provides a platform for visualizing pesticide exposure by farm animals under realistic feeding conditions. The tool consists of a robust probabilistic modelling approach, curated datasets, example outputs, and documentation, all aimed at delivering insight into farm-animal dietary exposure.

At its core, the tool employs **Monte Carlo simulations (10,000 iterations)** to capture the variability and uncertainty inherent in feed intake and bodyweight among farm animals. Exposure estimates are generated by integrating pesticide concentration data from the SPRINT feed dataset. Importantly, only concentration values exceeding the analytical limit of quantification (LOQ) are used, resulting in a **truncated distribution** that realistically reflects detectable contamination levels.

Methodology

To calculate individual pesticide exposure, the model combines these concentration values with **probabilistic distributions for daily feed intake (g/day) and animal bodyweight (kg)**. These distributions were developed based on a scoping review of the scientific literature, utilizing reported means and standard deviations to accurately represent typical feeding scenarios for different animal species.

By bringing these inputs together, the model estimates pesticide intake per kilogram of bodyweight, providing a detailed picture of potential exposure across livestock populations. The tool produces as output **exposure probability distributions** shown in an interactive visualization. All resources, including input data requirements, equations used, and example scripts to run the analysis, are fully documented and accessible via links to GitHub.

This approach not only accounts for co-occurrence of multiple pesticide residues in feed but also reflects the natural variability in animal feeding behavior and physiology.

Application

The farm-animal exposure tool is designed to address the needs of diverse stakeholders:

- **Scientists** can use it to perform detailed exposure assessments and compare scenarios.

- **Policy Makers** may rely on its outputs to evaluate compliance with safety thresholds or inform risk management strategies.
- The **General Public** can gain insights into the levels of pesticide residues that might be present in the diets of farm animals producing their food.

For comprehensive details on the underlying methodology, datasets, and step-by-step workflow of the tool, please refer to the dedicated documentation available on the toolbox website:https://sprint-toolbox.eu/index.php/animal-exposure-introduction .

Limitation

While the farm-animal exposure tool provides valuable insights into dietary exposure of livestock to pesticide residues, several important limitations should be acknowledged:

Representativeness of input data:
The pesticide concentration data used as input for the model originates exclusively from feed samples collected within the SPRINT project. As such, these samples may not be fully representative of the wider distribution of pesticide residues present in livestock feed across the entire EU. Differences in agricultural practices, feed sourcing, and regional pesticide usage patterns could influence actual contamination levels beyond what is captured here.

Variability in bodyweight and feed intake distributions:
Although a comprehensive scoping review was performed to compile data on bodyweight and daily feed intake across different livestock species, the resulting probabilistic distributions may not fully encompass the diversity of livestock subtypes. For instance, Holstein cows generally have higher body weights compared to other dairy breeds, which could affect exposure estimates. Similar considerations apply to specialized breeds or production systems not explicitly covered in the literature-derived inputs.

Use of truncated distributions for pesticide concentrations:
Exposure calculations were based solely on concentration values above the analytical limit of quantification (LOQ), resulting in a truncated distribution. This approach avoids introducing potentially speculative assumptions about non-detected residues. However, it may lead to a slight overestimation of exposure, as values below the LOQ were not imputed. Given the relatively low number of detects (>LOQ) in the dataset, alternative imputation methods (such as substitution with half the LOQ or statistical distribution fitting) were not applied here to avoid introducing further uncertainty.

Scope limited to four farm-animal types:
This tool was explicitly developed for four common farm-animal types based on the available data. Nevertheless, the underlying equations used to estimate exposure from feed intake and bodyweight are general and could readily be applied to other livestock types, provided appropriate species-specific input data are available or collected by the user.

Potential influence of co-occurring residues and feed blending:
The model does not explicitly account for potential interactions between different pesticide residues or for blending of multiple feed batches with varying contamination levels before consumption, which may affect actual exposure profiles.

Static model assumptions:
The tool does not incorporate dynamic factors such as seasonal variations in feeding regimes, changes in feed composition over time, or metabolic adaptation in animals that could influence effective pesticide intake.

Human Health Impact

Description

In this report we first provide a general description of the Health Impact Assessment (HIA) approach and further below provide two detailed examples of HIA studies for glyphosate.

Fig. 9: Example HIA approach outlined below

Health Impact Assessment

Health Impact Assessment (HIA) is a structured, evidence-based process for predicting the potential health effects of a policy, program or project before it is implemented. It typically follows five steps: screening to decide if an HIA is needed, scoping to define which health outcomes and populations to study, assessment of hazards and exposure pathways, development of recommendations to manage risks, and monitoring to track outcomes over time. By integrating quantitative exposure data, epidemiological evidence and stakeholder input, HIA helps decision-makers balance benefits and harms in areas ranging from urban planning to agriculture.

One of the objectives of the SPRINT project was to develop, test, validate and deliver a Global Health Risk Assessment Toolbox for the integrated assessment of the impacts of pesticides on terrestrial and aquatic ecosystems as well as on plant, animal and human health. Here, we will describe the HIA study on human health.

When applied to commonly used pesticides like glyphosate, HIA examines how people might get exposed to residues in food, water or the environment, quantifies internal doses through biomonitoring, and evaluates dose–response relationships for outcomes such as carcinogenicity or endocrine disruption.

It is important to recognize that causality cannot be derived when epidemiological and experimental evidence is insufficient. Without a robust body of consistent epidemiological findings and experimental studies that confirm biological plausibility, any observed associations remain tentative. This limitation means that while HIA can identify potential risks and highlight areas of concern, it cannot conclusively establish that an evaluated pesticide (e.g. here glyphosate) exposure causes specific adverse health outcomes. Instead, the assessment serves as a precautionary tool, guiding further research, regulatory decisions, and risk management strategies until stronger causal evidence becomes available.

In this report we first provide a general description of the steps we have taken for the HIA and then provide 2 detailed examples of HIA studies for glyphosate with results.

Methodology:

Step 1: Systematic review of literature

First, we performed a systematic review of literature to identify publications on the association of exposure to glyphosate/AMPA/tebuconazole with adverse health outcomes. In this initial phase, we designed and executed a comprehensive search across scientific databases to capture every study linking glyphosate, AMPA, or tebuconazole exposure with adverse health outcomes. We defined precise search terms, date ranges, and language filters to ensure consistency and reproducibility. We catalogued all retrieved records and removed duplicates. Our goal is to assemble a full inventory of published evidence before any screening begins, and step 1 served to find all potentially eligible studies. The search string used in each database is as follows:

Pubmed (https://pubmed.ncbi.nlm.nih.gov/):

(((((Acetamiprid OR Abamectin[Title/Abstract] OR Vertimec[Title/Abstract] OR "Tamaron Gold"[Title/Abstract] OR Asataf [Title/Abstract]OR Lancer[Title/Abstract] OR "td-2480"[Title/Abstract] OR "td-2472"[Title/Abstract]) OR (Glyphosate OR Roundup[Title/Abstract] OR Rodeo[Title/Abstract] OR Touchdown[Title/Abstract] OR KleenUp[Title/Abstract] OR Imitator[Title/Abstract] OR Eraser[Title/Abstract] OR Pronto[Title/Abstract])) OR (Tebuconazole OR Mirage[Title/Abstract] OR "Banner MAXX"[Title/Abstract] OR Alamo[Title/Abstract] OR "Propiconazole 14.3 phosphorous acid salts"[Title/Abstract] OR Alude[Title/Abstract] OR Magellan[Title/Abstract]))

AND

(("Epidemiologic Studies"[Mesh] OR epidemiolog*[Title/Abstract] OR crosssectional[Title/Abstract] OR cross sectional[Title/Abstract] OR cohort[Title/Abstract] OR case control[Title/Abstract])))

AND

(("Neoplasms"[Mesh] OR "Kidney Diseases"[Mesh] OR "Lung Diseases"[Mesh] OR "Heart Diseases"[Mesh] OR "Endocrine System Diseases"[Mesh] OR "Nervous System Diseases"[Mesh] OR "Reproductive Health"[Mesh] OR disease*[Title/Abstract] OR chronic*[Title/Abstract] OR neurological[Title/Abstract] OR reproductive[Title/Abstract] OR cancer[Title/Abstract] OR neoplasm*[Title/Abstract] OR diabetes[Title/Abstract] OR respiratory[Title/Abstract] OR kidney[Title/Abstract])))

NOT (("Animals"[Mesh] NOT "Humans"[Mesh]))

Web of science (https://www.webofscience.com/wos/woscc/smart-search):

TS=((Acetamiprid OR Abamectin OR Vertimec OR "Tamaron Gold" OR Asataf OR Lancer OR "td-2480" OR "td-2472") OR (Glyphosate OR Roundup OR Rodeo OR Touchdown OR KleenUp OR Imitator OR Eraser OR Pronto) OR (Tebuconazole OR Mirage OR "Banner MAXX" OR Alamo OR "Propiconazole 14.3 phosphorous acid salts" OR Alude OR Magellan))

AND

TS=((Disease* OR chronic* OR cancer OR neoplasm* OR neurological OR diabetes OR reproductive OR respiratory OR kidney))

AND

TS=((epidemiolog* OR crosssectional OR cross sectional OR cohort OR case control))

Embase (https://www.embase.com/):

(('neoplasm'/exp OR 'heart disease'/exp OR 'lung disease'/exp OR 'kidney disease'/exp OR 'neurologic disease'/exp OR 'endocrine disease'/exp OR 'genital system disease'/exp OR disease*:ab,ti,kw OR chronic*:ab,ti,kw OR cancer:ab,ti,kw

OR neurological:ab,ti,kw OR neoplasm*:ab,ti,kw OR diabetes:ab,ti,kw OR reproductive:ab,ti,kw OR respiratory:ab,ti,kw OR kidney:ab,ti,kw)

AND

('acetamiprid'/exp OR 'tebuconazole'/exp OR 'glyphosate'/exp OR acetamiprid:ab,ti,kw OR abamectin:ab,ti,kw OR vertimec:ab,ti,kw OR 'tamaron gold':ab,ti,kw OR asataf:ab,ti,kw OR lancer:ab,ti,kw OR 'td-2480':ab,ti,kw OR 'td-2472':ab,ti,kw OR glyphosate:ab,ti,kw OR roundup:ab,ti,kw OR rodeo:ab,ti,kw OR touchdown:ab,ti,kw OR kleenup:ab,ti,kw OR imitator:ab,ti,kw OR eraser:ab,ti,kw OR pronto:ab,ti,kw OR tebuconazole:ab,ti,kw OR mirage:ab,ti,kw OR 'banner maxx':ab,ti,kw OR alamo:ab,ti,kw OR 'propiconazole 14.3 phosphorous acid salts':ab,ti,kw OR alude:ab,ti,kw OR magellan:ab,ti,kw)

AND

('epidemiology'/exp OR epidemiolog*:ab,ti,kw OR crosssectional:ab,ti,kw OR 'cross sectional':ab,ti,kw OR cohort:ab,ti,kw OR 'case control':ab,ti,kw))

NOT

('animal'/exp NOT 'human'/exp)

Step 2: Systematic review of the search results

Two independent reviewers screened titles and abstracts against predefined inclusion and exclusion criteria (see below), considering populations of all ages and geographic regions:

Include:

1. Epidemiological studies with quantitative exposure estimate (objective measurements, modelling based on objective measurements, job/crop exposure matrices) on Acetamiprid, Glyphosate, or Tebuconazole (or synonyms) and chronic non-communicable disease (Cancer, Kidney Diseases, Lung Diseases, Heart Diseases, Endocrine Diseases, Nervous System (neurological) Diseases, and reproductive health).
2. Studies of all age groups.
3. Studies with a comparator (low or no exposed as reference/control group)
4. Studies published in any year and by default in English – studies written in other languages than English will be explored to some extent.

Exclude:

1. Studies on acute toxicity, most importantly acute intoxication.
2. Studies with subjective or qualitative exposure data measures (e.g., self-reported exposures from workers) – BUT with one exception – we included studies from the Agricultural Health Study.
3. Studies on symptoms.
4. Uncontrolled before-and-after studies, qualitative studies, case studies and non-original studies.

Each reviewer flagged studies for potential relevance, then they compared decisions to identify and resolve discrepancies. This dual process minimizes bias and ensures that no

pertinent study is overlooked. The outcome is a curated list of studies meeting basic quality and scope requirements.

We included studies that have investigated one or more of the following three pesticides: acetamiprid (or synonyms: Abamectin, Vertimec, Tamaron Gold, Asataf, Lancer, td-2480, td-2472); glyphosate (or synonyms. Roundup, Rodeo, Touchdown, KleenUp, Imitator, Eraser, Pronto); tebuconazole (or synonyms: Mirage, Banner MAXX, Alamo, Propiconazole 14.3 phosphorous acid salts, Alude, Magellan)

We identified 1362 papers, they were imported to Covidence, and after excluding 355 duplicates we performed title/abstract screening on 1007 papers. 946 papers were excluded; thus 61 papers were full text screened. 27 papers were excluded during full text screening (19 not quantifiable, 1 wrong setting, 3 wrong pesticide, 2 wrong outcome, 1 duplicate, and one study design). Eventually 34 papers were extracted. The search was updated in November 2024 to identify newly published studies. We identified 128 newly published studies, from which based on title and abstract screening, we included 17 additional studies.

Below the flowchart of study selection is presented:

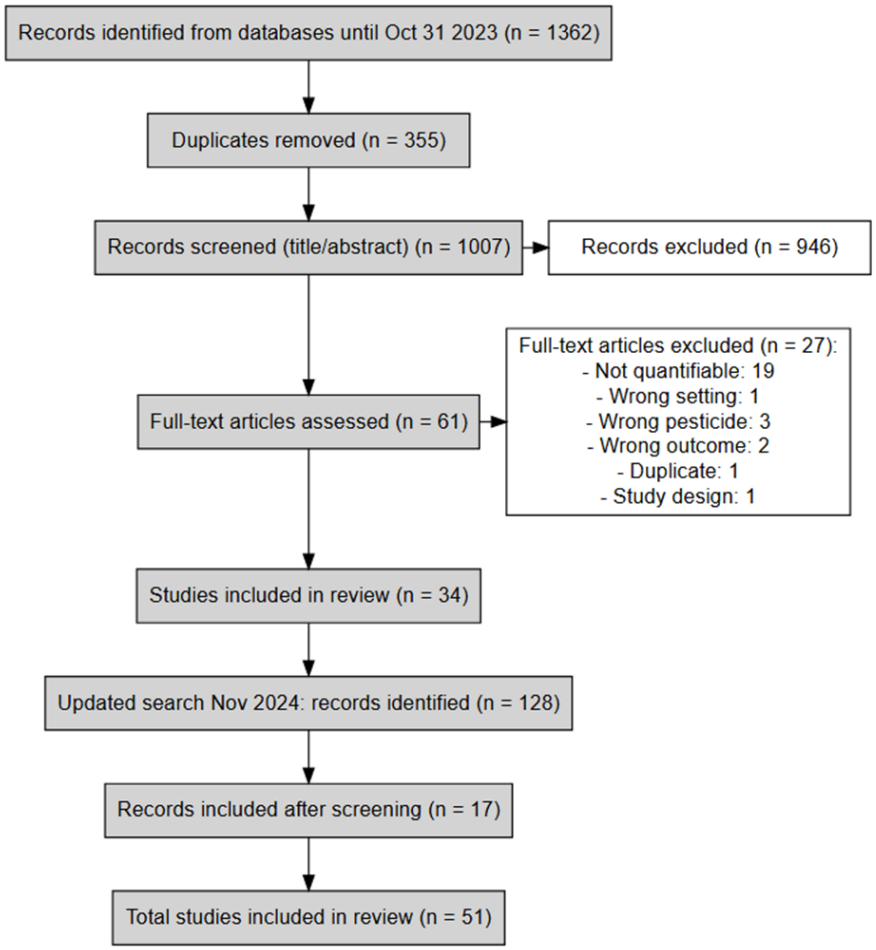

Fig. 10: Flow chart study selection

Step 3: Data extraction

From each included publication, we systematically extracted key information: sample size, measured pesticide concentrations, participant selection criteria, reported risk ratios for defined exposure levels, and the specific exposure assessment method. We entered data into a standardized extraction form. This step transforms narrative and tabular results into a harmonized dataset ready for analysis.

Step 4: Identify and select studies that report on the same adverse health outcome while using the same exposure assessment method

Studies that reported on the same exposure assessment type and identical outcome can be combined. To enable valid pooling (meta-analysis, see step 5), we identified studies addressing the same health endpoint and using identical exposure assessment techniques. For example, we might only advance studies measuring glyphosate in urine via LC-MS/MS that report incidence of non-Hodgkin lymphoma. Aligning outcomes and methods ensured the exposure–response relationships derived later rely on truly comparable data.

Step 5: Meta-analyze the reported risk ratio from the studies with the same method of exposure assessment and same outcome

We pooled the results of the selected studies through meta-analytic techniques to calculate a pooled risk ratio per unit of pesticide exposure. We chose fixed- or random-effects models based on heterogeneity and performed sensitivity analyses to test robustness. The resulting exposure–response function quantifies how incremental changes in exposure translate into changes in disease risk.

Step 6: calculate Population Attributable Fraction (PAF)

The PAF is the proportional reduction in disease incidence that would occur if exposure to the risk factor was reduced or increased to an alternative ideal exposure scenario. The "alternative ideal scenario" (sometimes called "counterfactual") can be a range of different values, for example zero (for a human-made pollution that could be prevented), or any other achievable reduction. In order to calculate the PAF we took the following steps:

1. *Quantify Population Exposure Distribution*. We compiled population-level exposure data using the same assessment method as the Exposure-Response Function (ERF) studies. This produces a distribution of exposure levels across individuals or subgroups in the target population.
2. *Obtain Baseline Disease Prevalence or Incidence.* We gathered epidemiological data on the current prevalence or incidence of the health outcome from national registries or surveys. These figures served as the baseline for estimating cases attributable to exposure. We used previously published data on incidence/prevalence of the disease in the target country, or used data from national/government databases on diseases. In the Netherlands, the https://www.vzinfo.nl/ website contains the data on incidence and prevalence of most many diseases in the Netherlands.
3. *Select the PAF Formula*. We used the following formula to calculate the PAF:

Pi = proportion of population at exposure level i , current exposure

P'i = proportion of population at exposure level i, recommended level of exposure

RRi = the relative risk at exposure level i

n = the number of exposure levels

OR if the exposed proportion of the population is 100%: *PAF= (RR-1)/RR*

4. *Compute Attributable Fraction and Cases.* We calculated the PAF using the chosen formula and then multiplied PAF by the total number of cases to estimate attributable cases. This quantifies the burden that could be prevented under a specified reference exposure. Because the chosen pesticide exposure could in theory be entirely prevented, we selected here a "zero exposure" scenario as our referent.

Application

Example 1: HIA of urinary levels of glyphosate and incidence of metabolic syndrome

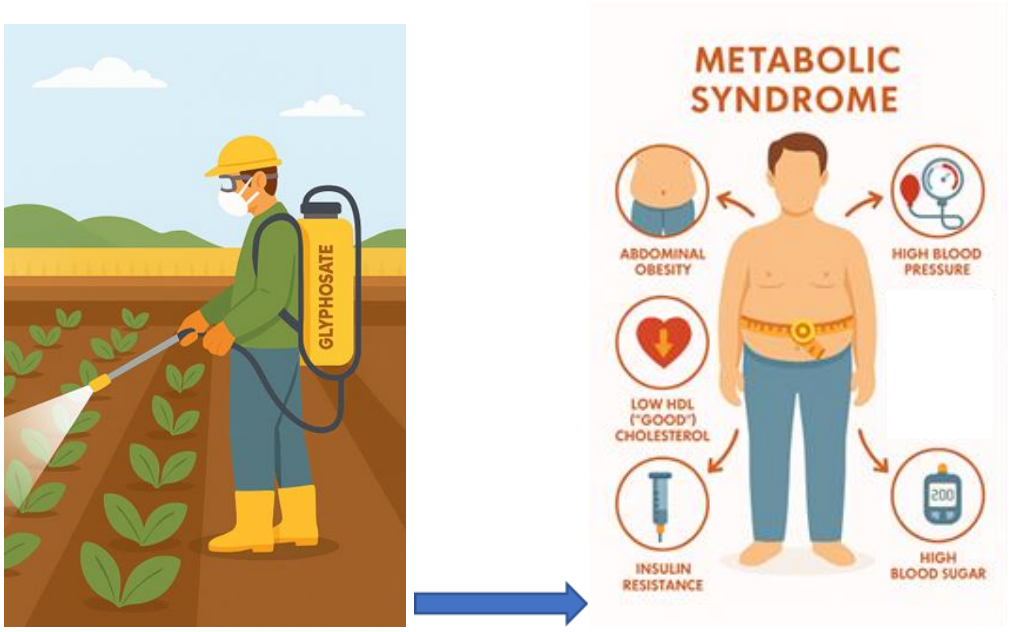

Fig. 11: Illustrations of pesticide application and metabolic syndrome

In the 1st example of HIA, based on the systematic review, we selected two population-based studies investigating the association of urinary levels of glyphosate with incidence of metabolic syndrome. The selection was based on the extracted data to find studies that were reporting on the same outcome with the same method of exposure assessment for the same pesticide. We could not find any other studies on glyphosate, AMPA or tebuconazole that had the same outcome or method. The two selected studies were the following:

1.Eskenazi, Brenda, et al. "Association of lifetime exposure to glyphosate and aminomethylphosphonic acid (AMPA) with liver inflammation and metabolic syndrome at

young adulthood: findings from the CHAMACOS study." Environmental health perspectives131.3 (2023): 037001.].

Glyphosate exposure was evaluated in the CHAMACOS prospective birth cohort (n = 480 mother–child dyads) and a nested case–control group (60 cases of elevated liver transaminases; 91 controls). Two exposure metrics were used: urinary glyphosate residues—calculated as glyphosate + 1.5 × AMPA—measured during pregnancy and at ages 5, 14, and 18; and the amount of agricultural glyphosate applied within a 1 km radius of each residence from birth to age 5. Metabolic syndrome was assessed at 18 years in the full cohort. A twofold increase in urinary glyphosate residues at age 14 was associated with an 88 % higher risk of metabolic syndrome at 18 years (RR = 1.88; 95 % CI: 1.03–3.42). Residence near agricultural glyphosate applications during early childhood was linked to a 53 % increased risk of metabolic syndrome in the nested case–control sample (RR = 1.53; 95 % CI: 1.16–2.02). This study did not check for possible effect modification by sex (via checking the interaction term) and as a result no sex-specific associations could be determined.

2. Glover, Frank, et al. "The association between glyphosate exposure and metabolic syndrome among US adults." Human and Ecological Risk Assessment: An International Journal 29.9-10 (2023): 1212-1225.

Data from the National Health and Nutrition Examination Survey were analyzed to assess the association between urinary glyphosate concentrations and metabolic syndrome, which was defined according to American Heart Association criteria. Urinary glyphosate served as the exposure metric, and chi-square tests, analysis of variance, and multivariable weighted linear and logistic regression analyses were conducted to evaluate relationships.

A total of 338 adults were included, and the prevalence of metabolic syndrome was determined to be 19 %. When treated as a continuous variable, a two-fold increase in urinary glyphosate was associated with a 2.24-fold higher odds of metabolic syndrome (OR = 2.24; 95 % CI: 1.23–4.08). Stratification into exposure quartiles revealed progressively higher odds of metabolic syndrome in quartiles 2 through 4—OR = 1.17 (95 % CI: 0.47–2.89), OR = 1.56 (95 % CI: 0.55–4.55), and OR = 3.29 (95 % CI: 1.38–7.42), respectively—using the lowest quartile as reference. This study did not check for possible effect modification by sex (via checking the interaction term) and as a result no sex-specific associations could be determined.

We meta-analyzed the reported OR for 1-unit increase in glyphosate from the two papers using the following syntax in R:

R Script for meta-analysis:

https://github.com/ArashDer/SPRINT-HIA/blob/main/SPRINT-WP5-HIA-meta-analysis.R

Result of the meta-analysis:

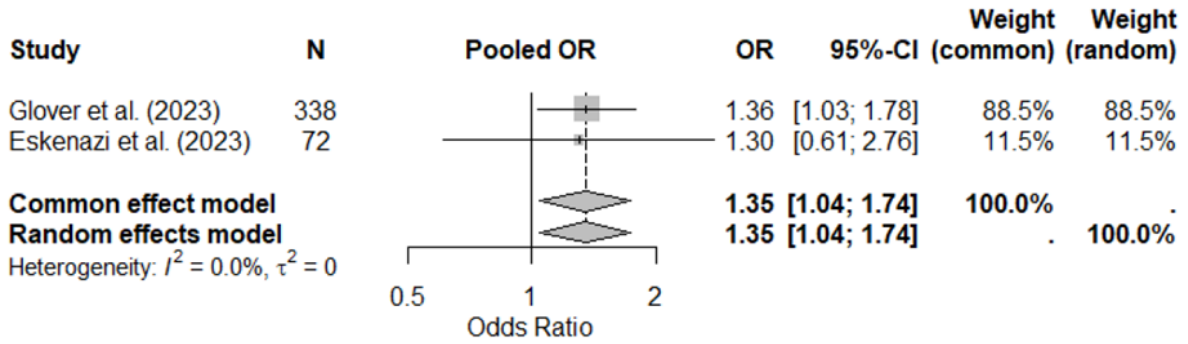

Fig. 12: Meta-analysis of risk estimates from studies that evaluated associations of urinary glyphosate exposure levels with metabolic syndrome

We used the random effect meta-analyzed (summary) OR (95%CI) of 1.35 (1.04 to 1.74) as the ERF for our HIA. However, note that due to absence of heterogeneity between the studies, fixed effects analysis provided the same result.

We estimated metabolic syndrome (MetS) cases in the adult population of the Netherlands, based on the prevalence of 29.2% reported in the paper by Sigit et al. 2020 (Other studies in Dutch and European populations have also reported prevalences of 20.0% [Frentz et al. 2024] and 28.2% [Pigeot et al. 2025] for metabolic syndrome in adults):

MetS Cases=14,500,000 × 0.292≈4,234,000.

The next steps towards HIA are described below:

Inputs and setup

- **Baseline cases:** 4,234,000 metabolic syndrome cases in the Netherlands.
- **Exposure level:** 0.17875 µg/L average urinary glyphosate.
- **Effect estimate (beta):** Natural log of the risk ratio per 1 µg/L.

Note that the average exposure level of glyphosate in urine was derived from the SPRINT case study site data, taking the following steps:

1. Compute beta from the reported risk ratio

- **Calculation:** Beta is the natural logarithm of the risk ratio per unit exposure.

  $\beta = \ln(1.35) \approx 0.3001$

- **Interpretation:** This means that each 1 µg/L increase in urinary glyphosate is associated with a multiplicative increase of *1.35* in risk; the log scale coefficient is *0.3001*.

2. Calculate the risk ratio at the observed exposure level

- **Calculation:** Apply the log-linear model to the average exposure.

$$RR = e^{\beta * exposure_level} = e^{0.3001 * 0.17875} \approx e^{0.05364} \approx 1.0551$$

- **Interpretation:** At the mean exposure of 0.17875 µg/L, the estimated risk is about 5.51% higher than baseline.

3. Compute the attributable fraction (AF)

- **Calculation:** AF is the proportion of cases attributable to the exposure given the estimated RR.

$$AF = RR - 1/RR = 1.0551 - 1/1.0551 \approx 0.0551 1.0551 \approx 0.0522$$

- **Interpretation:** Approximately 5.22% of cases are attributable to exposure at this average level.

4. Estimate the number of attributable cases

- **Calculation:** Multiply AF by the baseline number of cases.

$$Attributable\ cases = AF * baseline_cases = 0.0522 * 4{,}234{,}000 \approx 221{,}143$$

- **Interpretation:** About 221,143 metabolic syndrome cases are attributable to the exposure under these assumptions.

Rounded results

- **Attributable fraction (AF):** 0.0522
- **Attributable cases:** 221,143

R script for the above calculations: https://github.com/ArashDer/SPRINT-HIA/blob/main/SPRINT_WP5_HIA_Example1_MetS.R

In the above calculation exercise, we showed that the attributable cases of metabolic syndrome in the Netherlands in the year 2020 due to exposure to glyphosate could be nearly 221,143. These results should be interpreted with caution, as the current evidence base does not provide strong epidemiological support from large, well-designed human population studies. While the calculations suggest a potentially high burden of metabolic syndrome cases attributable to glyphosate exposure, such estimates rely on assumptions drawn from limited data and may not accurately reflect real-world risks. Without consistent findings across diverse populations and robust experimental confirmation of biological mechanisms, the observed associations remain uncertain. To move beyond preliminary estimates and better understand the true health implications, more comprehensive population-based studies are needed to investigate the relationship between glyphosate exposure and adverse outcomes, including metabolic diseases. The lack of epidemiological evidence is due to a limited number of studies that have been performed on this issue. With this calculation exercise we showed that the potential impact on public health could be very large because of the combination of two contributing factors: a high prevalence of exposure (many people are exposed) and a high prevalence of metabolic syndrome in the population.

Example 2: HIA of glyphosate for atrial septal defect:

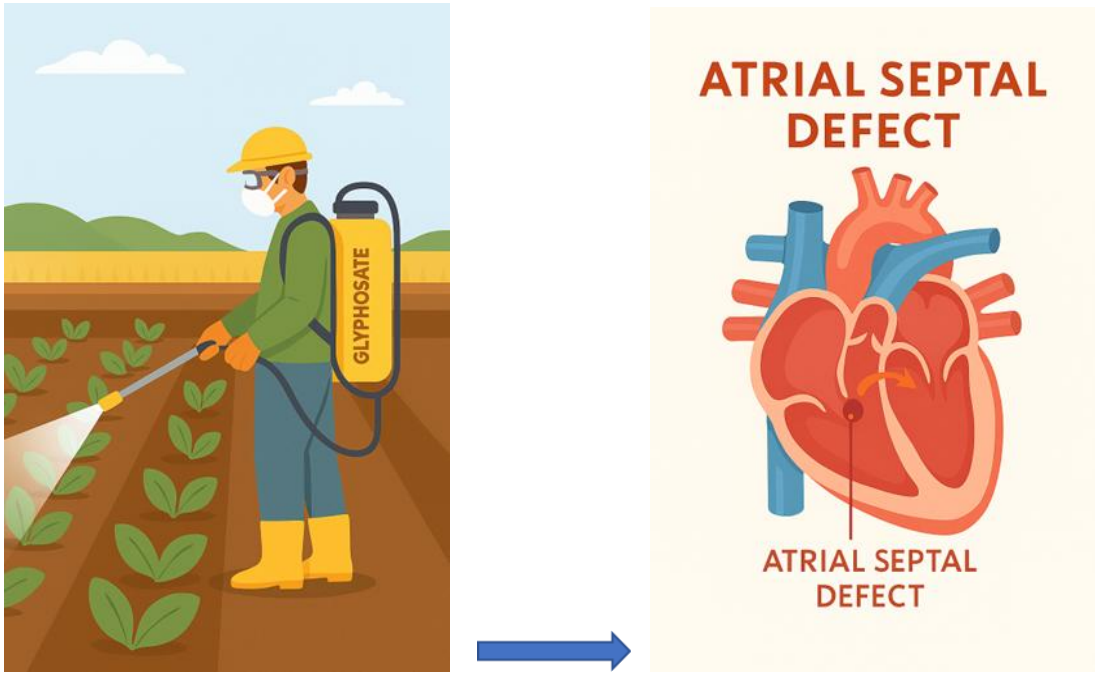

Fig. 13: Illustration of pesticide application and atrial septal defect

Step 1: Defining the Health Outcome and Exposure Categories and Data Extraction

A systematic review of the literature (and data extraction) was performed by two reviewers to identify epidemiologic studies reporting on adverse health outcomes of exposure to glyphosate. Based on quality of data, significance of results and method of exposure assessment, we decided to use the odds ratios (OR) reported by Rappazzo et al 2018 for percentiles of sum of pounds of glyphosate applied to any crop in 500 meter buffer during exposure window, with the target population of pregnant women and health outcome of atrial septal defect. Rappazzo et al 2018:

Table 7: Associations of glyphosate exposure percentile groups and risk of atrial septal defect (Rapazzo et al 2018)

	Groups	N control (%)	N ASD (%)	OR (95%CI)
Glyphosate	unexposed= referent	165,996 (56)	514 (50)	ref
	<10th percentile	13,282(4)	45 (4)	1.12 (0.82, 1.52)
	10-50th percentile	53,432(18)	186 (18)	1.14 (0.96, 1.35)
	50th-90th percentile	52,642 (18)	203 (20)	1.24 (1.06, 1.46)
	>90th percentile	13,196 (4)	72 (7)	1.72 (1.35, 2.21)

It should be noted that this study has not considered possible foetal sex-specific associations, due to the low number of exposed cases.

We contacted the author to acquire the corresponding levels of glyphosate for each percentile in pounds and converted the number to kilograms (kg):

Table 8: Associations of glyphosate exposure percentiles translated to amounts applied (Rapazzo et al 2018, personal communication)

	Groups	**Dose in pounds**	**Dose in kg**
Glyphosate	unexposed=referent	0	
	<10th percentile	0 < to <= 0.12463	0 to 0.057
	10-50th percentile	0.12463 < to <= 1.38832	0.57 to 0.63
	50th-90th percentile	1.38832 < to <= 20.9386	0.63 to 9.5
	>90th percentile	> 20.9386	> 9.5

Step 2: xxxxxxxx

We acquired the sum of kg of glyphosate applied to any crop in 500-meter buffer in 2020 for any grid in the Netherlands (N of grids= 2,256,482). Then we acquired the number of newborns within each grid in the Netherlands in 2020 and merged the two files (N of grids=9,144). The subset of grids with newborns in 2020 includes 1,141,440 total residents with N= 48,380 newborns.

In order to merge the information of number of newborns per grid, we downloaded the freely available data on this from CBS, and merge the data based on coordinates with the exposure file [https://www.cbs.nl/nl-nl/dossier/nederland-regionaal/geografische-data/kaart-van-100-meter-bij-100-meter-met-statistieken] .

The R script below shows the steps of merging.

https://github.com/ArashDer/SPRINT-HIA/blob/main/SPRINT_WP5_HIA_Example2_merging_exposure_population.R

Below are the maps of newborns N in the Netherlands in 2020 and the distribution of glyphosate exposure.

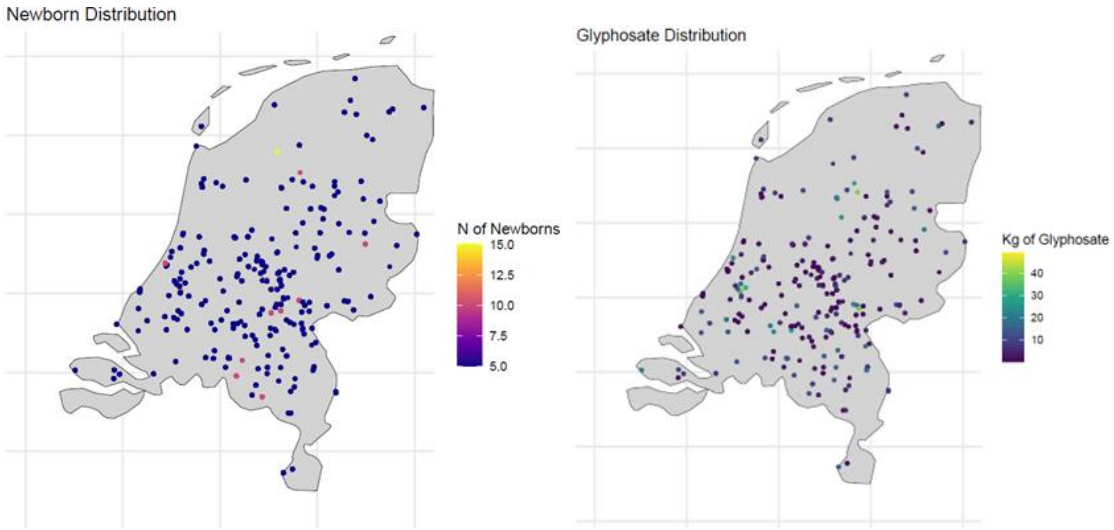

Figure 14: Localisation of newborns per grid cell and corresponding applied amounts of glyphosate in the surrounding

Step 3: Apply the glyphosate cut-offs based on Rappazzo et al 2018 to our measured glyphosate exposure

Table 9: Assigning the cut-offs of glyphosate application (Rapazzo et al 2018) to newborns

Glyphosate Dose in kg	N (%) of newborns
unexposed	200 (0.4)
0 to 0.057	1570 (3.1)
0.57 to 0.63	8255 (17.4)
0.63 to 9.5	28060 (59.2)
> 9.5	10295 (19.9)

Step 4: Calculate the Attributable Fraction (AF)

Based on the reported ORs, the Population Attributable Fraction (PAF) was calculated using the following formula:

$$AF_i = \frac{(OR_i - 1) \times P_i}{1 + (OR_i - 1) \times P_i}$$

Where:

OR_i : Odds ratio for exposure category i relative to the reference group (no exposure).

P_i : Proportion of the population in the exposure category.

The PAFs according to each glyphosate exposure group in our population was the following:

Table 10: Calculation of the PAF per amount of pesticide applied in the vicinity

Dose in kg	PAF %
0 to 0.057	0.37
0.57 to 0.63	2.36
0.63 to 9.5	12.5
> 9.5	12.5

Step 5: Calculate the Total Population Attributable Fraction (PAF)

Next, we calculated the overall PAF based on the following formula:

$$PAF = \sum AF_i \times P_i$$

Where:

AF_i : Attributable Fraction for each category of glyphosate exposure.

P_i : Proportion of the population in exposure categories of glyphosate.

Overall PAF= 0.103

Step 6: Estimate the Impact on Health Outcome

The incidence of ASD in the Netherlands according to https://www.vzinfo.nl/aangeboren-afwijkingen-van-hartvaatstelsel/leeftijd-en-geslacht/geboorteprevalentie is 6 per 10,000 live births per year.

N of newborns in 2020 in our file is 48,380, thus expected cases of ASD in 2020 in our file = 48380 * (6/10000)= 29 expected cased of ASD

We calculated the attributable cases of ASD due to exposure to glyphosate, based on the following formula:

Attributable cases=PAF×Total cases of ASD in the population

Attributable cases= 0.103 *29=3 cases of ASD per year

R script to perform steps 3-6: https://github.com/ArashDer/SPRINT-HIA/blob/main/SPRINT_WP5_HIA_Example2_steps_3_6.R

In this example we show that there could be 3 possible cases of ASD among newborns due to maternal exposure to glyphosate in the Netherlands in year 2020**.** Similar to example 1, these findings should be interpreted with caution, as the current body of evidence does not provide strong epidemiological confirmation from large-scale, well-conducted human studies. Although the calculations point to a possible contribution of glyphosate exposure to the occurrence of ASD, such estimates are based on limited data and rest on

assumptions that may not accurately capture real-world risks. In the absence of consistent results across diverse populations and without solid experimental evidence to clarify biological mechanisms, the suggested associations remain speculative. To gain a clearer understanding of potential health effects, more rigorous population-based research is needed to examine the link between glyphosate exposure and adverse outcomes, including congenital heart defects such as atrial septal defect.

Shiny app for calculation of attributable fraction and cases

To facilitate simulation of HIA in different scenarios of exposure levels, exposure-response-function, we have made a simple Shiny app available at https://aderakhshan.shinyapps.io/SPRINT-HIA4/. In this app the user can enter the desired exposure level in the biological sample, the ERF with the option to provide the 95%CI, as well as extra options to provide the baseline prevalence of the outcome (and total population). The app will then show as a result the calculated attributable fraction as well as attributable cases, with a graphical representation of the changes of AF and prevalence with the increase in exposure.

Monte Carlo simulation Shiny App

https://aderakhshan.shinyapps.io/Monte_Carlo_Simulation/

This is a Monte Carlo simulation tool to estimate potential health effects from exposure to multiple pesticides. It lets the user define exposure distributions and dose–response slopes for three pesticides, combine them under different interaction assumptions (additive, synergistic, antagonistic), and then calculate population-level health impacts.

How it works:

Inputs (sidebar):

Number of simulations (e.g. 10,000).

Exposure parameters for pesticide 1– pesticide 3 (lognormal mean & SD).

Dose–response slope ranges (95% CI).

Interaction type (additive, synergistic, antagonistic) with multiplier.

Population size and disease prevalence.

Simulation (server):

For each pesticide:

Draw exposures from a lognormal distribution.

Draw slopes from a normal distribution based on CI.

Multiply exposure × slope → effect distribution.

Combine pesticides effects:

Additive = sum of effects.

Synergistic = sum × multiplier (>1).

Antagonistic = sum × multiplier (<1).

Interpret combined effect as Relative Risk (RR).

Compute Attributable Fraction (AF) = (RR-1)/RR.

Compute Attributable Cases (AC) = AF × (population × prevalence).

Outputs (main panel):

Histogram: distribution of simulated health effects.

CDF plot: cumulative distribution of health effects.

Summary stats: mean and 95% CI for AF and AC, plus descriptive stats of effects.

This app lets you explore how uncertain exposures and dose–response relationships for multiple pesticides translate into population-level health risks. It shows both the distribution of possible outcomes and summary measures like attributable fraction and cases.

Further information on the methods and interpretation of the results are provided in the README section of the app.

Limitation

As mentioned above, our HIA tool is based on limited data and rest on assumptions that may not accurately capture real-world risks. In the absence of consistent results across diverse populations and without solid experimental evidence to clarify biological mechanisms, the suggested associations remain speculative. To gain a clearer understanding of potential health effects, more rigorous population-based as well as sex-specific research is needed to examine the link between glyphosate exposure and adverse outcomes, including congenital heart defects such as ASD. Our HIA highlights the fact that, despite the relevance and importance of studying the health impact of exposure to pesticides, not enough attention has been given to perform human population-based studies on pesticides and adverse health outcomes.

Toxicity/Ecotoxicity

Human and Animal Toxicity Results

Description

The widespread use of pesticides in agriculture makes it important to understand the long-term effects on animal and human health. Nevertheless, knowledge on the effects of pesticides and, even more so, their mixture is still fragmented and unequal. This is why the SPRINT project aimed to assess the effects of pesticides mixtures on animals and humans using in silico, in vitro and in vivo methods. The results of these assessments are the focus of this tool.

The SPRINT toxicity assessment was done in WP4 by adopting a tiered approach based on the EFSA guidelines for combined exposure to multiple chemicals using a component-based approach (EFSA, 2019). In particular, we used available data and in silico modelling to assess the top 20 pesticides of concern (Tier 1), then studying in vitro models for the top 10 pesticides of concern (Tier 2) and then studying in vivo only the Top 3 pesticides of concern (Tier 3).

This tool presents the main results obtained from the different experiments performed, with the objective to make them readable and informative for the widest possible audience.

Methodology

A tiered approach has been used in the SPRINT project based on the EFSA guidelines for combined exposure to multiple chemicals using a component-based approach (EFSA, 2019). Here we present in more detail the approach used for animal toxicity testing much similar as used for human toxicology.

In Tier 1, based on the available data from the SPRINT CSS on over 200 AS and in silico modelling, the top 20 pesticides of concern were assessed and prioritized for in vitro testing based on occurrence and weighted Hazard Quotient (wHQ). A systematic procedure was developed (Scheepers et al., 2022) to prioritise pesticides for toxicology testing using a systematic stepwise procedure based on occurrence (exposure), hazard and risk information. The decision to select the top 10 pesticides to be tested for the in vitro studies was through occurrence via SPRINT CSS data, and by toxicity, based on updates of the EFSA guidance on Acceptable Daily Intake (ADI) and Acceptable Operator Exposure Level (AOEL).

In Tier 2, standard in vitro models such as cytotoxicity assays and micronuclei assays (EFSA tests) along with new models like kidney cells assays and organoid assays (New Sprint Indicators) were used to test the Top 10 pesticides and mixtures of concern. This battery of assays allowed to show cytotoxic and genotoxic effects in a linear and additive dose-response (no synergistic effects observed), along with alterations of piglet organoids and human kidney cell line viability and transcriptome.

In Tier 3, standard in vivo models such as the 13-weeks toxicity study in rats exposed from prenatal life (EFSA tests) along with new models like a series of behavioural and microbiome studies in mice (so-called New Sprint Indicators) were used to test the Top 3 pesticides of concern (glyphosate, acetamiprid and tebuconazole) and their mixtures. In addition, two other analyses were performed based on samples derived from the main studies: microbiome analyses in rats and kidney microscopy and morphometric analyses in rats and mice. These assays highlighted endocrine disruptive effects, liver toxicity, kidney toxicity, microbiome and behavioural alterations, even at doses corresponding to levels that are currently considered safe in humans (or without adverse effects in animals, i.e. between ADI and NOAEL).

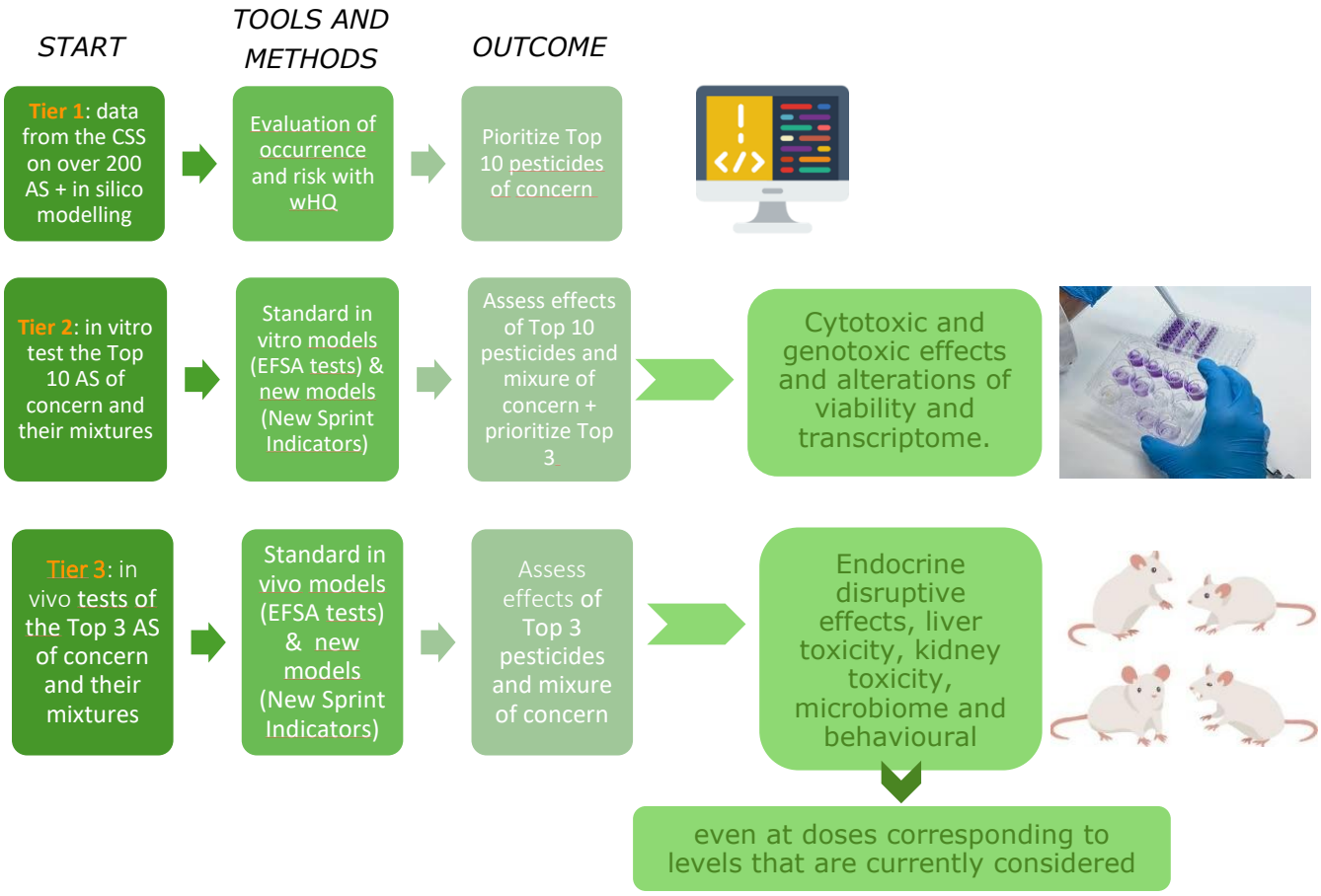

Figure 15 – Overview of the tool underlying workflow.

This tool presents the main results from all the studies and assays performed in this part of the SPRINT project, together with plots and graphical representations whenever possible to improve readability; an effort is made to aggregate and visualize results specified by sex, system/organ and substance.

Application

This tool helps to browse the toxicity studies performed within the SPRINT project and their results. In a clear and structured way it provides new information and insights into the hazards and risk for human health linked to the exposure to the op Top 3 pesticides of concern and their mixture based on the SPRINT CSS monitoring result, allowing to integrate the actual knowledge and filling gaps for both further scientific research and policy decisions relating to pesticides use, limits and authorizations, as well as informing the public about the possible consequences for workers, neighbours living close to pesticide field applications and consumers in general.

An intriguing and innovative feature is the very low doses that were tested in the experiments starting from pre-natal life. This allows for drawing conclusions that can be considered relevant to the general population, informing all actors about the outcomes related to a realistic exposure scenario. This includes sensitive time windows of exposure such as during pregnancy and developmental age. The same consideration is valid for the fact that mixtures are considered, which provide again both innovative and realistic information, and represents a branch that needs to be further researched.

Another useful feature is the variety of outcomes of interest that were investigated (cytotoxic and genotoxic effects, toxicity, neurotoxicity and behavioural effects, microbiome alterations etc). This can shed light on the multiple dimensions of health, some of which were previously often overlooked. Instead they should all be taken into account, for example in the debates that shape the public perception on pesticides and policies, as well as in academic and research context. This will ensure that knowledge gap can be filled, and uncertain aspects can be analysed more in depth.

From a methodological point of view, we found that the combination of tests and indicators that SPRINT used can represent a valid approach for future research: the New SPRINT Indicators, which include both in vitro and in vivo, proved to be sensitive and relevant for different toxicological endpoints of interest. The mechanistic information provided by these New SPRINT Indicators informs hazard assessment on standard endpoints such as in vitro kidney toxicity and in vivo behavioural effects as well as new endpoints such as in vivo microbiome effects. Our tiered approach was successful and allowed optimization of resources on pesticides of greatest concern: all pesticides that were tested in Tier 2 and 3 showed at least one positive signal. Our in vitro and in vivo human toxicology findings confirm that a component-based approach is predictive and adequate for hazard and risk assessment of mixtures.

Limitation

The New SPRINT Indicators need further validation for using in risk assessments and pre-market evaluations. Furthermore, technical limitations such as e.g. solubility of the mixture components and the number of components that can be tested in a single run represent important challenges for adequate dose-response modelling in human toxicological studies of mixtures, both in vitro and in vivo.

Ecotoxicity results

Description

A significant goal of the SPRINT project was to conduct ecotoxicity testing of pesticide mixtures on aquatic and terrestrial non-target species. The focus of that effort is not only on standardized single-species low-tier assays with EFSA test organisms but also on native species, new endpoints, and higher-tier testing systems, named hereby SPRINT indicators (Fig. 16).

The testing concept chosen for the SPRINT project was based on a whole-mixture approach, where organisms are exposed to the pesticide mixtures and the effects are evaluated.

Selection of the pesticide mixtures was based on a prioritization process using the pesticide residue data based on the SPRINT survey 2021 performed at case study sites (CSS), substance properties, and hazard data (Abrantes et al., 2024; Jegede et al., 2025).

This tool presents the main results obtained from the different ecotoxicity experiments performed, with the objective to make them readable and informative for the widest possible audience.

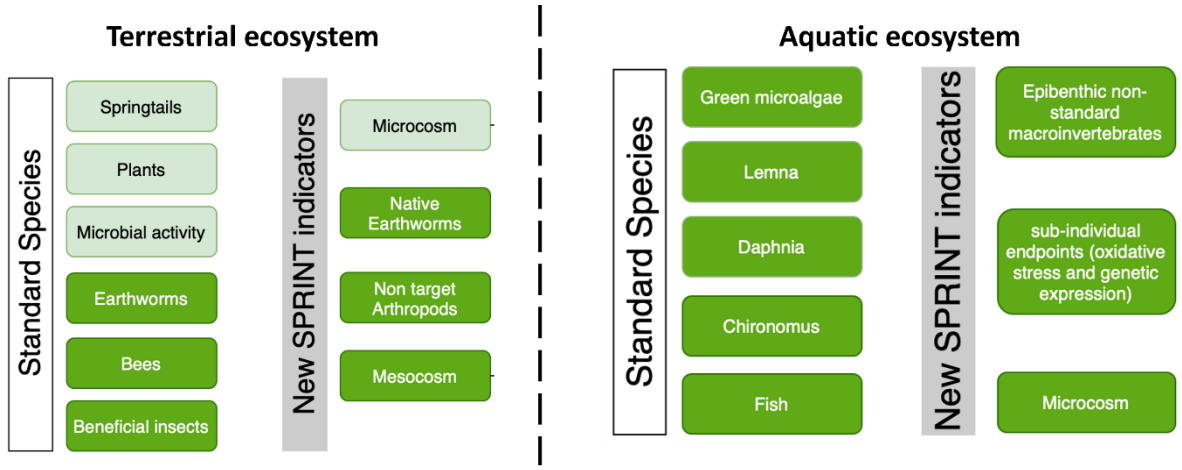

Figure 16 – Overview of the ecotoxicological assays considered

Methodology

Terrestrial ecotoxicity tests were conducted on a range of organisms, including earthworms, springtails, terrestrial plants, soil microbes, beneficial insects, and bees. These tests followed, or were adapted from, standard guideline protocols and were performed either in laboratory or greenhouse settings. Test organisms were exposed to pesticide mixtures applied to agricultural soil, except for bees and beneficial insects, which were exposed via contaminated food sources. In addition to single-species tests, a tiered approach was applied. A terrestrial microcosm study was conducted using the most toxic pesticide mixture identified for earthworms. This higher-tier test assessed the combined

effects of the mixture on earthworms, plants, and soil microbial activity over a 56-day period.

Aquatic ecotoxicity tests included multiple trophic levels, such as algae, aquatic plants, crustaceans, and fish. Standard guideline protocols were followed for acute toxicity, growth inhibition, and reproduction endpoints. All mixtures were prepared in the laboratory. A tiered approach was also applied to the aquatic tests, progressing from basic laboratory assessments to more complex, higher-tier evaluations. At the highest tier, an aquatic microcosm experiment was conducted using a simplified trophic chain model. This included a primary producer (watercress), a primary consumer (shrimp), and a secondary consumer (red swamp crayfish), allowing the assessment of mixture effects across multiple trophic levels.

Application

A battery of ecotoxicological tests is required for the authorization of pesticides. These tests are typically conducted using individual active substances, however organisms are exposed to complex mixtures of multiple pesticides in the environment. Assessing the toxicity of realistic pesticide mixtures, based on both measured and predicted environmental concentrations, provides important new insights for environmental risk assessment. This approach helps determine whether pesticides, when present as mixtures, still comply with legal safety thresholds, and highlights potential risks that may be underestimated when only single-substance tests are considered.

The results from the ecotoxicity tests helped fill important knowledge gaps regarding the effects of complex pesticide mixtures on a wide range of species. By testing mixtures with realistic compositions, the study provided valuable data on how multiple pesticides interact and affect different organisms.

Limitation

A key limitation of the ecotoxicity tests was that the individual contribution of each pesticide to the observed effects remained unknown. The test design followed a whole-mixture approach, which enabled the assessment of several mixtures. For determining the role of individual substances, a component-based approach (where single substances are tested as well as binary, tertiary, and quaternary combinations) would be required. However, the data generated provided a valuable basis for future studies to investigate mixture composition and specific contributions in more detail.

Models library

Description

This tool is a library of models relevant to pesticide fate and transport in various environmental compartments (soil, water, air, and multimedia systems). It was created to systematically collect, describe, and facilitate access to models identified through a dedicated review. It serves multiple purposes:

a. To support the selection of appropriate models for pesticide fate assessments in projects such as SPRINT.
b. To document models that were actually applied in SPRINT Work Packages, notably WP3 (environmental fate modelling) and WP5 (exposure and risk assessment).
c. To host models newly developed within SPRINT, such as the SWIPPE model for spatial prediction of pesticide concentrations from wind-erosion.
d. To identify knowledge gaps in pesticide fate modelling.

This resource is needed because the landscape of pesticide fate models is broad and scattered across academic publications, technical reports, and regulatory documents. A consolidated, searchable library helps scientists, regulators, and other stakeholders quickly identify models suited to specific assessment needs. Other platforms exist, such as the https://www.pesticidemodels.eu/, however this often only showcases few models from the many available in the field.

Overall, the models tool serves as a reference hub for pesticide fate models identified and/or used within SPRINT, including the SWIPPE (wind-erosion model) developed within WP3, supporting transparent model choice and encouraging harmonization across studies. As future studies or new regulations emerge, the library can be updated to remain a current and practical resource.

Methodology

Scoping review: The model inventory was built by systematically searching:

SCOPUS for peer-reviewed literature and Google search engine for grey literature (e.g. regulatory guidance, institutional reports). The following keywords were used:

> ("Pesticide" OR "PPP[9]") AND ("Water" OR "Soil" OR "Air" OR "multimedia") AND ("model" OR "simulation" OR "calculation")

Screening & data extraction:

Identified documents were screened for relevance. Information on model name, purpose, environmental compartment(s), input requirements, outputs, and references was

[9] Please note that the more generic pesticide terminology used in this deliverable and SPRINT in general, to reflect the inclusion of some dual use substances (approved as PPP and as biocide) into the list of substances under investigation, along a comprehensive PPP list.

extracted into a structured database. Specific contacts and information about the model being open-source or "available upon request" were extracted when available.

Integration of SPRINT-specific applications:

Models selected and used in SPRINT WP3 and WP5 for environmental fate simulations (e.g. spatial modelling of PECs) were highlighted.

The newly developed SWIPPE model was documented and included in a separate tab.

Tool implementation:

The collected data were processed and catalogued using Excel sheets and exported for online viewing via the SPRINT toolbox platform.

Application

This tool allows the scientists to identify suitable models for pesticide transport and multimedia fate analysis, assess input data requirements, and explore opportunities for model integration in future studies. This tool also provides insights for the policy makers to understand which models are commonly used for regulatory fate assessments, their limitations, and which were actually employed in SPRINT supporting evidence-based policy design. It also gives the general public transparent information and access to the tools underpin environmental pesticide assessments, promoting trust in model-based decision making.

Limitation

While this library offers a consolidated view of pesticide fate models, note the following:

Scope limitations:
The scoping review was restricted to SCOPUS-indexed peer-reviewed literature and grey literature accessed via Google using specified keywords. Models published outside these channels or under different terminology might not be captured. Hence, if a user notices a model is missing, we invite them to send an email with the relevant model information to be added to the tool.

Lacking of model performance evaluation:
The tool does not benchmark or validate model performance. Users seeking quantitative model intercomparison or suitability checks for specific local conditions should perform their own testing or look into more detail into available documentation for each specific model.

Not a platform for direct simulation:
The tool does not execute model runs; it merely catalogues models with links to original sources or code where available.

Species, processes, or regions not explicitly covered:
Some models are generic or focus on specific crop systems, climatic zones, or regulatory

contexts. Users must assess the relevance of a model's assumptions and scope before applying it to new cases.

Tool should not replace expert judgement:
While helpful for screening options, model selection still requires expertise to evaluate input data availability, boundary conditions, and regulatory acceptability.

Impact & Future Use of the toolbox

Enhancing Accessibility and Integration of Knowledge

THE GLOBAL HEALTH RISK ASSESSMENT TOOLBOX - the SPRINT toolbox - is an open-access, web-based platform designed to support policymakers, regulators, researchers, and the general public in understanding pesticide risks. The toolbox impacts diverse target groups via improving their access to data on pesticide occurrence, environmental fate, exposure, and (eco)toxicological effects. It helps to streamline the impact of the entire SPRINT project via integrating the project results on one platform – a website with multiple tools linking exposure measurements (from WP2/WP3) and modelling (using already existing big data) with hazard data (from WP4 and literature) to assess ecological risks and impacts on human health.

Methodological Innovation and Multi-Scale Approach

The SPRINT Toolbox provides an important step in developing the underlying methodology and vision to using big data on pesticide use, authorisation and monitoring to predict the pesticide exposure distributions across ecosystems and populations in Europe and assess their risks. The toolbox brings not only new measurements from the SPRINT project but also builds on existing pesticide-related big data in EU to predict pesticide exposure distributions across ecosystems and populations in Europe and assesses risks for human health and ecosystems. The big novelty is that the approach is independent of monitoring actions or farmers' surveys. It works as a demonstration of post-registration tools that are currently lacking to support EU pesticide-reducing policies. This demonstration is particularly timely given the recent withdrawal of the Sustainable Use Regulation (SUR); without binding regulation, there is an urgent "policy vacuum" where the Toolbox can serve as a critical blueprint for monitoring and risk assessment that keeps the "Farm to Fork" ambition alive. The toolbox is unique in its use of different scales: from the local CSS level to regional, national, and European levels. Scaling up existing pesticide data improves evaluation of the exposure and risk to the environment and human health across selected countries in Europe, supporting targeted risk reduction at the European, national, and regional level. Consequently, the toolbox presents not only the SPRINT results from large monitoring campaign but also demonstration of modelling approaches of pesticide exposure and risk at the large scale, complementing the value of monitoring.

Identification of Spatio-Temporal Risks and Hotspots

There is a need for approaches that identify risks and impacts from real pesticide uses with spatial resolution (showing geographic hotspots for risk) and across timescales (allowing for the assessment of trends in risk). The pesticide concentration maps predict the pesticide exposure distributions across ecosystems. Together with ecological risk maps they identify the most harmful agricultural practices and pesticide uses, based on real pesticide usage, to elucidate the spatio-temporal cumulation of hazardous exposures and unacceptable risks resulting from the spatio-temporal combination of crops and pesticide applications, and to indicate the cumulative risks of environmental pesticide mixtures based on typical application series and crop treatment scenarios. By pinpointing which crops, farming methods, and pesticide applications pose the greatest risks, policymaker and regulator can more effectively target interventions, prioritize action, withdrawal or substitution. Moreover, this can be done explicitly geographically.

Digital Support for Policy and Sustainable Transition

The SPRINT Toolbox provides practical tools to strengthen risk assessments by regulators and scientists and, in turn, guide environmental and health protection policies. Presenting these data as interactive presentations, models, and maps provides digital support for decision-making and strategy-building in pesticide-related policy and governance. Such tools can help to track changes in pesticide risk, evaluate mitigation strategies or policies and prioritise regions for intervention. So, the SPRINT Toolbox is a policy-ready tool that identifies clusters of risk to ecosystem and human health, based on real patterns of pesticide usage, allowing for informed pesticide reduction strategies, at the national and EU level. The toolbox can help to direct sustainable agricultural production and to support more evidence-based and tailored agri-environmental policy. The toolbox provides tools for visualizing and estimating the health impacts of pesticides on ecosystems and humans. The toolbox directly supports the Farm to Fork Strategy and the Sustainable Use Directive (SUD) by providing: i) Better Indicators: Moving beyond simple sales-based indicators (like HRI 1)—which are fundamentally flawed because they rely on sales volume rather than actual toxicity or exposure pathways—to risk-based indicators that account for toxicity and spatial usage patterns; ii) Targeted Intervention: The maps allow policymakers to identify high-risk regions or cropping systems for targeted reduction or substitution strategies; iii) Harmonization: SPRINT recommends harmonizing national pesticide usage registries to enable this type of upscaling and modelling at the EU level.

Advocacy for Data Harmonization

Finally, the tools showcase what kind of information is available if the right supporting data exists. They highlight the need for public disclosure and harmonization of pesticide-related data (usage statistics and authorization data, including information on pesticide application mixture, timing, quantity, crop, localisation and application method) to support transparent pesticide exposure and health impact assessment at EU level. With improvements to EU-level data harmonization of pesticide usage and authorisations, the toolbox methodology could be used to determine highest-risk pesticide application patterns and cropping

systems across Europe, motivating measures with a large potential for protecting health and the environment.

References

Abrantes, N., Pereira, J. L., González, A. B. M., Campos, I., Navarro, I., De la Torre, A., Martínez, M. Á., Osman, R., Khurshid, C., Harkes, P., & Lwanga, E. H. (2024). Towards a comprehensive methodology for ecotoxicological assessment: Prioritizing plant protection products for mixture testing in edge-of-field surface waterbodies. Science of the Total Environment, 956, 177322.

Ballabio, C., Panagos, P., & Monatanarella, L. (2016b). Mapping topsoil physical properties at European scale using the LUCAS database. Geoderma, 261, 110–123. https://doi.org/10.1016/j.geoderma.2015.07.006

Benfenati, E., Manganaro, A., & Gini, G. (2013). VEGA-QSAR: AI inside a platform for predictive toxicology. In Proceedings of the Workshop on Popularize Artificial Intelligence (PAI 2013). http://ceur-ws.org/Vol-1107/paper8.pdf

Berenzen, N., Lentzen-Godding, A., Probst, M., Schulz, H., Schulz, R., & Liess, M. (2005). A comparison of predicted and measured levels of runoff-related pesticide concentrations in small lowland streams on a landscape level. Chemosphere, 58, 683–691. https://doi.org/10.1016/j.chemosphere.2004.05.009

Bey, I., Jacob, D. J., Yantosca, R. M., Logan, J. A., Field, B. D., Fiore, A. M., Li, Q., Liu, H. Y., Mickley, L. J., & Schultz, M. G. (2001). Global modeling of tropospheric chemistry with assimilated meteorology: Model description and evaluation. Journal of Geophysical Research: Atmospheres, 106, 23073–23095. https://doi.org/10.1029/2001JD000807

Dijkman, T. J., Birkved, M., & Hauschild, M. Z. (2012). PestLCI 2.0: A second generation model for estimating emissions of pesticides from arable land in LCA. The International Journal of Life Cycle Assessment, 17, 973–986. https://doi.org/10.1007/s11367-012-0439-2

Fischer, G., Nachtergaele, F. O., Van Velthuizen, H., Chiozza, F., Franceschini, G., Henry, M., Muchoney, D., & Tramberend, S. (2021). Global agro-ecological zones v4 – Model documentation. Food & Agriculture Organization.

Franco, A., Vieira, D., Clerbaux, L. A., Orgiazzi, A., Labouyrie, M., Köninger, J., Silva, V., van Dam, R., Carnesecchi, E., Dorne, J. L. C., & Vuaille, J. (2024). Evaluation of the ecological risk of pesticide residues from the European LUCAS Soil monitoring 2018 survey. Integrated Environmental Assessment and Management, 20(5), 1639–1653.

Gutsche, V., & Strassemeyer, J. (2007). SYNOPS – Ein Modell zur Bewertung des Umwelt-Risikopotentials von chemischen Pflanzenschutzmitteln. Heft, 9, 197–210.

Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G., & Jarvis, A. (2005). Very high resolution interpolated climate surfaces for global land areas. International Journal of Climatology, 25(15), 1965–1978. https://doi.org/10.1002/joc.1276

Jegede, O., Tourinho, P. S., Geissen, V., & Hofman, J. (2025). Prioritization of currently used pesticides in soils of main European cropping systems and an Argentinian cropping system for assessment of mixture toxicity and risk on terrestrial biota. Journal of Hazardous Materials, 495, 138942.

Jolliet, O., Wannaz, C., Kilgallon, J., Speirs, L., Franco, A., Lehner, B., Veltman, K., & Hodges, J. (2020). Spatial variability of ecosystem exposure to home and personal care chemicals in Asia. Environment International, 134, 105260. https://doi.org/10.1016/j.envint.2019.105260

Lehner, B., Verdin, K., & Jarvis, A. (2008). New global hydrography derived from spaceborne elevation data. Eos, Transactions American Geophysical Union, 89, 93–94. https://doi.org/10.1029/2008EO100001

Lewis, K. A., Tzilivakis, J., Warner, D. J., & Green, A. (2016). An international database for pesticide risk assessments and management. Human and Ecological Risk Assessment, 22(4), 1050–1064. https://doi.org/10.1080/10807039.2015.1133242

Linke, S., Lehner, B., Dallaire, C. O., Ariwi, J., Grill, G., Anand, M., Beames, P., Burchard-Levine, V., Maxwell, S., Moidu, H., Tan, F., & Thieme, M. (2019). Global hydro-environmental sub-basin and river reach characteristics at high spatial resolution. Scientific Data, 6, 283. https://doi.org/10.1038/s41597-019-0300-6

Margni, M., Pennington, D. W., Amman, C., & Jolliet, O. (2004). Evaluating multimedia/multipathway model intake fraction estimates using POP emission and monitoring data. Environmental Pollution, 128, 263–277. https://doi.org/10.1016/j.envpol.2003.08.036

Nemecek, T., Antón, A., Basset-Mens, C., Gentil-Sergent, C., Renaud-Gentié, C., Melero, C., Naviaux, P., Peña, N., Roux, P., & Fantke, P. (2022). Operationalising emission and toxicity modelling of pesticides in LCA: The OLCA-Pest project contribution. The International Journal of Life Cycle Assessment, 27, 527–542. https://doi.org/10.1007/s11367-022-02048-7

Olesen, M. H., & Jensen, P. K. (2013). Collection and evaluation of relevant information on crop interception. EFSA Supporting Publications, 10(6), 438E. https://doi.org/10.2903/sp.efsa.2013.EN-438

Probst, M., Berenzen, N., Lentzen-Godding, A., & Schulz, R. (2005). Scenario-based simulation of runoff-related pesticide entries into small streams on a landscape level.

Ecotoxicology and Environmental Safety, 62, 145–159. https://doi.org/10.1016/j.ecoenv.2005.04.012

Rosenbaum, R. K., Bachmann, T. M., Gold, L. S., Huijbregts, M. A. J., Jolliet, O., Juraske, R., Koehler, A., Larsen, H. F., MacLeod, M., Margni, M., McKone, T. E., Payet, J., Schuhmacher, M., van de Meent, D., & Hauschild, M. Z. (2008). USEtox—the UNEP-SETAC toxicity model: Recommended characterisation factors for human toxicity and freshwater ecotoxicity in life cycle impact assessment. The International Journal of Life Cycle Assessment, 13, 532–546. https://doi.org/10.1007/s11367-008-0038-4

Schriever, C. A., Ball, M. H., Holmes, C., Maund, S., & Liess, M. (2007). Agricultural intensity and landscape structure: Influences on the macroinvertebrate assemblages of small streams in northern Germany. Environmental Toxicology and Chemistry, 26(2), 346–357. https://doi.org/10.1897/05-629R.1

Silva, V., Alaoui, A., Schlünssen, V., Vested, A., Graumans, M., van Dael, M., Trevisan, M., Suciu, N., Mol, H., Beekmann, K., Figueiredo, D., Harkes, P., Hofman, J., Kandeler, E., Abrantes, N., Campos, I., Martínez, M. A., Pereira, J. L., Goossens, D., Gandrass, J., Debler, F., Lwanga, E. H., Jonker, M., van Langevelde, F., Sorensen, M. T., Wells, J. M., Boekhorst, J., Huss, A., Mandrioli, D., Sgargi, D., Nathanail, P., Nathanail, J., Tamm, L., Fantke, P., Mark, J., Grovermann, C., Frelih-Larsen, A., Herb, I., Chivers, C. A., Mills, J., Alcon, F., Contreras, J., Baldi, I., Paskovic, I., Matjaz, G., Norgaard, T., Aparicio, V., Ritsema, C. J., Geissen, V., & Scheepers, P. T. J. (2021). Collection of human and environmental data on pesticide use in Europe and Argentina: Field study protocol for the SPRINT project. PLOS ONE, 16, e0259748. https://doi.org/10.1371/journal.pone.0259748

Wannaz, C., Fantke, P., & Jolliet, O. (2018a). Multiscale spatial modeling of human exposure from local sources to global intake. Environmental Science & Technology, 52, 701–711. https://doi.org/10.1021/acs.est.7b05099

Wannaz, C., Fantke, P., Lane, J., & Jolliet, O. (2018b). Source-to-exposure assessment with the Pangea multi-scale framework – Case study in Australia. Environmental Science: Processes & Impacts, 20, 133–144. https://doi.org/10.1039/C7EM00523G

Wannaz, C., Franco, A., Kilgallon, J., Hodges, J., & Jolliet, O. (2018c). A global framework to model spatial ecosystems exposure to home and personal care chemicals in Asia. Science of the Total Environment, 622–623, 410–420. https://doi.org/10.1016/j.scitotenv.2017.11.315

Yu, Q., You, L., Wood-Sichra, U., Ru, Y., Joglekar, A. K. B., Fritz, S., Xiong, W., Lu, M., Wu, W., & Yang, P. (2020). A cultivated planet in 2010 – Part 2: The global gridded agricultural-production maps. Earth System Science Data, 12, 3545–3572. https://doi.org/10.5194/essd-12-3545-2020