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Maps illustrating the estimates of possible health impacts of exposure to mixtures of PPPs

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1 Summary

Deliverable 5.3 describes the "upscaling", "mapping", and "impact assessment" components of the SPRINT Toolbox. It details the methodology behind the **Pesticide Concentration Maps**, which use environmental fate modeling to predict pesticide exposure in soil, water, and air at field, national, and Pan-European scales, and the associated **Ecological Risk Maps**, which translate these modeled concentrations into risk quotients (RQ) for terrestrial and aquatic ecosystems, which were also presented in maps. It shows the calculation of **Human Dietary Exposure** using European data and brings dietary exposure maps for individual countries. Concentrations in air modelled in the maps were used to calculate **human exposure from inhalation** and assess **human health risk** by comparing with available toxicological reference values. Furthermore, the deliverable presents the **Health Impact Assessment (HIA)** tool, demonstrating how to link exposure estimates with epidemiological data to calculate the potential public health burden (e.g., attributable disease cases). The deliverable showcases a spatially explicit framework for identifying high-risk areas and cropping systems across Europe

2 Introduction

The SPRINT project aims to develop and integrate **tools and novel data to assess risks and impacts of pesticides**[1] on the environment and human health. Using this, the SPRINT project supports accelerating innovative transition pathways towards **more sustainable plant protection**.

A significant part of the SPRINT work package five (WP5) goals focused on **collecting and processing data on** pesticide use, occurrence, exposure, and impacts on human and ecosystem health. Using different approaches at **local, national, and pan-European levels**, WP5 demonstrates that high-resolution spatial **maps** can be generated for predicted concentrations of pesticides in soil, water, and air, exposure via food and feed, and finally, risks to selected endpoints: earthworm reproduction, fish toxicity, and human health.

Pesticides are used and released into the European environment. Despite their use being regulated by stringent pre-market evaluation, it is common to find mixtures of multiple substances that can negatively affect soil and aquatic organisms. While monitoring data are limited, tools can be developed **to estimate pesticide emissions, their distribution in the environment, and accumulated levels** based on existing data on pesticide use and properties. Such efforts are showcased in the SPRINT Toolbox.

The goals of the maps are

- to visualize predicted pesticide input (i.e., emissions, pesticide usage data) to the environment (utilizing "generalized pesticide application patterns" – see the SPRINT deliverable 5.2),
- model pesticide concentrations in the environmental compartments (soil-water-air),
- calculate expected ecological risks,
- calculate inhalation exposure of the human population and assess human health risks,
- assess the potential exposure of the European population via dietary intake.

At the **field-resolution and national levels**, the focus was on data-rich countries with different registration characteristics and agronomic profiles (Czechia, Denmark, the Netherlands). These countries are considered to have very good spatial (high resolution) and temporal (different years) data, such as i) crop types and their location; ii) pesticide usage, including frequency and quantity applied; iii) several weather stations.

At the **pan-European level**, the maps demonstrate the utilization of global usage data combined with global environmental models.

The SPRINT toolbox is designed to **support governance, regulation, and policy- and decision-making** for the transition towards more sustainable pesticide use. Most tools

[1] Please note the adoption of pesticide terminology in SPRINT to better reflect the scope of consortium activities. Some of the compounds under investigation are dual-use (Plant Protection Products and biocides). The deliverable name was kept as PPP in line with the original Grant Agreement term.

will be useful for the **post-registration phase of pesticide regulation**. Spatially explicit maps of predicted pesticide applications, environmental distributions, exposure, and associated risks can inform discussions and prioritization of pesticide use and risk-reduction measures.

The map-based tools within the SPRINT Toolbox serve as a critical interface for translating complex environmental data into actionable spatial information. **For the scientific community,** these maps validate transport and fate models and identify geographic "hotspots" where chemical mixtures accumulate, enabling researchers to prioritize specific regions or river basins for urgent monitoring or ecotoxicological study rather than relying on generalized averages. **For policy and regulation,** the ability to zoom from a pan-European overview down to field-level resolution offers a powerful decision-support system; it allows regulators to move beyond blanket legislation toward targeted interventions, pinpointing exactly where regulatory thresholds (such as risk quotients for aquatic and terrestrial life) are being exceeded. Finally, **for general literacy,** these visualizations democratize access to invisible data, allowing the public to clearly see the link between agricultural practices and their local environment or food, thereby transforming abstract chemical statistics into a tangible understanding of personal and ecological exposure.

Together, these maps/tools represent a significant step towards integrated, spatially explicit pesticide risk assessment and provide a robust knowledge base for advancing the European transition to more sustainable agriculture.

3 Concentration and exposure maps

3.1 Introduction

The concentration maps created in the SPRINT project can help **to identify areas vulnerable to the accumulation and transport of pesticides.** The added value of this work results from the **spatio-temporal combination of crops and pesticide usage** from publicly accessible real data, including geospatial products, offering an opportunity for **more realistic retrospective and prospective risk management** of pesticides. 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).

The development of **spatially explicit pesticide concentration maps** marks a significant step in understanding the environmental footprint of pesticide use across Europe. By integrating real-world usage data with environmental modeling, these maps contribute to informed decision-making. While **not a replacement for site-specific monitoring**, they serve as tools for identifying regional differences in concentrations, guiding policy development, and engaging the public in the transition toward more sustainable and health-conscious agricultural practices. Continued collaboration will help ensure these insights are effectively translated into practical support for ongoing efforts in sustainable agriculture and environmental protection.

The Concentration Maps comprise three complementary tools operating at different spatial scales:

1. Field-resolution Concentration Maps: This tool demonstrates spatio-temporal simulation methods to estimate pesticide concentrations in soil and river water at individual field-resolution and river-segment-resolution (distributed modelling). It uses detailed data on farming practices, climate, soil properties, and hydrology to simulate pesticide interactions within soil and water systems. The tool is demonstrated on three randomly selected districts from Czechia, but the approach is applicable wherever the required input data are available.

2. National Concentration Maps: These maps are available for soil, river water, and air. For soil and water, these maps spatially aggregate finer-resolution data to coarser scales, such as river basins or country districts. For air, it calculates concentrations at varying time resolutions, accounting for initial spray drift and subsequent volatilization of active substances from treated surfaces. The model estimates airborne concentrations based on factors like application method, meteorological conditions, and crop canopy characteristics.

3. Pan-European Maps: This tool provides European-level concentration maps for various environmental compartments, including agricultural soil, natural soil, freshwater bodies, and the atmosphere. These maps offer annual average concentrations across

Europe at high spatial resolution, integrating real-world pesticide usage data (2016–2020) with environmental emission and fate models. The maps are modeling outputs rather than direct field measurements.

Both the pan-European and national concentration maps can be viewed at the level of individual watersheds. Subsequently, individual fields can be examined in the field-resolution maps to pinpoint specific locations contributing to a hotspot within a given district or watershed (**Figure 1**).

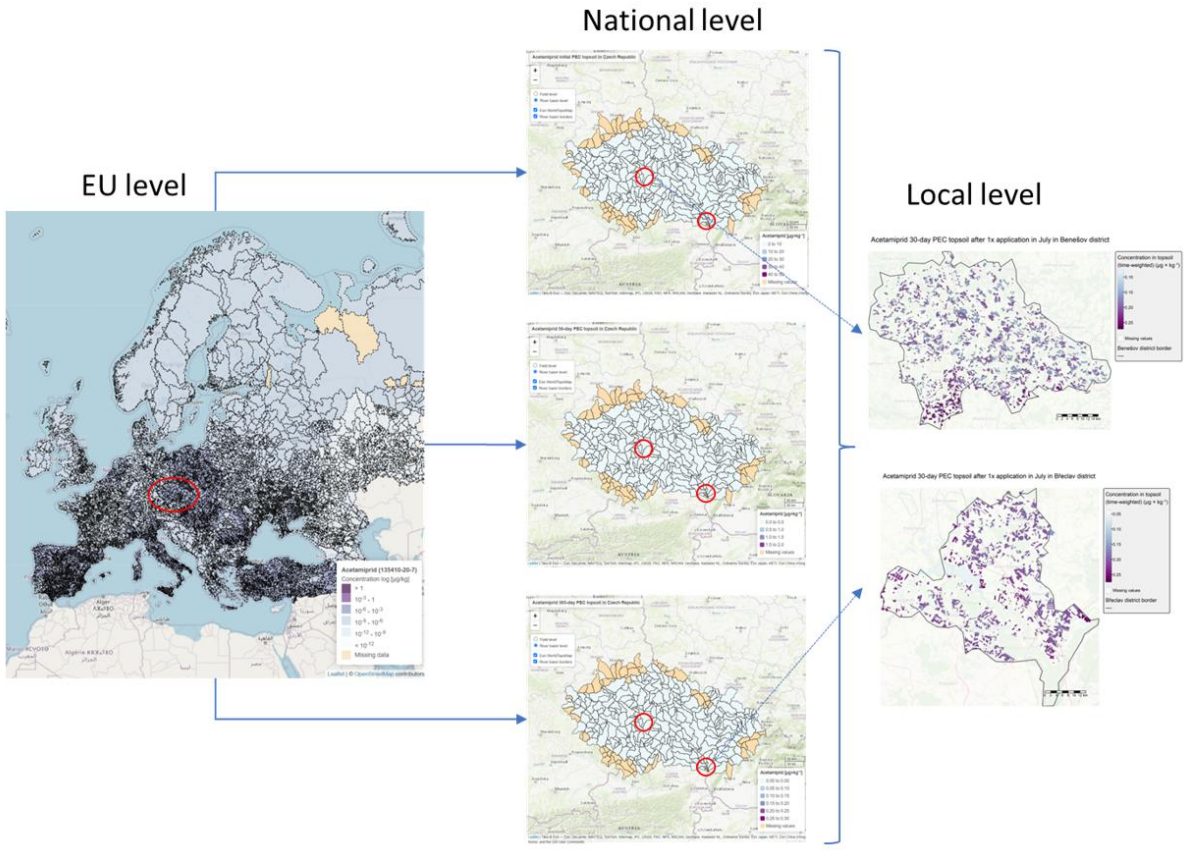

Figure 1 *- The Concentration Maps tool at three spatial scales based on acetamiprid concentration in an agricultural soil scenario.*

3.2 Field resolution maps and national maps

3.2.1 Soil

3.2.1.1 Input data

Model parameters used to calculate forcing and state variables are grouped by purpose in the model: *climate*, *farming*, *chemical*, *topsoil*, *crop*, and *hydrology*.

Crop names and codes are used to assign crop-specific variables such as interception factors and plant protection product usage data. EPPO codes are mostly used as keys to join various datasets, such as national crop names and codes, with the Focus crops.

National crop codes are used predominantly for mapping. Whenever possible, they were attributed to respective EPPO codes. Additionally, EuroCrop codes were used as crop attributes to further harmonize crop coding across countries.

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. The area of an individual parcel may undergo changes from year to year. The concentration maps presented in the toolbox were produced using crop and parcel maps available for 2021, the same year as the SPRINT field campaign (**Figure 2**). The reason was that the model outputs were to be validated using the real measured values.

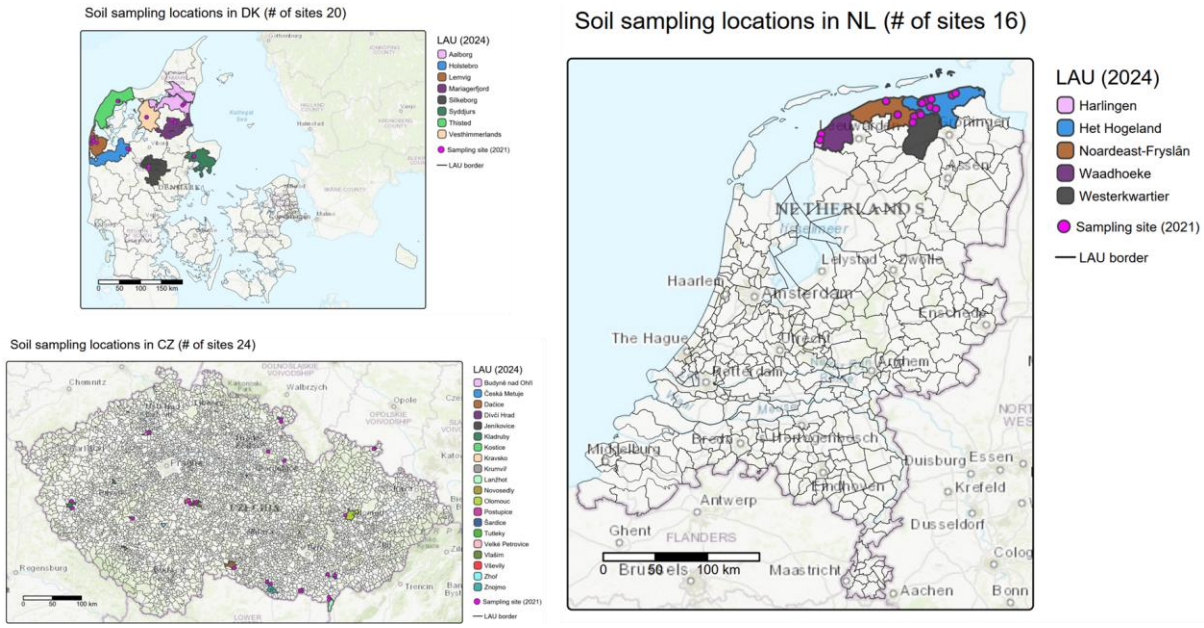

Figure 2 - *Sampling locations across local administrative units (Eurostat, 2024) in Czechia, Denmark, and the Netherlands.*

Local, high-resolution datasets were preferred for obtaining parameters and forcing variable values. Sources for these datasets are diverse, including governmental bodies such as cadastres, statistical, and meteorological authorities. Such data are often publicly available at high temporal and spatial resolutions. However, if not available, global digital datasets were selected. For consistency, HydroSHEDS database version 1.0 was preferred, as it contains a large number of actively maintained, well-documented datasets and secondary products (Lehner et al., 2008). Products such as the HydroATLAS Version 1.0 (Linke et al., 2019) provide data on 56 variables, partitioned into 281 individual attributes and organized into six categories: hydrology; physiography; climate; land cover & use; soils & geology; and anthropogenic influences.

3.2.1.2 Methodology

Pesticide application patterns include information about when, how much and what surface area is covered by application of active substances (ASs). The target spatial unit for producing pesticide application patterns and the subsequent concentration maps is an

individual field. At such a fine spatial scale, the major source of uncertainty in estimating AS application patterns is often a lack of information on how much AS is actually used on individual parcels, and which areas are actually treated with a given substance. Therefore, before modeling Predicted Environmental Concentration (PEC) for topsoil and surface water, crops grown on individual fields must be matched with reported chemical usage data for individual crops (Figure 3); alternatively, reported chemical volume sales data can be used (Eurostat, 2022). The usage or sales data for individual chemicals is commonly reported for districts, regions or a country as a whole. To represent such lumped usage data statistics at the individual field level, the "Proxy method" and spatial weighting was implemented (Patil et al., 2024). "Proxy method" uses a proxy variable which ideally should be highly correlated between a source zone e.g., a district, and a target zone, e.g., individual fields. Here, a proxy variable is a crop name or ID that allows linking pesticide usage and mass between source and target zones (**Figure 3**).

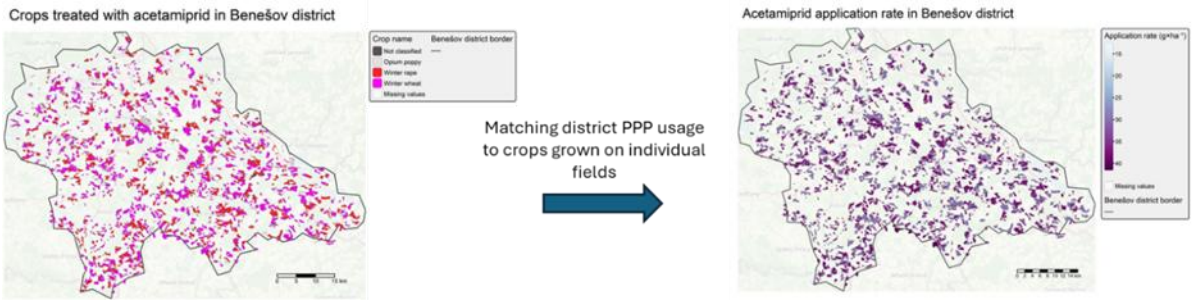

Figure 3 *- Creating AS and crop-specific application patterns at the individual field level*

Spatial (aerial) weighting takes the ratio of the actual field areas to the reported treated area in a region, and then it can be used as a "weighting factor" when calculating spatially explicit variables (Clifford et al., 1995). The "weighting factor" fractions are then specific to a given area, allowing for downscaling of reported AS usage quantities (**Equation 1**).

$$AR_{field,crop,AS} = \frac{M_{AS,crop}}{A_{field,crop}} \times \frac{\sum_{i=1}^{patch} A_{field,crop}}{A_{crop,AS}} \qquad [\textbf{Equation 1}]$$

M_as_crop (kg/year) and A_as_crop (ha/year) are non-spatial pesticide mass applied and crop area, respectively. When divided, it yields an "apparent" application dose. The "weighting factor", a ratio $\frac{\sum_{i=1}^{patch} A_{field,crop}}{A_{crop,AS}}$ of all crop areas to treated crop areas, is then used to obtain more realistic application doses. Comparison with surveyed pesticide usage across all three case study countries involved in 2021 monitoring campaign, Czechia (oilseed rape), Denmark (cereals), and the Netherlands (potatoes), shows the estimated pesticide application rates cluster near the 1:1 line and within the ±1 standard deviation (SD) bounds of reported pesticide usage (**Figure 4**). The clearest outliers are prosulfocarb in Denmark and propyzamide in the Netherlands, which plot far to the right and left of the 1:1 line, respectively, meaning the downscaling model tends to under- and overestimate their application rates (~2x the surveyed value). However, most substances with low

application rates cluster near the origin, showing generally good agreement at lower application rates and that downscaling models perform satisfactorily overall.

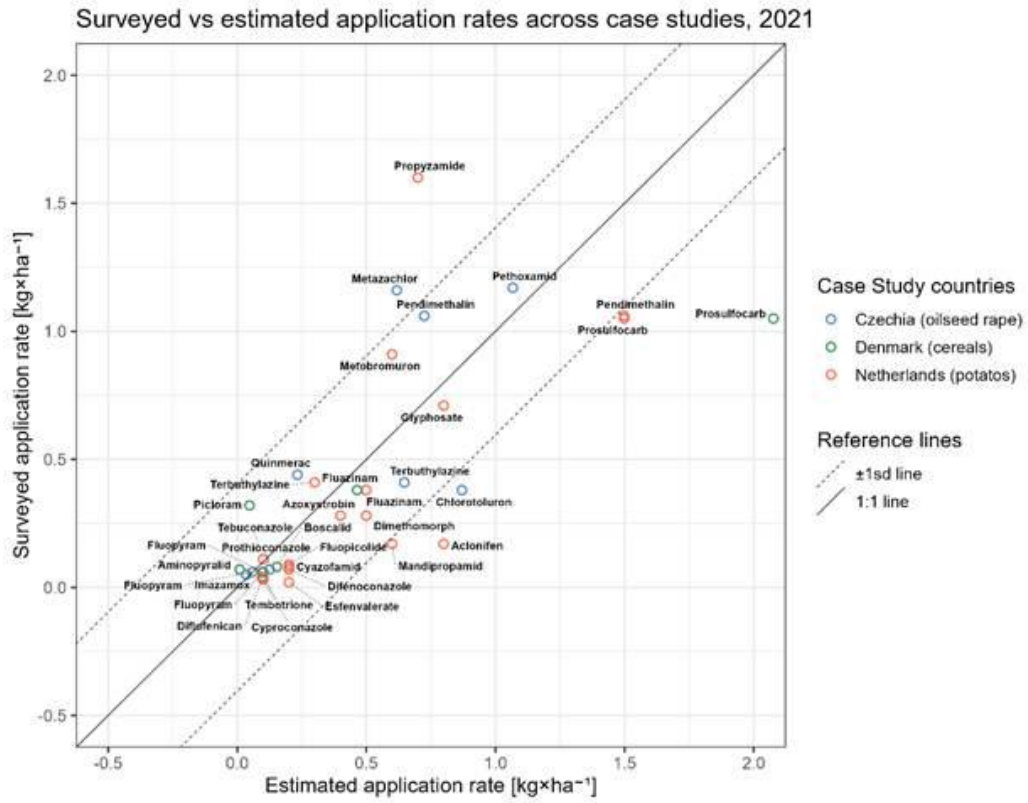

Figure 4 *- Combined comparison of estimated and surveyed pesticide usage in 2021 in Czechia, the Netherlands, and Denmark.*

All results derived for individual fields and river segments are presented at the local administrative units (LAU), which are delineated for each EU member state into the degrees of urbanisation (DEGURBA) categories based on population density and geographic contiguity using 1 km² population grid cells. This system divides areas into (1) cities (densely populated), (2) towns/suburbs (intermediate density), and (3) rural areas (thinly populated) (Eurostat, 2024).

Crop spatial data can be obtained from publicly available country authorities' resources in vector map format and then matched with AS usage information. This process involves operations on relational data. It is done by the "Proxy method", that is matching geo-referenced crops reported for individual fields with not-geo-referenced pesticide usage data for each crop-AS unique combination, and with EPPO crop ID for matching additional attributes. The key variable for joining data sets is "ID", being a unique crop code and/or name. The primary key "ID" variables are georeferenced crop names/codes. Dataset joining can be easily implemented by using for example spatial functions available from R packages such as *merge(x, y, all.x = TRUE),* where *x* is geo-referenced crops' IDs from the country parcel maps and *y* any other dataset to be joined, providing that it has correct be described as a union of two Cartesian products (**Equation 2**). The example in Equation 2 shows the "Proxy method" used for obtaining a georeferenced field-crop treated area

A_field_crop_AS (ha) with additional spatial attribute EPPO code. *A_field_crop_id* (ha) is a georefenced field-crop area, *M_crop_AS_id* (kg) is a non-geo-referenced PPP usage data, and *EPPO_id* is a crop taxonomical identification key to facilitate translation between crop naming systems.

$$A_{field,crop,AS} = (A_{field,crop\ id} \times M_{AS,crop\ id}) \cup (A_{field,crop\ id} \times EPPO_{crop\ id}) \qquad [\textbf{Equation 2}]$$

Because *M_AS_crop_id* (kg) represents pesticide usage, specific to the crop coding system of a given country, it should be developed on a case-by-case basis. The scripts to develop pesticide usage patterns for Denmark, Czechia, and the Netherlands are available on GitHub[2] under **_AppPatt.R* which can be used to build country-specific GeMUP (GEneralised Mapped Usage Patterns). Only for CZ, there is also *CZ_PPPusage.R* used for cleaning PPP usage data. For crop maps, EuroCrops data can be used; PPP usage data must be obtained from the relevant EU country authority (**Table 1**).

Table 1 *- Compiled crop map and pesticide usage data sources for individual countries*

Country	Sources for parcel maps	Country pesticide use metadata sources
Czechia	Czech Ministry of Agriculture (EAGRI)[3] / EuroCrops[4]	Czech Statistical Office[5]
The Netherlands	Netherlands Enterprise Agency (RVO)[6] / EuroCrops[4]	Statistics Netherlands[7]
Denmark	EuroCrops[4]	Ministry of Environment and Food of Denmark[8]
Portugal	EuroCrops[4]	Statistics Portugal[9]

ID subscript is a unique matching key; the coding of individual field IDs is specific to a crop dataset of the country of origin; however, in secondary products such as EuroCrops[4] datasets, such as field IDs and crop names were homogenized across EU countries (Schneider et al., 2023).

We have adopted the SYNOPS-GIS approach to perform geospatial fate modelling of pesticides in soil and surface water (Strassemeyer et al., 2017) (**Figure 5**). SYNOPS is an indicator model designed to perform trend analysis of chemical loads and levels in environmental compartments, offering a simplified formulation compared to complex models such as MACRO, PRZM, or SWAT, which are often used by regulatory agencies. In this work, SYNOPS is used to temporally and spatially define vulnerable areas for pesticide accumulation or transport, based on pesticide properties, landscape features, use of plant protection products, soil characteristics, and climate. The model is suitable for providing decision-makers, the public, and researchers with means for decision-making in the area

[2] https://github.com/bobski1986/Sprint_swaq/blob/main/DK_AppPatt.R
[3] https://eagri.cz/public/portal/mze/farmar/elektronicka-vymena-dat/prehled-vystavenych-sluzeb
[4] https://zenodo.org/records/14230621
[5] https://ec.europa.eu/eurostat/cache/metadata/EN/aei_pestuse_esqrspu_cz.htm
[6] https://www.rvo.nl/onderwerpen/gewascodelijst
[7] https://ec.europa.eu/eurostat/cache/metadata/EN/aei_pestuse_esqrspu_nl.htm
[8] https://ec.europa.eu/eurostat/cache/metadata/EN/aei_pestuse_esqrspu_dk.htm
[9] https://ec.europa.eu/eurostat/cache/metadata/EN/aei_pestuse_esqrspu_pt.htm

of sustainable pesticide use (OECD, 2016). The model provides time-dependent and geo-referenced deterministic PEC estimation in topsoil and river water at individual field and river segment level on the one hand and frequency distribution or lumped PEC values at coarser scales on the other hand. Temporal profile of calculated PECs includes initial values right after application of ASs and time-averaged values over the duration of the simulation scenario.

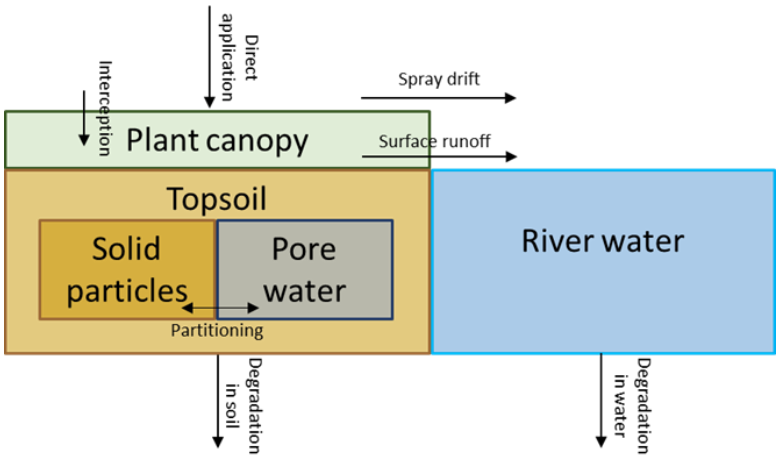

Figure 5 *- Compartments and processes included in the model.*

3.2.2 Water

3.2.2.1 Input data

The width of individual rivers and river segments has to be specified in order to delineate buffer polygons around them and calculate the area for each element. At individual field resolution, a 100 m buffer area around river segments (Ippolito et al., 2015) is plotted to intersect all fields potentially contributing pesticide loads to river water. At the catchment scale, river basin polygons are basic area units for any crop, AS, topsoil, and river water-related data aggregation and zonal processing.

3.2.2.2 Methodology

Surface water is coupled to the soil compartment by transport processes: surface runoff and spray drift. The time resolution is dictated by the input parameter used to calculate PEC_{soil}.

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 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 soil's solid phase to estimate the amount transported into 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) (**Figure 5**). 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).

Similarly, the spray drift is represented as percentages of applied pesticide drifting beyond the borders of a treated field depending on the crop type, the crop stage and the distance from the last nozzle of the spray equipment (Strassemeyer, 2017). The model implements spray drift values that represent the variability of spray drift depositions along the field edge as observed in the drift trials (Bub, 2020).

3.2.3 Output (Soil & Water)

Field resolution soil and water concentration maps:

https://sprint-toolbox.eu/index.php/pec-maps-shiny

National level soil and water concentration maps:

https://sprint-toolbox.eu/index.php/soil-water

3.2.4 Limitations (Soil & Water)

The model is based on pre-existing formulas constituting SYNOPS Model for synoptic assessment of risk potential of chemical plant protection products[10]. Being an indicator model, it is predominantly used as a screening tool. Thus, the model does not fully account for environmental dynamics or variability in factors such as soil type, runoff rates, topography, or the substance's half-life in soil and water, and therefore limits the number of environmental scenarios to which it can be applied. These assumptions can significantly influence the results, making it difficult to independently verify the findings or compare them to those of other environmental models. The model does not account for continuous, long-term environmental dynamics, seasonal variations, or the effects of specific weather events. The accuracy of the PEC values is entirely dependent on the quality and resolution of the input data, including stream locations and basin boundaries. Inaccuracies in the source data, such as outdated stream maps or incomplete datasets, can lead to misleading PEC values and conclusions. The PEC modelling involves aggregating input data across the river basin using a summary statistic method. This may oversimplify complex hydrological processes and the granularity of model input data that influence the actual concentration.

[10] https://web.jrc.ec.europa.eu/policy-model-inventory/explore/models/model-synops-gis-print/

3.2.5 Air

3.2.5.1 Input data

Input data includes crop names and codes, which were used to assign crop-specific variables such as interception factors and plant protection product usage data. For usage data, we used Generalized Application Patterns - GenAPs (developed within SPRINT, see D5.2) for the Czech Republic and Denmark. For the Netherlands, we used the pesticide registration database (CTGB, 2026) directly. Different approaches were taken intendedly to test the robustness of the modelling approach used.

The air concentration maps presented in the toolbox were produced using crops and parcel maps available for the year 2021.

Meteorological data, namely cloud cover, rainfall, wind speed, wind direction and temperature, were collected from different sources depending on the simulated country. For the Netherlands, these data are publicly available and were retrieved from Royal Netherlands Meteorological Institute[11]. For Denmark, these were retrieved from Danish Meteorological Institute[12]. Whilst for the Czech Republic, the data was ordered for the year 2021 from the Czech Hydrometeorological Institute[13].

Pesticide properties relevant for modelling purposes, namely vapor pressure, were retrieved from the PPDB[14].

3.2.5.2 Methodology

To estimate airborne pesticide concentrations at the national scale, we developed a spatially explicit modelling framework integrating agricultural field data, pesticide application information, meteorological observations, and atmospheric dispersion modelling. The approach accounts for two primary pathways by which active substances (AS) enter the atmosphere following application:

- Initial spray drift, defined as pesticide droplets transported outside the target application area during spraying.
- Post-application volatilization, defined as evaporation of active substances from soil and plant surfaces after deposition.

The modelling framework follows the same rationale as the OBOmod framework (see Figueiredo et al., 2022), with the main differences being a) not simulating all droplet classes, but only an average size; b) replacing OPS-st with RTdrift, making therefore the model less computationally demanding and still accounting for initial dispersion (see equation 1 from Lebeau et al., 2021). The approach was implemented separately for each

[11] https://www.knmi.nl/nederland-nu/klimatologie/daggegevens
[12] https://www.dmi.dk
[13] https://www.chmi.cz
[14] https://sitem.herts.ac.uk/aeru/ppdb

country to evaluate computational feasibility, usability, and to stress the importance of methodological settings on model outputs.

For each crop type, the applied mass of active substance was calculated by multiplying the recommended or reported application rate by the field area. Only downward spraying applications were included in the simulations. Hence, orchards, where sideway spraying often occurs, are not well represented in this approach.

Each agricultural field polygon was paired with the geographically closest meteorological station using a nearest-neighbor approach implemented in R (distance-based matching). Meteorological variables included: Wind speed; Wind direction; Air temperature; Relative humidity; Cloud cover and Precipitation. If a meteorological station lacked one or more required variables for the modelling period, that station was excluded from further analysis. Fields assigned to excluded stations were reassigned to the next closest station with complete data.

This procedure ensured consistency in the meteorological inputs used to parameterize the dispersion and volatilization processes.

The Gaussian plume formulation estimates downwind concentrations based on: Emission rate (from spray drift and volatilization); Wind speed; Atmospheric stability; Downwind distance; Lateral and vertical dispersion coefficients. Here, cloud cover and wind speed were used to establish the Pasquill stability classes, which were then used to estimate the dispersion coefficients. The model incorporates real-world meteorological observations from the paired stations to dynamically simulate pesticide transport in the air.

Volatilization from soil and plant surfaces was modelled using equations consistent with the PEARL model framework (Van den Berg et al., 2016). The volatilization module accounts for: Temperature-dependent vapor pressure; Soil–air partitioning; Crop canopy interception and Soil moisture effects. Here, a conservative approach where we ignore degradation kinetics was taken, due to a lack of available data to estimate all separate degradation processes. The combined spray drift and volatilization emissions were used as source terms in the atmospheric dispersion model.

Simulation Framework and sensitivity testing

For each country, multiple simulation configurations were tested to evaluate: Computational efficiency; Sensitivity to spatial resolution; Influence of meteorological assumptions, and Variability in application timing. These simulations demonstrated that model outputs can vary substantially depending on: Downwind receptor distance; Assumed droplet size class; Wind direction resolution, and Spatial aggregation method.

For the Netherlands, simulations were repeated multiple times to account for variability within legally permitted pesticide application periods. Meteorological boundary conditions during spraying were constrained based on expert input, based on both regulatory constraints (for wind speed) and good agricultural practices:

- No rainfall during application

- Air temperatures between 5°C and 28°C
- Relative humidity > 40% [*below 40% can cause rapid droplet evaporation*]
- Wind speed < 5 m s^{-1}

Air concentrations were calculated at 10 m downwind from each field edge. The resulting concentrations were averaged per field across simulation runs.

Maps were created by spatially aggregating the data into a 1 km × 1 km grid resolution by averaging all field-level values within each grid cell. The final output represents yearly mean airborne concentration at 10 m downwind under constrained (realistic during spraying) meteorological conditions.

For the Czech Republic, due to the lower density of agricultural plots per km^2, a different spatial approach was applied. For each field, air concentrations were estimated at 50 m distance from the field centroid. Simulations were conducted for the eight predominant wind directions. A low droplet size class of 30 µm was assumed to represent a conservative drift scenario. Concentrations from all fields were averaged within 2.5 km × 2.5 km grid cells (1x1km was possible, but not suitable for visualization purposes in the toolbox). The final output represents the mean concentration per grid cell derived from all contributing fields and wind directions.

For Denmark, the modelling approach followed the same methodology as applied in the Czech Republic: 50 m distance from field centroid; eight predominant wind directions; 30 µm droplet size class. However, concentrations were aggregated to a finer spatial resolution of 1 km × 1 km grid cells. The output represents the average concentration from all fields contributing to each grid cell.

For all countries, the data behind the maps can be accessed, so averaging later at different grid resolutions is always possible.

3.2.5.3 Output

National level air concentration maps:

https://sprint-toolbox.eu/index.php/introduction-pesticide-in-air

3.2.5.4 Limitations

The approach used and produced maps includes several limitations:

- Results represent scenario-based averages, not maximum episodes
- Meteorological data from the nearest station were assumed representative for the entire field polygon.
- Spatial aggregation may smooth local concentration peaks
- Inter-country differences partly reflect non-harmonized modelling settings
- Only downward spraying and selected droplet sizes were considered

Based on the above limitations, the tool is not intended for regulatory risk assessment without further refinement. The modelling settings can, however, be harmonized if necessary.

3.3 Pan-European maps

3.3.1 Input data

- Global pesticide usage data for 2016-2020 have been obtained from an external data provider (https://lexagri.com/products/agrowin). These data have high granularity, providing actual pesticide use information at the crop, country, active ingredient, crop growth stage, and application method levels.
- Globally spatialized crop production maps at a 5×5 arcminute resolution using the Spatial Production Allocation Model (https://mapspam.info).
- Emission model (PestLCI Consensus model)
- Copernicus European Landcover from 2018 (https://land.copernicus.eu/en/products/corine-land-cover)
- Pangea model with the 3D atmospheric grid based on the default GEOS-Chem layers (Bey et al., 2001) and the terrestrial grid of clusters delineated by watersheds based on the catchment-based HydroBASINS dataset (https://www.hydrosheds.org)

3.3.2 Methodology

Global pesticide usage data for 2016-2020 were projected on globally spatialized crop production maps at a 5×5 arcminute resolution using the Spatial Production Allocation Model (https://mapspam.info).

Pesticide emissions (primary distribution) to different compartments were modelled using the emission distribution model PestLCI using information on crop, crop growth stage, and pesticide application method to derive a set of environmental primary emission distributions, building on a mass balance after pesticide application (Dijkman et al., 2012; Nemecek et al., 2022; Zhang et al., 2024). Emission compartments include air, field crop surface, field soil surface, and off-field surface areas, including other agricultural fields, natural soil surfaces, and freshwater surfaces. Environmental processes beyond primary distribution among the above-mentioned compartments are considered in subsequent fate models. For breaking off-field area into the defined compartments, spatialized land use data were extracted from the 2018 version of the Copernicus European Landcover (Büttner et al., 2004).

For the next step, the geospatial Pangea model was used. This model builds a set of grids for relevant compartments using its GIS engine and a set of Environmental Models (EMs), which simulate physical systems such as the atmosphere, hydrology, and terrestrial environments. This system is called the geometric system, and all geo-referenced data are projected in this system. This system includes grid cells with homogenous (e.g., air)

and inhomogeneous (e.g., soil) compartments. The geometric system includes the following grids:

- A 3D atmospheric grid of 17 layers covering altitudes ranging from around 100 m to 15 km. This is based on the default GEOS-Chem layers which is the wind field dataset (Bey et al., 2001). This dataset is developed with a time resolution of 6 hours and spatial resolution of 2° x 2.5°, provides wind velocities for each defined atmospheric layer in different directions. This dataset is then interpolated to the resolution for the geometry of the atmospheric grid.
- A terrestrial grid of clusters delineated by watersheds delivering to a global ocean, which is based on the catchment-based HydroBASINS dataset (https://www.hydrosheds.org), which provides separate river and lake datasets. This dataset has been used as a basis for computing flows between watersheds.

The gridded data and geometric and topological parameters are re-indexed into a virtual system to split inhomogeneous contents into homogenous cells. With homogenous cells, pesticide mass evolution in compartments can be described using first-order differential equations with constant coefficients. Using these re-indexed parameters and a set of Environmental Processes Models (EPMs), Pangea builds a mathematical compartmental system, which is solved for environmental concentrations of pesticides at a steady state. The solution is re-indexed backward to the relevant grids for analysis and visualization. EPMs are specific to each compartment for the elimination process (degradation and advection), to each pair of compartments for transfer processes (diffusion, deposition, and runoff), and to each exposure pathway for exposure processes. EPMs are based on IMPACT 2002 (Margni et al., 2004; Pennington et al., 2005), and USEtox (Rosenbaum et al., 2008).

The following figure (**Figure 6**) shows the considered compartments, fate, and environmental processes in Pangea (Wannaz et al., 2018):

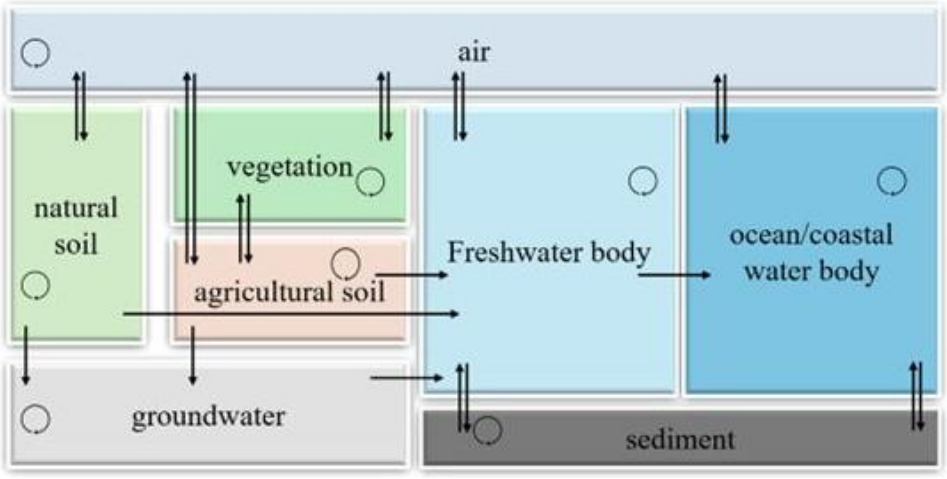

Figure 6 *- Set of compartments and related environmental processes involved in Pangea*

To specify constraints on the output map resolution, Pangea uses a practical solution, called refinement potential (RP), as a basis for building multi-scale grids. It is by definition

a global scalar field whose value in each point of the globe defines the user's "interest for high resolution". In practice, it is a raster resulting from multiple weighted contributions. In the pan-European maps tool, the refinement potential was defined based on the weight of terrestrial catchment areas based on the ratio of the population to freshwater volume and ecotoxicity impacts of pesticides related to the emissions sources and regions, so that the areas with the higher population/volume ratio and higher potential ecotoxicity impacts from pesticide use get higher resolution. **Figures 7 and 8** show the scales used for this process and also refined maps.

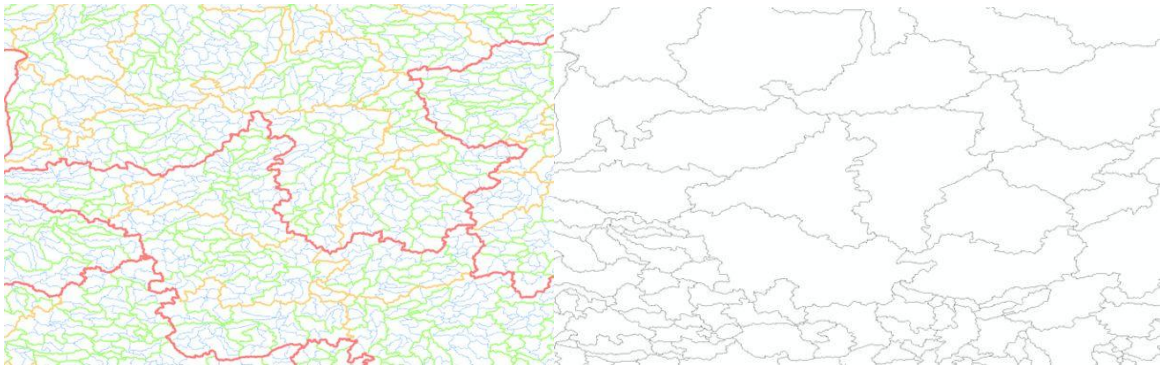

Figure 7 *– The left map shows different levels of terrestrial grids used for refining the grids based on HydroBASINS dataset. Watershed levels 4 (red line), 6 (orange line), 8 (green line), and 10 (blue line). Higher levels represent higher resolution. The right map shows the refined grids based on defined constraints.*

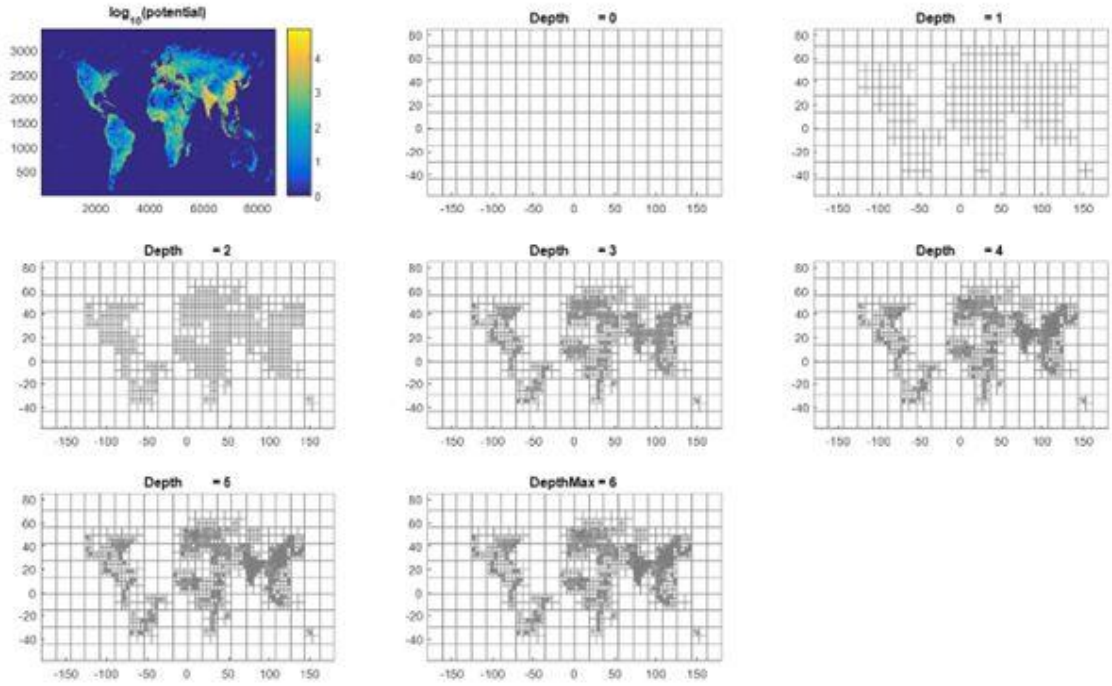

Figure 8 *- Overview of refinement procedure for atmospheric grids. Further depths show higher resolution based on user-defined constraints*

3.3.3 Outputs

Separate maps are provided to show modelled pesticide concentrations in agricultural soil, natural soil, freshwater bodies, and the atmosphere as the main environmental compartments.

https://sprint-toolbox.eu/index.php/concentrations-in-agricultural-soil

https://sprint-toolbox.eu/index.php/concentrations-in-natural-soil

https://sprint-toolbox.eu/index.php/concentrations-in-fresh-water

https://sprint-toolbox.eu/index.php/concentrations-in-air

These interactive maps display modeled environmental concentrations of individual pesticides across Europe, expressed in µg/kg for soils, µg/dm^3 for water, and ng/m^3 for air. The polygon boundaries represent terrestrial catchments from Pangea's multi-scale grid architecture, which provides variable spatial grid areas with high resolution in regions of high agricultural activity. The color-coded legend uses percentile-based bins spanning more than 7 orders of magnitude, calculated across all values for consistent comparison between chemicals, and with grey areas indicating regions with no data.

These maps demonstrate an integration of real pesticide use data (by crop, country, and pesticide application method) with environmental fate and distribution modeling. They account for chemical transport, phase partitioning, and degradation processes across the European landscape. They illustrate spatial variation in environmental pesticide concentrations, showing regional hotspots and less affected areas.

These maps help to understand where pesticides end up in the environment, even in areas far from where they were applied. They identify regions with potentially elevated environmental and human exposure to pesticides. This information can help governments and researchers make better decisions to protect public health and the environment from exposure to agricultural pesticides. The geospatial pesticide concentration maps can support:

i) Targeted policy interventions in high-risk areas for pesticide accumulation and exposure.
ii) Risk prioritization for improving environmental quality and reducing potential human health impacts from pesticide emissions.
iii) Monitoring and evaluation of pesticide regulation effectiveness, such as pesticide reduction efforts.
iv) Strategic planning for reducing pesticide use or exposure in line with sustainable agricultural and public health goals.

3.3.4 Limitations

As for other SPRINT maps, the concentration values displayed are not measured field data, but represent steady-state model-based estimates of annual average pesticide

concentrations in soil, water, and air, across Europe. These concentrations also do not indicate levels after a specific application of pesticides. They also do not show short-term exposure levels, because the model simulates time-integrated conditions for overall annual pesticide use, not daily or event peaks. These maps cannot be used to determine whether a specific location is "safe" or "unsafe" without additional local data and temporal modeling. They also do not reflect enforcement thresholds or allowable pesticide concentrations.

Many local factors (e.g., wind, behavior, microclimate) influence actual exposure levels (precise exposure to humans or wildlife), which are beyond the scope of the maps.

Therefore, the interpretation of these maps should be contextual and comparative (e.g., higher vs. lower risk zones), not absolute risk or safety, and as averages over a year (not temporal peaks). Regions with lower data quality or model resolution (e.g., remote or under-monitored areas) may have greater uncertainty.

These maps are intended for awareness-raising, planning, and research, not for direct regulatory or legal decisions or for assessing risk at the local scale.

3.4 Dietary exposure maps

Dietary exposure maps exhibit the estimation of the average amount of pesticides to which the European adult population may be exposed through food consumption over a calendar year at the country level.

3.4.1 Input data

To estimate average dietary exposure and to generate the European maps, two datasets were utilized:

- **Pesticide residue data from EU food monitoring programs (2011–2020) published by EFSA** (Carrasco Cabrera & Medina Pastor, 2022; EFSA, 2014). The data are open-source and are downloadable on an annual basis from the Open Science platform Zenodo. **Table 2** shows the availability of these data based on year and country.
  Relevant EFSA catalogues (Ioannidou, 2019) were used to add descriptive details to the open source data reported in the unified raw format.
- **Food consumption data from the RPC model**. The RPC database contains the consumption of European countries' populations based on unprocessed single primary ingredients. The database is available online for downloading in Excel format (Dujardin and Kirwan, 2019). **Table 2** shows the availability of the data based on the country.

Table 2 - *Availability of pesticide monitoring data in food for the years 2011 to 2020, and data on consumption of 10 selected food commodities for the adult population in the EU countries.*

Country of origin	Active substance residue concentration–data availability										EU Adults' food consumption–RPC data availability for 10 selected food commodities
	Year of report										
	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	
Austria	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Belgium	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bosnia and Herzegovina	-	-	-	-	-	-	✓	✓	✓	✓	-
Bulgaria	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Croatia	-	-	-	✓	✓	✓	✓	✓	✓	✓	-
Cyprus	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-
Czech Republic	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Denmark	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Estonia	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Finland	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
France	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Germany	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Greece	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-
Hungary	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Iceland	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-
Ireland	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Italy	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Latvia	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lithuania	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-
Luxembourg	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-
Malta	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-
Montenegro	-	-	-	-	-	-	✓	✓	✓	✓	-
Netherlands	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
North Macedonia	-	-	-	-	-	-	✓	✓	✓	✓	-
Norway	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-
Poland	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Portugal	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-
Romania	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Slovakia	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Slovenia	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Spain	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sweden	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
United Kingdom	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

"✓": Available
"-": Not available

3.4.2 Methodology

One issue to tackle in dietary exposure calculation was treating the concentrations lower than the Limit of Quantification (LOQ) in pesticide residue concentration data. The common approach regarding this issue is considering lower or upper bound scenarios. However, for generating the dietary exposure maps in this research, we performed an imputation of the missing values in the pesticide residue concentration data. This approach aims to reduce systematic overestimation or underestimation of the output that is common when following other scenarios.

Considering the fact that a noticeable number of reports in the pesticide residue concentration database were below the LOQ, only pesticides 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 (Gleit, 1985; Madley-Dowd et al., 2019). The missing residue data were imputed using a parametric

survival regression model (Fuhrimann et al., 2022; Lubin et al., 2004; Figueiredo et al., 2022).

Utilizing the RPC database, the total number of consumers for each food commodity across Europe was calculated, and 10 highly consumed primary food commodities were identified and selected for dietary exposure estimation. The selected food items were onions, tomatoes, carrots, apples, potatoes, sweet peppers, parsley, oranges, strawberries, and lemons.

The average dietary exposure (µg pesticide/kg bodyweight) was calculated by multiplying the average residue concentrations of selected pesticides (after imputation of missing data) for selected food commodities for individual European country in each calendar year, by the adult's average consumption rate of the respective food commodity (g/kg bodyweight) as provided by the RPC database for each EU country. The estimated average dietary exposure to selected pesticides and selected food commodities was visualized as country-level exposure maps for each individual combination. These maps are accessible in the online platform of the SPRINT toolbox.

3.4.3 Output

Maps of pesticide residues in food commodities:

https://sprint-toolbox.eu/index.php/pesticide-residues-in-food

Maps of human dietary exposure to pesticides from food commodities:

https://sprint-toolbox.eu/index.php/dietary-exposure

3.4.4 Limitations

Limitations of this estimation stem from both the quality of its underlying data and the challenges of imputing missing values.

At the country level, there were insufficient data available in the pesticide residue concentration database to impute missing data. As a result, imputation was not feasible at the country level; consequently, it was performed at the European level to obtain more reliable output. There were also inconsistencies in this database regarding analytical methods and instrumentation across countries, resulting in non-uniform LOQs and highlighting the lack of uniformity.

Further uncertainty stems from the RPC food consumption database, which was used as provided and incorporates modelled estimates of raw primary commodity intake derived from composite food data (Dujardin and Kirwan, 2019). The uncertainties inherent in this database introduce uncertainty into the exposure estimates in our work as well. Moreover, consumption data were unavailable in the RPC database for several countries—such as Portugal, Iceland, Norway, and Greece—despite the availability of corresponding residue

concentration data, leading to their exclusion from parts of the analysis (i.e. dietary exposure estimation).

The estimated average dietary exposure provided by this tool is derived from a selection of ten commonly consumed food commodities. Although these items represent a considerable share of total food intake according to the RPC database, they cannot capture the full diversity of dietary habits across Europe. Food consumption patterns vary substantially between countries, regions, and individuals due to cultural traditions, availability, and personal preferences. As a result, the reported exposure values should be understood as broad population-level estimates that describe general trends rather than exact representations of individual dietary behaviours.

The imputation approach was further limited by the high proportion of missing data, which, although still valid, reduced the precision of the estimates. Inconsistencies in analytical standards and methods across studies led to variable LOQs for the same pesticide analysed in the same food commodity, thereby hindering the identification of suitable predictors and parameters that could be robustly applied for a more precise imputation.

It is worth noting that, due to the limited availability of data on food processing factors, dietary exposure estimates are based exclusively on raw agricultural commodities and do not account for food processing. However, it is important to bear in mind that processing steps such as washing, peeling, or cooking may substantially alter residue levels and, consequently, influence the actual dietary exposure of consumers.

These factors collectively contribute to uncertainty in the exposure estimates and should be considered when interpreting results.

The estimates presented in this tool cover the period from 2011 to 2020. Users who wish to extend the analysis to other years or additional food commodities may do so by applying the scripts and methodological descriptions made available through the SPRINT sharing platforms and/or publications.

4 From concentration and exposure maps to impact on ecosystems and humans

4.1 Ecological risk maps

In terrestrial and aquatic ecosystems, organisms' exposure is determined mainly by the concentrations of pesticides in their surrounding environments. As a result, predicted environmental concentrations (PECs) in soil and surface water can serve as reliable proxies for exposure when assessing ecological risk.

A straightforward approach to ecological risk assessment is the calculation of the risk quotient (RQ), defined as the ratio of predicted environmental concentration (PEC) to an ecotoxicological threshold (NOEC). When multiple pesticides co-occur, cumulative RQs (∑RQ) can be calculated by summing individual RQs, providing a measure of mixture-related ecological risk. Ecological risk maps visualize these RQs across space, highlighting areas where pesticide use may pose the greatest risk to soil and aquatic organisms and supporting data-driven prioritization of risk mitigation measures.

4.1.1 Input data

Outputs from the concentration maps, including predicted environmental concentrations in soil (PECsoil) and surface water (PECwater) as calculated in **Chapter 3.2**, were combined with toxicity thresholds to assess ecological risk. For each pesticide, the lowest available chronic no-observed-effect concentration (NOEC) for earthworms and fish was selected from three toxicity databases (PPDB, EFSA OpenFoodTox, and USEPA ECOTOX). These PEC and NOEC values formed the basis for calculating soil and aquatic risk quotients and for subsequent spatial risk analysis.

4.1.2 Methodology

The following methodology is described for the example of Czechia. However, a similar approach can be applied for other countries.

Due to the large number of active substances applied, a prioritization procedure was implemented to focus the spatial risk assessment on the most relevant pesticides. The pesticide usage data were used as the starting point to select substances for risk maps. Usage data for Czechia in the year 2021 was obtained from the Central Institute for Supervising and Testing in Agriculture[15]. In 2021, 287 distinct substances were applied in Czechia. Since our focus was on conventional synthetic pesticides, non-relevant

[15] https://ukzuz.gov.cz/public/portal/ukzuz/pripravky-na-or/ucinne-latky-v-por-statistika-spotreba/spotreba-pripravku-na-or/spotreba-v-jednotlivych-letech/spotreba-roky-neviditelny/2021-en/_22_6_2022_celek_EN_z.pdf

substances (e.g., microbial agents, pheromones, growth regulators, synergists, and inorganic or natural compounds) were excluded.

The remaining 182 pesticides were ranked based on their usage and chemical/ecotoxicological properties. Chemical and ecotoxicological properties of the pesticides were retrieved from the PPDB database[16]. Chronic NOEC for earthworms (56 days) and fish (21 days) were used when available. If not, acute LC_{50} values (14 days for earthworms, 96 hours for fish) were divided by 10 as a proxy (Franco et al., 2024). Chemical parameters included DT_{50} in soil, DT_{50} in water, water solubility (at 20 °C), Koc, and Kfoc. Missing values were supplemented by EFSA reports.

All data (usage, toxicity, chemical properties) were normalized to a 0–1 scale, with the highest value of each property corresponding to 1. Using these normalized values, the pesticides were scored as follows:

Soil score = (Usage * DT50soil) / NOECearthworm (1)

Water score = (Usage * DT50soil * DT50water) / (NOECfish * Koc) (2).

The normalized values were used to score and rank the pesticides. The top 95% substances (based on cumulative scores) were selected for the risk maps.

Once the substances were selected, the PEC estimation in topsoil and surface water were calculated for individual fields and river segments, as outlined in **Chapter 3.2**. The PECs in topsoil and surface water were calculated as the 56-day time-weighted average concentration following pesticide application. This approach was chosen to account for temporal fluctuations and to provide a more realistic estimate of long-term exposure.

A hazard database was prepared by collecting chronic NOEC values for reproduction in earthworms and fish. The toxicity data were collected from the PPDB, EFSA OpenFoodTox, and USEPA ECOTOX databases. The three databases were merged in R, and duplicates were removed by checking rows with the same CAS number and toxicity value. It resulted in 72 and 64 distinct entries for terrestrial and aquatic studies, respectively. Then, the lowest toxicity value for each pesticide was kept in the final database. The studies retained from ECOTOX database were checked for quality using Criteria for reporting and evaluating ecotoxicity data (CRED) (Franco et al., 2024; Moermond et al., 2016).

The soil and aquatic risk quotient (RQ) were calculated as PEC/NOEC. The cumulative RQ (∑RQ) was calculated to integrate the ecological risk of pesticides applied in a same area. For soil, the RQ in individual fields were summed (∑RQ soil). The ∑RQ surface water for individual river segments were calculated from the pesticide loadings from individual fields and flow of receiving river water segments. ∑RQ surface water is then spatially weighted by agricultural area contributing to aquatic risk of individual river segments which is derived from spatial intersection of all pesticide-treated fields within 100-meter buffer area around individual river segments. Total area of treated fields within a river segment buffer

[16] https://sitem.herts.ac.uk/aeru/ppdb

and area of buffer around an individual river segment are then used to calculate fraction of area contributing to aquatic RQ. Likewise, area of individual river segment in a river buffer and area of a respective buffer are used to derive fraction of receiving area in the buffer. Both fractions are then used to derive river and pesticide specific weights and used to obtain area-weighted RQ surface water (Strassemeyer et al., 2003).

According to EU regulatory guidelines, environmental concentrations of individual pesticides should be maintained at levels at least fivefold lower than the NOEC for earthworms and tenfold lower than the NOEC for fish. Therefore, safety thresholds were established at 0.2 for earthworms and 0.1 for fish.

4.1.3 Output

Ecological risk maps:

https://sprint-toolbox.eu/index.php/ecological-risk-maps-l2

4.1.4 Limitations

The ecological risk maps presented here are subject to several limitations, related to both exposure and hazard, that should be considered when interpreting their results. The ecological risk estimates presented in the maps are not based on direct field measurements or monitoring data. Instead, exposure concentrations in soil and water (PECs) were predicted using models that integrate pesticide usage data, authorized application scenarios following good agricultural practices, and crop distribution maps. These estimations are based on many simplifications and assumptions, which are also propagated into the ecological risk calculation. Therefore, the resulting maps must be used and interpreted cautiously, considering the provided information on the methodology used for their creation and limitations and uncertainties inherently coupled with each of the maps.

Additional limitations arise from specific aspects of the hazard data and risk calculation approach. Toxicity data were limited to single representative species (e.g., earthworms for soil and fish for water) and endpoints which may not fully capture the sensitivity of the broader ecological community, nor of indirect ecological effects. Finally, the cumulative risks were calculated using a concentration-addition approach, which assumes strictly additive effects of multiple pesticides. Potential synergistic or antagonistic interactions between substances were not considered, introducing further uncertainty into the assessment.

4.2 Human health risk

The Human Health Risk Assessment (HHRA) was conducted using the spatially explicit air concentration maps generated within the SPRINT toolbox and population inhalation estimates (not food intake). Rather than applying a spatial, point-based exposure

estimate, the assessment was performed in a non-spatially resolved manner to reflect variability in predicted pesticide concentrations and variability in population characteristics that can affect inhalation rates, such as age and sex. The quantitative output behind the modelled air concentration maps (**Chapter 3.2.5**), was used to calculate exposure from inhalation (daily) and compare with available toxicological reference values for each respective pesticide for chronic-exposure based endpoints (i.e. long-term).

Inhalation rates and body weight assumptions to estimate chronic inhalation exposure were based on the recommended values from US EPA (2011). Consequently, the risk characterization is done for the full population and not per region. Methodological workflow is explained in **Figure 10**.

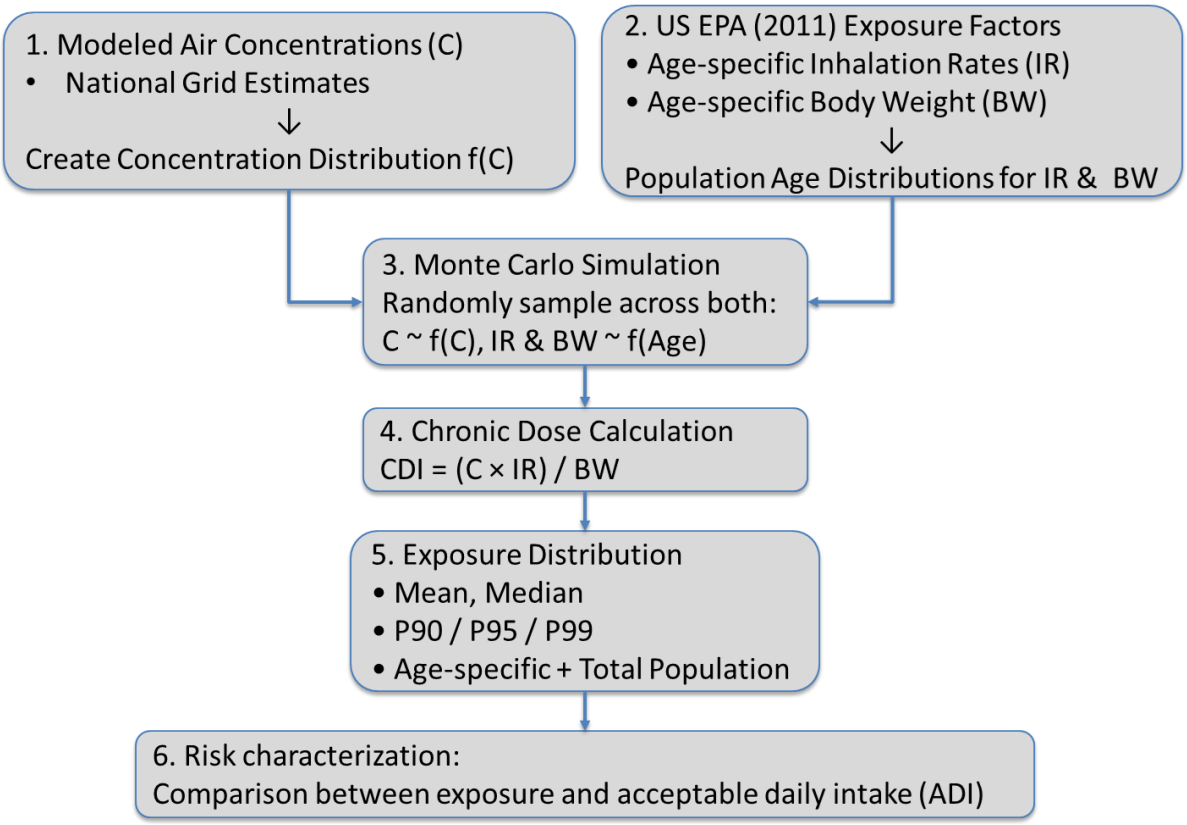

Figure 10 *– Workflow from concentrations in air to exposure calculation and risk characterization.*

For the substances assessed, namely glyphosate, acetamiprid and tebuconazole, the estimated chronic exposures did not exceed the relevant toxicologically-based guidance values for most of the population, indicating that predicted inhalation exposure levels are unlikely to pose a health concern under the modelled conditions. However, it should be noted that for many pesticides, realistic inhalation-specific endpoints or points of departure are not available, given that a) no inhalation toxicity studies conducted; b) minimal inhalation exposure expected and c) oral endpoint used instead (Route-to-Route

Extrapolation). Most toxicological studies underlying regulatory reference values are based on oral (rat gavage or dietary) studies, and inhalation-specific chronic data are often limited. This introduces uncertainty when interpreting inhalation-based risk estimates.

An example of the method and results used above is given below for the case of acetamiprid in the Czech Republic, in a worst-case scenario simulation. **Figure 11** depicts all modelled acetamiprid air concentration values across the year 2021 and **Figure 12** shows estimated inhalation exposure across different age groups.

Acetamiprid was selected as a case-study here given that in recent years its toxicological-based guidance values have dropped from 0.025 mg/kg to 0.005 mg/kg (EFSA 2024), one of the lowest acceptable daily intakes (ADIs) across all pesticides. The results show that depending on the age group, sex and inhalation rate, ADI couldbe exceeded by between 0.1% and 4.1% of the population during long-term exposure. As an example, ADI could be exceeded by 2.2% of persons in the age groups 1-2 years; assuming an average inhalation rate. This is unlikely to occur since i) it would require that the exposed individual would be continuously exposed always at the time of spraying and at that location and ii) the modelled scenarios include a low droplet size class of 30 µm, which is conservative and can lead to higher predicted concentrations than occurred in reality. Independently, the results do warrant more attention for more acetamiprid measurements to be carried out regarding air.

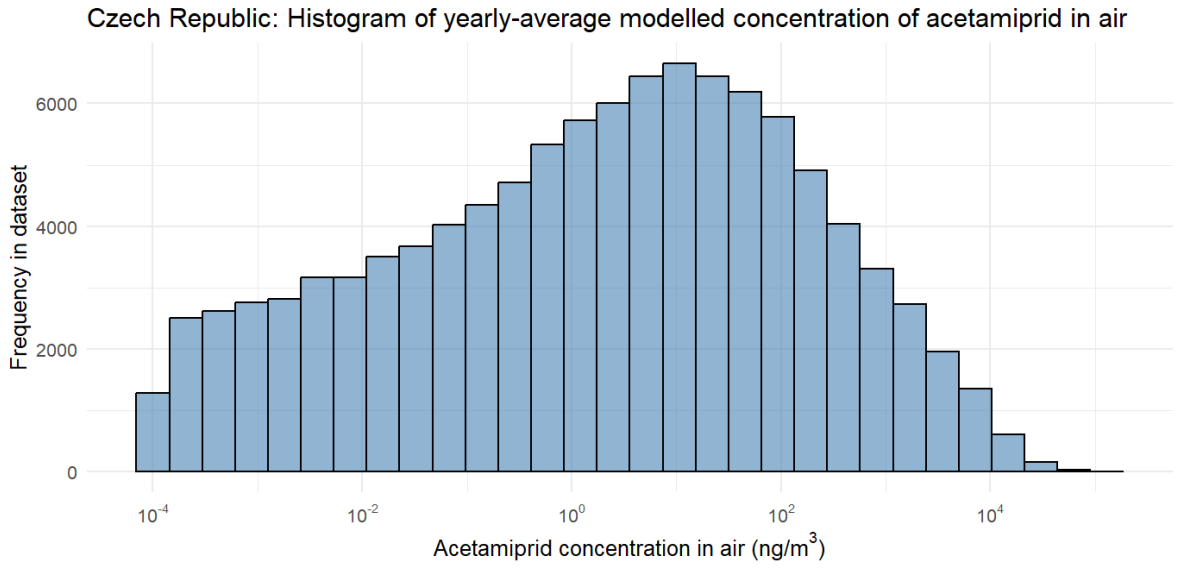

Figure 11 *– Modelled acetamiprid concentrations in air (ng/m3) for the Czech Republic and year 2021.*

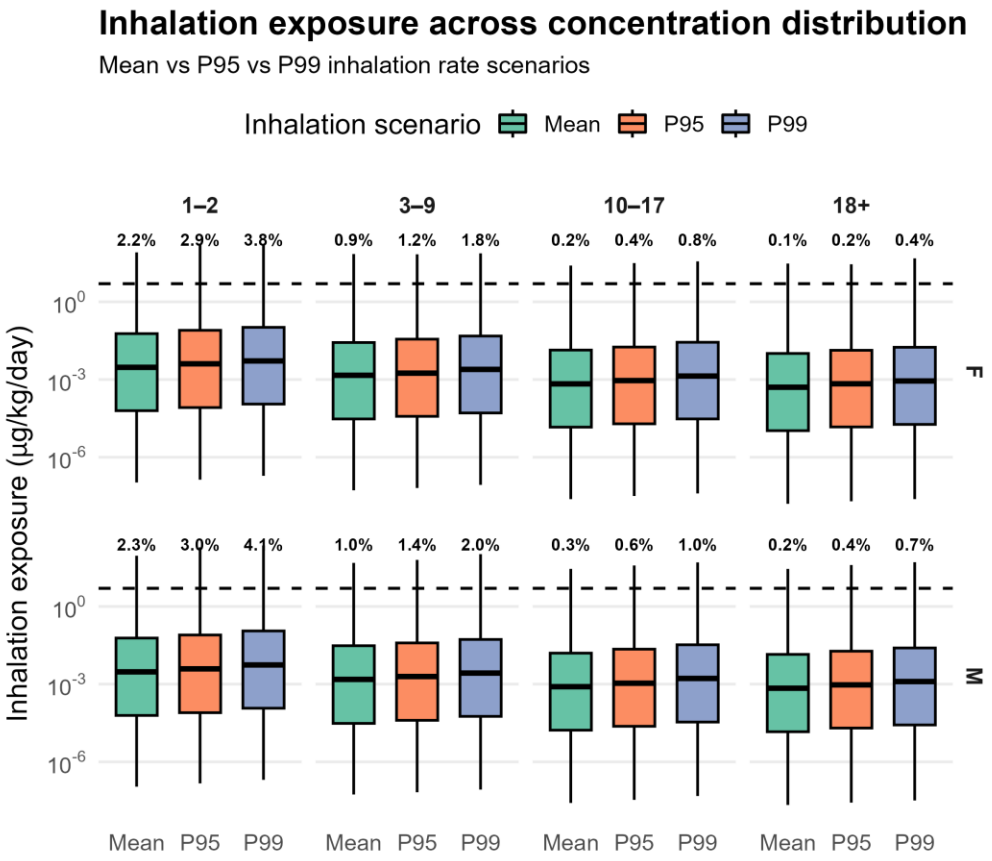

Figure 12 *– Worst-case scenairo estimations for Inhalation exposure to acetamiprid for the Czech population in the year 2021. Dashed horizontal line is the ADI (=5 ug/kg bw). In the x-axis inhalation exposure calculated for mean, p95 and p99 inhalation rates, varying per sex (second y-axis) and age groups (above plots), from 1-2 years, 3-9, 10-17 and 18+. Primary y-axis is calculated inhalation exposure in ug/kg bw/day.*

4.2.1 Use of Dietary Exposure Data

The estimated average dietary exposure presented in the maps is valuable not only for epidemiological analyses but also as a direct quantitative input for HHRA. The exposure values can be compared with health-based guidance values such as the Acceptable Daily Intake (ADI), for example, those available in the Pesticide Properties Database (PPDB[17]), which are integrated into the SPRINT toolbox alongside the dietary exposure outputs. Stratification by country and year allows identification of spatial and temporal trends in exposure, facilitating evaluation of regulatory measures and risk management actions. For the substances assessed, the calculated dietary exposures did not exceed the corresponding ADI values, indicating no expected chronic health concern based on average intake levels. Nevertheless, these comparisons provide a structured basis for risk characterization and prioritization of substances or populations that may warrant further toxicological refinement or epidemiological investigation.

[17] https://sitem.herts.ac.uk/aeru/ppdb

4.3 Human health impact

We performed a Health Impact Assessment (HIA) for a frequently used pesticide (glyphosate) and used two different health outcomes to illustrate how this could be performed, what the approach is, and what insights it provides. The HIA result was not mapped across Europe, contrary to our initial expectation. The reason for that is that HIA produces a calculation for larger population groups (e.g. a country or region). A HIA calculation requires knowledge about the exposure distribution of that population, exposure-response functions, and incidence/prevalence information of the disease of interest (the "response") in the respective population. The exposure-response functions are derived from existing epidemiological studies, and the disease incidence/prevalence numbers from national registries or similar sources. This means that to produce maps that illustrate health impact of exposure to pesticides across Europe, population exposure distribution needs to be available. As could be seen in the previous parts of the SPRINT toolbox, the upscaling of exposure models to all countries so far still lacks necessary underlying data sources. Hence, our approach outlines how a HIA can be done in the case that all necessary information can be obtained. Please note that if such data become available, mapping as such is not complicated, as it corresponds to displaying a table in a map with a number per country. Corresponding examples and code are provided in the chapter on dietary intake of pesticides above.

4.3.1 Input data

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 was to assemble a full inventory of published evidence before any screening. Two independent reviewers screened titles and abstracts against predefined inclusion and exclusion criteria, considering populations of all ages and geographic regions. 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 was a curated list of studies meeting basic quality and scope requirements. Types of exposure: 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). Included studies: 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. From each included publication, we systematically extract key information: sample size, measured pesticide concentrations, participant selection criteria, reported risk ratios for defined exposure levels, and the specific exposure assessment method. We enter data into a standardized extraction form. This step transforms narrative and tabular results into a harmonized dataset ready for analysis.

To enable valid pooling, we isolated 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 ensures the exposure–response relationships derived later rest on truly comparable data.

4.3.2 Methodology

We pooled the results of the selected studies through meta-analysis techniques to calculate a pooled risk ratio per unit of pesticide exposure (if more than one study is available). We chose fixed- or random-effects models based on heterogeneity and performed sensitivity analyses to test robustness. The resulting exposure–response function quantified how incremental changes in exposure translate into changes in disease risk.

Calculation of the 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. 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 studies reporting exposure-response functions. This produced a distribution of exposure levels across individuals or subgroups in the target population.

2. Obtain Baseline Disease Prevalence: We gathered epidemiological data on the current prevalence or incidence of the health outcome from national registries or surveys. These figures serve as the baseline for estimating cases attributable to exposure. We can use 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 diseases in the Netherlands.

3. Select the PAF Formula: We use the following formula to calculate the PAF:

$$PAF = \frac{\sum_{i=1}^{n} Pi\ RRi - \sum_{i=1}^{n} P'i\ RRi}{\sum_{i=1}^{n} Pi\ RRi}$$

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 the PAF by the total number of cases to estimate attributable cases. This quantified the burden that could be prevented under a specified reference exposure.

4.3.3 Output

The output of the HIA calculation includes the methodology, two worked examples, and tools to calculate HIA if the corresponding underlying data are provided. It also includes an explanation and a flow chart of all necessary steps.

4.3.4 Limitations

HIA of pesticides currently still has major uncertainties that relate to a) the underlying exposure distribution of the population, b) exposure-response functions that reflect causality and realistic shapes of the functions, and c) depending on the outcome of interest, also incidence or prevalence numbers in the population may include major uncertainties. For example, many different types of cancers in a population are often included in specialized registries and therefore reflect the best knowledge of the status of a particular disease in a population. Other health outcomes are not registered in specialized databases and therefore, numbers across populations have much higher uncertainties. Examples for this include e.g. metabolic syndrome, sleep disorders, and so on. A HIA is a powerful tool as it can provide insight about what happens to a populations' health status if a policy change occurs. For mapping across regions or multiple countries, better data is necessary to render such maps informative.

5 Impact and outlook

The Toolbox impacts **diverse target groups** via improving their access to data on pesticide occurrence, environmental fate, exposure, and (eco)toxicological effects.

The SPRINT Toolbox provides an important step toward developing the underlying methodology and vision for using big data on pesticide use, authorisation, and monitoring to predict pesticide exposure distributions across ecosystems and populations in Europe and to assess their risks to human health and ecosystems. A key innovation of the Toolbox is the independency 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 an EU-wide, binding implementation mechanism, there is an urgent need for tools that support voluntary or nationally driven pesticide reduction strategies. The SPRINT Toolbox and its embedded maps can serve as **a critical blueprint for monitoring and risk assessment**, keeping the "Farm to Fork" ambition alive.

The toolbox is unique in its **use of different scales**: from the local Case Study Site 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 levels.

There is a need for approaches that identify risks and impacts from real pesticide use at spatial resolution (showing geographic hotspots of risk) and across timescales (allowing assessment of risk trends). The Toolbox maps provide **digital support for decision-making and strategy-building in pesticide-related policy and governance**. Pesticide concentration maps predict distributions of pesticide exposure across ecosystems. Together with ecological risk maps, they identify **agricultural practices and pesticide applications associated with elevated cumulative risks**, elucidate on **the spatio-temporal cumulation of hazardous exposures and unacceptable risks** resulting from the spatio-temporal combination of crops and pesticide applications, and 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, policymakers and regulators can more effectively target interventions, prioritize action, and decide on withdrawal **or substitution**. Moreover, this can be done **explicitly at the geographic level**. Outlook

Finally, the tools showcase what kinds of information are available when the right supporting data is available. 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, and application method) to support transparent pesticide exposure and health impact assessment at EU level. With improvements to EU-level data harmonization on PPP usage

and authorisations, the Toolbox methodology could be used to identify the highest-risk pesticide application patterns and cropping systems across Europe, thereby motivating measures with a large potential to protect health and the environment.

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