Ecological risks of pesticides under future climate and land-use scenarios:

A Bayesian network approach

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“Do the best you can until you know better. Then when you know better, do better”
– Maya Angelou

Abstract

Environmental risk assessment frameworks are a crucial element of many chemical legislations and essential to inform risk management decisions. Risks posed by environmental stressors such as chemical pollutants are expected to increase and diversify. This has led scientists and regulators to request an adaptation and improvement of the current risk assessment frameworks to communicate uncertainties better and consider future global changes. Improvements in handling uncertainties related to emissions, exposure and effects of chemicals, and their mixtures now and in the future are essential when pursuing policy targets such as a toxic-free environment in 2050 (e.g., European Green Deal).

To this end, there is a need to combine knowledge of future global changes and their influence on the behaviour and effect of chemicals to forecast future risks to the ecosystem better. As future projections of environmental conditions and chemical emissions are highly uncertain, the need for risk assessment methods to quantify and propagate these uncertainties is evident.

Despite their apparent advantages, probabilistic methods still have limited application in environmental risk assessment in practice. The use of Bayesian networks for probabilistic risk assessment has increased in recent years. They better communicate uncertainties than most currently used probabilistic methods and can be used as a meta-model combining various sources of information in a single model. Exploring the use of this highly versatile tool to improve current risk assessment has been the focus of this synthesis. A core model for the probabilistic risk characterisation of pesticides was developed. For a Norwegian case study, it enabled retrospective assessment that uses distributions fitted to monitoring data and toxicity tests to parameterise the core model.

This PhD project also explored the application of Bayesian networks for prospective risk assessment under future climate and land-use scenarios. The core model was adapted to integrate scenarios for changes in climate and agricultural practices for another Norwegian case study. This Bayesian network model was parameterised with probabilities for predicted exposure concentrations derived from a process-based exposure model (WISPE - World Integrated System for Pesticide Exposure) and probability distribution that were fitted to data from toxicity tests.

The latest developed Bayesian network model integrated inputs from a case-based effect model (PERPEST - Predicts the Ecological Risks of PESTicides) that estimated effects on various biological endpoints and the aquatic community. Also, it linked future scenarios to the exposure assessment using output from another process-based exposure model (RICEWQ - Rice Water Quality Model) for a Spanish case study. In general, the developed Bayesian networks produce output that can easily be communicated and aid better-informed and targeted risk management decisions through transparent uncertainty assessment for all model compartments.

Preface

This synthesis is submitted in partial fulfilment of the requirements for the degree of *Philosophiae Doctor* at the University of Oslo. The presented research was conducted at the University of Oslo and the Norwegian Institute for Water Research (NIVA) under the supervision of S. Jannicke Moe, Merete Grung, Knut Erik Tollefsen, Marianne Stenrød, and Ketil Hylland.

The presented work was carried out between 2019 and 2022 and supported by ECORISK2050, which has received funding from European Union's Horizon 2020 research and innovation program under grant agreement No. 813124 (H2020-MSCA-ITN-2018).

This synthesis is a collection of three papers within the domain of ecotoxicology. These papers all use Bayesian network models as a tool for the probabilistic risk assessment of pesticides. The papers proceeded with a background chapter putting the synthesis into context. The following chapter describes the research aim of this synthesis and a state-of-the-art chapter describing existing frameworks, methods, and applications of the existing work. They were followed by the main contribution of the papers being presented. Finally, the discussion and concluding remarks turn the work into context and describe further improvements.

Acknowledgments

I want to thank my supervisors for their support and encouragement during my PhD. Also, I want to raise special gratitude to Jannicke and Merete, who had given me considerable help in times when the world went crazy, and without whom, this PhD would not have been possible. During the three years working there, my employer, NIVA was most supportive and facilitated the work environment I needed. Thank you to all my NIVA colleagues and friends for helping me during my PhD keeping me motivated and making lunch my favourite time of the day. To my section, I can only quote our leader; you are indeed - “the best of the best of the best”. Furthermore, I like to thank my secondment hosts, the Norwegian Institute of Bioeconomy Research (NIBIO), Wageningen University & Research (WUR), and Instituto Madrileño De Estudios Avanzados (IMDEA) water for their hospitality and support in improving my research. Also, I thank Randi Bolli and Roger Holten for their discussions and support on exposure modelling and pesticide application. In addition, I like to express special thanks for the discussions and help with Bayesian network modelling to Wayne Landis and John Carriger. To everybody in the ECORISK2050 project, thank you all for the great work, help, and support during the last few years, and all the effort that went into the workshops and conferences. To all my fellow ESRs, especially Sam, it was great to make this PhD journey together with you not only as colleagues but also as friends. You guys made this project a great experience and so much fun. I enjoyed every virtual coffee break and all the in-person get-togethers we were able to have– may there be more to come. Moreover, I want to thank the Mentzel side of my family for their support and for cheering me on during all the years of studying and PhD work. Grandma Rosemarie and my brothers - Paul, Steffen, and Ian - I am forever grateful for your love and for always believing in me even when I could not. To all my friends, thank you for putting up with my stress and anxiety, I am so lucky to have you all in my life. Chloe, pretty Maria, Rachel, and Christina, thank you so much for keeping me sane and for helping me grow as a person. Last but not least, mevrouw Wanke, mijn Suikerklontje, and Sonja, I appreciate all our years of friendship, you guys are always there for me, even though we are hundreds of kilometres apart.

Oslo, October 2022
Sophie Mentzel

List of papers

Paper I: Development of a Bayesian network for probabilistic risk assessment of pesticides

Sophie Mentzel, Merete Grung, Knut Erik Tollefsen, Marianne Stenrød, Karina Petersen, and S. Jannicke Moe. 2022a. Development of a Bayesian network for probabilistic risk assessment of pesticides. Integrated Environmental Assessment Management; 18: 1072–1087 .
(doi: 10.1002/ieam.4533)

Paper II: Probabilistic risk assessment of pesticides under future agricultural and climate scenarios using a Bayesian network

Sophie Mentzel, Merete Grung, Roger Holten, Knut Erik Tollefsen, Marianne Stenrød, S. Jannicke Moe. 2022b.Probabilistic risk assessment of pesticides under future agricultural and climate scenarios using a Bayesian network. Frontiers in Environmental Science.
(doi: 10.3389/fenvs.2022.957926)

Paper III. Using a Bayesian network model to predict effects of pesticides on aquatic community endpoints in a rice field - A southern European case study

Sophie Mentzel, Claudia Martínez-Megías, Merete Grung, Knut Erik Tollefsen, Paul van den Brink, Andreu Rico, and S. Jannicke Moe. 2022c. Using a Bayesian network model to predict effects of pesticides on aquatic community endpoints in a rice field – A southern European case study. bioRxiv. [preprint]
(doi: https://doi.org/10.1101/2022.10.19.512688)

Note:
Within Paper II and Paper III, Mentzel et al. (2022a) (Paper I) has been referred to by the online publication year (2021) instead of the publication in volume year (2022) within Paper II and Paper III.

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Abbreviations

AF	Assessment Factor
AOP	Adverse Outcome Pathways
AUC	Area Under Curve
BN	Bayesian Network
CA	Concentration Addition
CDF	Cumulative Distribution Function
CPT	Conditional probability Table
DAG	Direct Acyclic Graph
DEBtox	Dynamic Energy Budget Applied to ecotoxicology
DR	Dose Response Model
EAP	Environmental Action Programme
EC	European Commission
EC_{50}	50% Effective Concentration (concentration effective in producing 50% of the maximal response)
EQS	Environmental Quality Standard
ERA	Environmental Risk Assessment
EU	European Union
GC	Global Change
GUTS	General Unified Threshold Models of Survival
HC_x	Hazard Concentration for x% of the species
HC5	Hazard Concentration for 5% of species
IA	Independent Action
IPCC	Intergovernmental Panel on Climate Change
JPC	Joint Probability Distribution
LC_{50}	Half Maximal Lethal Concentration
LOAEL	Lowest Observed Adverse Effect Level
LOD	Limit of Detection
LOEC	Lowest Observed Effect Concentration
LOQ	Limit of Quantification
MEC	Measured Environmental Concentration
NGO	Non-Governmental Organization
NOAEL	No Observed Adverse Effect Level
NOEC	No Observed Effect Concentration
NOEL	No Observed Effect Level
OECD	Organization for Economic Cooperation and Development
PAF	Potential Affect Fraction
PEC	Predicted Environmental Concentration
PERPEST	Predicts the Ecological Risks of PESTicides
PNEC	Predicted No Effect Concentration
PRZM	Pesticide Root Zone Model
QSAR	Quantitative Structure Activity Relationship
RAC	Regulatory Acceptable Concentration
REACH	Registration, Evaluation, Authorisation, and Restriction of Chemicals
RICEWQ	Rice Water Quality Model
RIVWQ	RIVerine Water Quality model
RQ	Risk Quotient
SSD	Species Sensitivity distribution

STU	Sum of Toxic Unit
TGD	Technical Guidance Document
TKTD	Toxicokinetic-toxicodynamic
TU	Toxic Unit
TWA	Time Weighted Average
WISPE	World Integrated System for Pesticide Exposure
WFD	Water Framework Directive

Introduction

I Background

Pesticides are vital for the protection of crops and food security, although their use can have harmful effects on non-target species. Future global changes are related to shifts in land-use and weather patterns. These are expected to affect the emission of pesticides as well as their fate, transport, and effect on the environment. Examples of these impacts include the increased frequency of extreme weather events such as droughts, floods, and heat waves. Disruption through climate conditions will directly impact the agricultural sector's productivity, which is one of the socio-economic sectors that most depend on climate (EEA, 2019). In the European Union (EU), climate change impacts are expected to lead to a significant loss for the agricultural sector, with up to a 16% of loss of agricultural income (with considerable variations between regions) (EEA, 2019).

Looking into the future, the following vision was formulated in the 7th Environmental Action Programme (EAP): "*In 2050, we live well, within the planet's ecological limits. Our prosperity and healthy environment stem from an innovative, circular economy where nothing is wasted and where natural resources are managed sustainably, and biodiversity is protected, valued and restored in ways that enhance our society's resilience. Our low-carbon growth has long been decoupled from resource use, setting the pace for a safe and sustainable global society*" (EC, 2014). The 7th action in EU EAP also recognizes the potential opportunities for economic growth and societal well-being through environmental and climate change. At the same time, it recognized that there are remaining challenges associated with uncertainties that can cause worldwide environmental degradation. The EU has thorough regulation of pesticides and other chemicals when they are placed on the market, even though, up to date, 46 % of EU surface water bodies do not achieve a good chemical status (EEA, 2018). Recently, European Commission (EC) published a new strategy, "the EU Green Deal", building up on the 7th EAP, with the intention for Europe to be the first climate-neutral continent that conserves, enhances, and protects the environment by 2050. For the aquatic environment, chemical pollution of water is addressed, and it is stated that there is a need to restore the natural functions of ground and surface water (EC, 2019; van Dijk et al., 2021).

Safeguarding ecosystem biodiversity and human health requires a better understanding of the current and future impacts of food production, for example, pesticide impact on non-target biota. Current environmental risk assessment models and methods were not designed to incorporate future global changes. Therefore, they need better implementation of changes into environmental risk assessment (Gagnon et al., 2016; Landis et al., 2013; Stahl et al., 2013). Some other shortcomings are associated with a lack of spatial and temporal consideration when predicting risk to the aquatic ecosystem (Topping et al., 2020). To accomplish the 7th EAP vision and policy targets by the EU Green Deal, new approaches and technologies are needed to minimise the risk posed on the environment.

II Objective and aim

2.1 ECORISK2050 project objective

This PhD project is one out of thirteen PhD projects in the Environmental risks of chemicals in the future (ECORISK2050) Innovative Training Network (www.ecorisk2050.eu). It was established to help meet the aforementioned EU's 7th EAP vision that seeks to protect biodiversity, enhance society's resilience and aims for a safe and sustainable global society until 2050. An interdisciplinary consortium of research institutes, universities, regulators and industry were brought together in this project.

The intention was to evaluate the effects of global change (GC) on the use and emission of emerging chemicals, their ecotoxicity and risk to aquatic organisms, as well as their transport and fate in agricultural and urban-dominated catchments. This was achieved by combining innovative and novel modelling-based approaches and experimental investigations. Overall, the focus was on chemical emission pathways related to rural (such as pesticides and veterinary medicines) and urban land-use (such as personal care products and pharmaceuticals) (Welch et al., 2022). Moreover, as there are apparent differences in climate, demography, management practices, and wastewater treatment, chemical emission scenarios were evaluated in three biogeographic regions in Europe: Northern (boreal), Central (Atlantic), and Southern (Mediterranean).
Its project aims were:

- To assess how the inputs of chemicals from agriculture and urban environments and their fate and transport will be affected by GC for different European scenarios in order to assess the likely increase in the ecological risks arising from these changes for human and ecosystem health;
- To identify potential adaptation and mitigation strategies, which can be implemented in the short and medium term, to abate unacceptable changes in risks, and use the GC scenarios to develop robust implementation pathways for these strategies;
- To develop a set of tools for use by industry and policymakers, which allow the impacts of a range of GC-related drivers on chemicals risks to be assessed and managed (Welch et al., 2022).

The innovative training network consisted of four interlinked main work packages (Scenarios, Exposure, Effect, and Risk & Mitigation). This PhD project was part of the risk assessment and mitigation work package that focused mainly on the risk assessment for emerging chemicals from agricultural and urban sources, separately and in mixtures, under current and future scenarios (Welch et al., 2022).

2.2 Research objective and tasks

This PhD project explores developing and applying a modelling tool for risk assessment of agricultural chemicals (initially titled: "*Novel tools for forecasting chemical risks in agricultural systems in the future*"). Environmental risk assessment (ERA) paradigms are often limited by an ineptitude to account for spatial and temporal variation in chemical exposure (EUFRAM, 2006; Verdonck, 2003). Furthermore, the currently used probabilistic approaches pay little attention to the visualisation of risk output and uncertainty (Verdonck, 2003). Changes on the implementation of ERA are required due to changing stressors, sources, habitats, and toxicological effects related to changing climate conditions and agricultural practices (Landis et al., 2013; Stahl et al., 2013).

Bayesian networks (BN) can overcome some of these limitations of ERA, as they are able to incorporate probability and probability distributions and have flexibility in data sources (Hamilton & Pollino, 2012; Kaikkonen et al., 2021).

Therefore, the main objective of this PhD was to explore BN application as a tool for pesticide risk assessment and the development BN models that could integrate future scenarios. Hence, the main tasks of this PhD project were to explore the following:

- the development and application of a BNs for probabilistic risk assessment of pesticides on the aquatic environment in northern Europe (Paper I),
- the application of a BN model for risk assessment of pesticides that integrates future scenarios (Paper II), and
- the application of BN model for pesticides effect on various biological endpoints in Southern or Central European (Paper III)

III State of the art

3.1 Regulatory risk assessment of pesticides

In Europe, environmental risk assessment evaluates the complex impacts of chemicals on the environment while applying a comprehensive, straightforward, and reproducible set of protocols (Brühl & Zaller, 2019; EU, 2019; Hunka et al., 2015; Newman et al., 2006). It is an essential tool to inform decision-makers and a key element of the EU's chemical legislation. To ensure the reliability, quality, and integrity of study data, rules known as good laboratory practices were implemented by the Organization for Economic Cooperation and Development (OECD) (EU, 2019). In principle, today's ERA usually incorporates exposure and effect assessment to characterize a substance's risk to the environment and, more specifically, the exceedance of a safe threshold (van Leeuwen & Vermeire, 2007) (Figure 1). Exposure assessment is the evaluation of predicted concentration through scenarios and models (prospective) or measured concentration through monitoring studies (retrospective) of a compound in the environment. In contrast, effect assessment focuses on the response of species exposed to a chemical (standard toxicity tests) and is usually based on one or more endpoints.

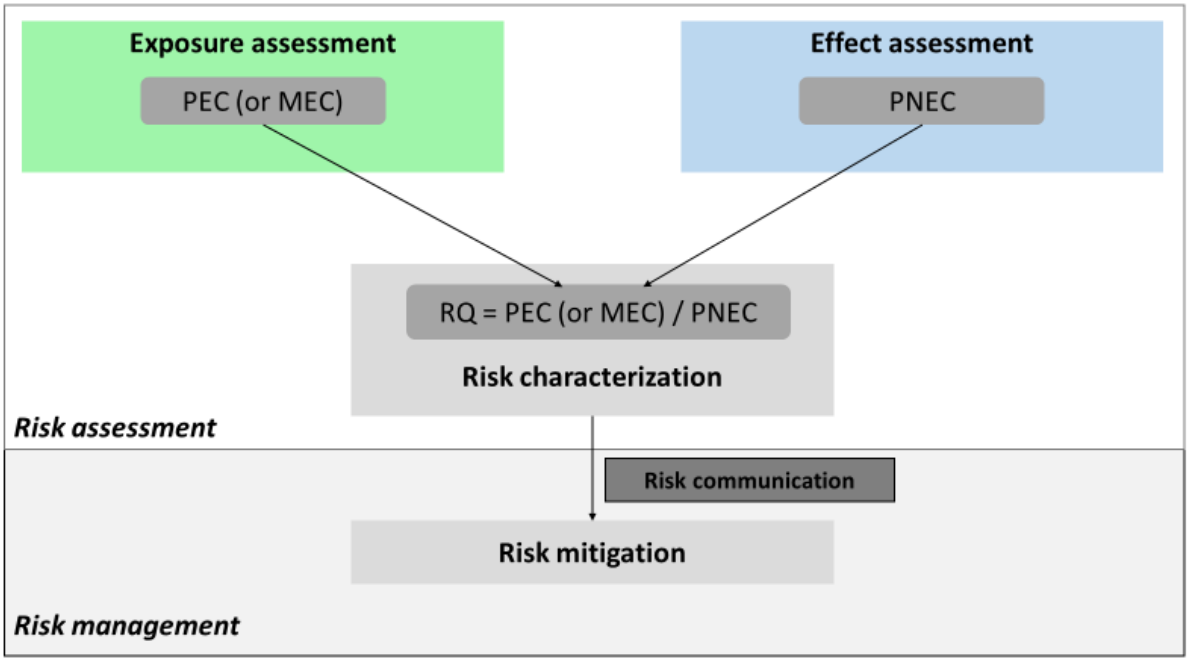

Figure 1 Conceptual environmental risk assessment. AF = Assessment factor, MEC = Measured environmental concentration, PEC = Predicted environmental concentration, PNEC = Predicted no effect concentration, RQ = Risk quotient (Modified from Paper I)

Broadly divided, ERA has two paradigms, prospective and retrospective assessment. Prospective assessment is carried out prior to chemicals entering the market, such as Registration, evaluation, authorisation, and restriction of chemicals (REACH) (EC 1907/2006). Retrospective assessment is carried out for chemicals already in the environment, for example, the water framework directive (WFD). Most of the currently used frameworks are built upon a fundamental concept of comparing a predicted (PEC) or measured environmental exposure concentration (MEC) to a hazard/ effect threshold concentration (Jørgensen & Fath, 2011; Syberg & Hansen, 2016; van Dijk et al., 2021). Prospective assessment for the market placing of pesticides uses a tiered approach to carry out an aquatic risk assessment. The prospective assessment usually applies predicted environmental

concentrations (PEC) in relation to the potential hazard caused by using newly manufactured substances. Prospective risk assessment is based on the tiered approach concept, begins with a simple and conservative assessment and tries to efficiently use resources. Usually, the first and second tiers are based on standard toxicity tests. These are commonly carried out as single species and single substance laboratory tests deriving effect or lethal concentration based on dose-response (DR) model. An organism's response to chemical exposure is dependent on the duration and magnitude of the exposure; usually, toxicity tests are differentiated between acute and chronic tests. Acute tests focus on the occurrence of adverse effects within a short time after a single dose (or multiple doses within 24 hours) exposure to the chemical (e.g., half maximal effective concentration (EC_{50})). Contrarily, chronic tests refer to repeated dosing for a longer duration of time (e.g., 90 days for some test species). These tests can establish a dose-response relationship and determine no effect levels (e.g., no effect concentration (NOEC)) (van Leeuwen & Vermeire, 2007).

If a compound fails the first tier by exceeding the safety threshold, additional and more precise studies are carried out. Some tier 2 assessments can also be complemented with toxicokinetic-toxicodynamic models (TKTD). The two higher tiers combine experimental data and modelling that assesses population and community-level responses. In tier 3, population/community-level experiments and models may be used, whereas tier 4 contains field studies and landscape-level models (EFSA, 2013). The general approach in prospective pesticide risk assessment in the EU can be considered bottom-up as it encourages more industry involvement. In contrast, retrospective assessment is carried out for the post-market monitoring of chemicals, where measured concentrations in the environment are compared to pre-defined hazard-based thresholds for the substances. An example of a retrospective assessment paradigm is the WFD (Directive 2000/60/EC) that guides surface water assessment and management in Europe. It applies a one-out-all-out principle that assumes a water body does not have good chemical status if one chemical exceeds the hazard threshold – environmental quality standard (EQS). It focuses on 45 priority and some national river-basin-specific substances (Backhaus et al., 2019; Munthe et al., 2019). Two EQSs are used for the evaluation of the maximum allowable concentration and the annual average MAC described in the Directive 1013/39/EU amending WFD and Directive on EQS (EC, 2013).

The technical guidance document (TGD) supports legislation such as Commission Directive 93/67/EEC, Commission Regulation (EC) No 1488/94, and Directive 98/8/EC. TGD mentions two approaches to carry out ERA, deterministic and probabilistic (De Bruijn et al., 2002). The deterministic approach is based on point estimates (Rai et al., 2002) referred to as PNEC, derived by applying an assessment factor (AF) to the lowest credible toxicity value available (Figure 1). Vermeire et al. (1999) defined AFs as a "*general term to cover all factors designated as safety factor, uncertainty factor, extrapolation factor, etc and the composite thereof*". For a freshwater environment, the AFs range from 1 to 1000 (in the TGD). If a base set of data containing acute 50% effective concentration (EC50) values for algae, aquatic invertebrates, and fish is used, an AF of 1000 can be applied. When conducting additional ecotoxicological tests, the AF can be lowered as uncertainty is reduced (ECHA, 2008). Some alternative to SSD and NOEC approach is the benchmark dose. It is based on single-species dose-response data for a particular endpoint (EFSA et al., 2017). For the benchmark dose, usually, a dose where the change in response is smaller than 5%, the AF is applied in the same manner (EFSA et al., 2017)

The probabilistic method currently mentioned in TGD is the species sensitivity distribution (SSD) which uses ranked reliable toxicity data (e.g., NOEC or EC_{50}) for a set of species and fits a distribution (minimum 8 taxonomic groups, 10 species, adverse effect-based) (De Bruijn

et al., 2002). An example is shown in Figure 2; here, the PNEC is derived by using the lower bound of the confidence of a hazard concentration (HC_x), which is considered 'safe' for a certain percentage of the population (usually 95%) (Brock et al., 2004; De Bruijn et al., 2002; Posthuma et al., 2001). Then an AF (in the range 5-1) is applied to HC_5 to account for uncertainty related to modelling and experimental toxicity data (e.g., laboratory studies, extrapolation) to derive a PNEC value.

Apart from toxicity, other chemical properties are assessed, such as persistence and bioaccumulation (De Bruijn et al., 2002), and more recently, mobility has become of more interest (Hale et al., 2020).

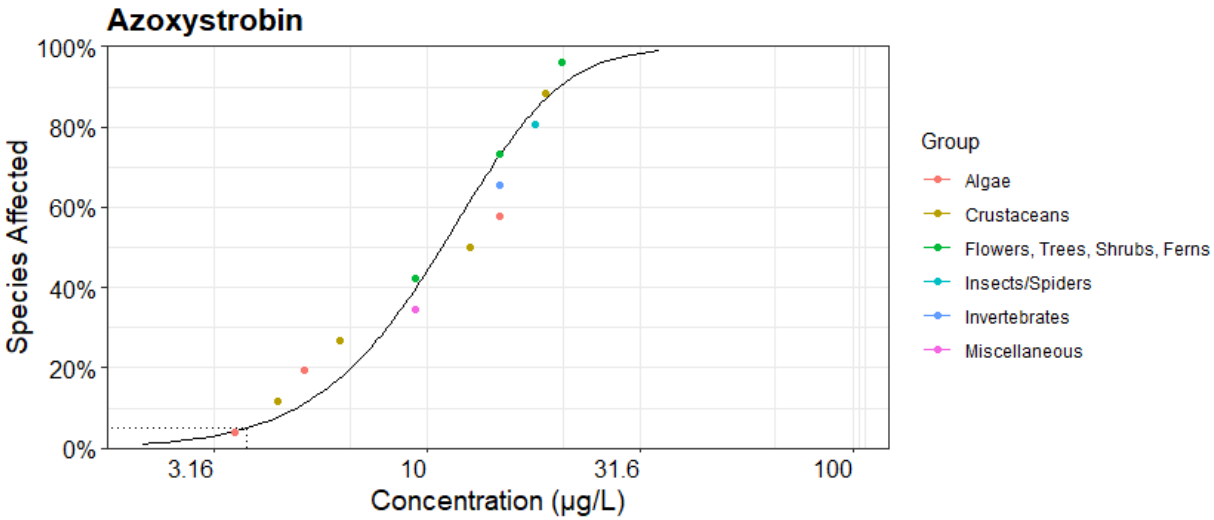

Figure 2 Species sensitivity distribution for the pesticide azoxystrobin based on means for multiple toxicity test values for the same species. The dotted line indicates the derived 5% hazard concentration (HC5) used to derive the PNEC concentration in this study. (modified from Paper I Supplement material I)

ERA is usually focused on single compound exposure, even though ecosystems and humans are exposed to a mixture of chemicals. (Backhaus et al., 2010; Van den Brink et al., 2018). Chemical mixtures can be divided into three types (following Kienzler et al. (2016)):

- intentional: formulated products that are put on the market,
- unintentional: originating from the same source (e.g., discharge during transport or disposal of goods)
- coincidental: originate from countless sources.

Intentional mixtures often have well-known compositions. During the prospective assessment, the properties of the components and their toxicity have been studied under regulations related to their purpose, for example, plant protection products and biocides (at least in Europe). Unintentional mixtures are regulated through WFD or waste-related regulations. Their composition can be known and analysed to some extent through whole mixture approaches when coming from specific effluents. On the other hand, the composition of coincidental mixtures is mostly unknown as they vary temporally and spatially. So far, assessment of this type of mixture is often optional (Kienzler et al., 2016).
There are two mathematical methods for calculating risk when assuming non-interaction mixtures: Concentration addition (CA) and independent actions (IA). CA is applied as the sum of the toxicity of the individual components is equal to the whole mixture toxicity.
IA or response addition calculates the combined effect of an individual component response by applying the independent random event concept (Backhaus et al., 2010; Heys et al., 2016; Kienzler et al., 2016). Standard mixture toxicity models, such as CA and IA cannot always reflect the "real world" where interaction between mixtures occurs. These interactions can be

assumed as antagonism, synergism, or potentiation (Heys et al., 2016). According to Van den Brink et al. (2018), identifying combinations of chemicals that are deviating from the CA or IA is still a challenge and needs further exploration.

3.2 Role of uncertainty in current environmental risk assessment

In this PhD project, risk is referred to as the risk of pesticides to the aquatic ecosystem and describes the likelihood of a negative effect (event) occurring (McCarty et al., 2018). A hazard is usually considered as a source of danger. For example, a pesticide becomes a hazard if it is exposed to non-target biota in the environment. Usually, risk is characterised by its severity (magnitude) of the occurring adverse effects and by the probability (likelihood) of the occurring effects (Maertens et al., 2022; Solomon, 2010). Risk identification is carried out by determining the source and consequence of an event (Stenzelmueller 2018).
Uncertainty is based on the lack of knowledge one has on a true value or relation between quantities (Maertens et al., 2022) and is defined rather generally in ERA (Larras et al., 2022) "*Variability and uncertainty have the potential to result in overestimates or underestimates of the predicted risk*" (USEPA, 2014). Usually, uncertainty can be categorised and defined in several ways, one of the more common distinctions between sources of uncertainty is the differentiation between aleatory and epistemic sources. Aleatory uncertainty is related to natural variability and not reducible, whereas epistemic uncertainty is associated with the lack, insufficient or inadequate knowledge that are reducible (EFSA, 2018; Hora, 1996; Kennedy et al., 2015; Skinner et al., 2014a; Skinner et al., 2014b). These different categories of uncertainties are present in the different risk assessment process steps (Sahlin et al., 2021).

For exposure assessment, uncertainty is often related to the variability in data and parameters in connection to environmental conditions, such as the behaviour linked to exposure potential or the conservativeness in estimations of emission (ECHA, 2012). Here, spatial and temporal variations are caused by many factors, such as changing environmental characteristics and contamination sources (Artigas et al., 2012), and can lead to uncertainty in applied scenarios. Regulatory frameworks deal with these uncertainties by MEC based on "worst-case scenarios"; the measured maximum (peak) concentration is used for pesticides. More realistic exposure assessment is frequently hindered by incomplete knowledge of fate, behaviour, and transport. In addition, inaccurate measurements through sampling methods, e.g., undetected peak concentrations or concentrations below the limit of quantification (LOQ) and limit of detection (LOD) (EFSA, 2013). Other sources of uncertainty, especially when it comes to measured concentrations, are historical concentrations, naturally occurring substances, and other existing stressors (Artigas et al., 2012; Rasmussen et al., 2015). For retrospective assessment (e.g., monitoring carried out under the WFD), the sampling methods used can significantly impact the representativeness of the measured concentration (Table 1). It can be influenced by factors such as the good practice of handling samples (procedures during transport and storage of the samples) (Bundschuh et al., 2014) or by planning-related factors of the sampling campaign. The latter could often be overcome by adapting the frequency of samples to the temporal variation of the occurrence of chemical concentration (Poulier et al., 2014). In general, higher frequency leads to better estimates of peak concentrations (Morrison et al., 2016).

Table 1 Overview sampling active and passive sampling methods, also detailing advantages and disadvantages (Bundschuh et al., 2014; Morrison et al., 2016; Poulier et al., 2014; Spycher et al., 2018; Zhang et al., 2016).

	Sampling strategy	**Approach**	**Advantages**	**Disadvantages**
Active sampling	Grap sampling (or Spot (grap) sampling), discrete sampling	Specific/ certain day and location. ("snapshot")	Sensible results for chemicals with stable properties and for low water renewal rates. Give information about the level of contamination at a certain point in time.	Fail to appropriately capture or completely miss peak exposure concentrations (pulse). Tend to underestimate the (maximum) exposure concentrations. Lack of temporal representativeness and information about exposure during the sampling campaigns. Can have an inadequate sampling frequency Results can have bias for chemicals with short half-lives. Have the highest frequency of LOD and LOQ.
Passive sampling	Time-proportional (composite) sampling (or Time-weighted average concentration (TWA) - automated grap sampling)	Collects samples for predetermined frequency over a certain time period.	Accurate representation of the exposure concentration over a longer time-period, with uniform intervals. Can capture time of peak, but not how long it occurs (peak height). More accurate compared to discrete sampling. Able to assess chronic exposure. Reliable planning of time and expenses.	Peak concentrations are underestimated. Compared to flow-event-triggered sampling, its underestimated pesticide concentrations by a factor of 5. May underestimation of negative effects of short-term/ peak exposure due to dilution of collected samples over time (if composite sample). May have some technical constraints depending on the technology and timely resolution of choice.
	Flow-event-trigger (composite) sampling (or event-based composite sample)	Collection of single samples triggered by stream flow velocity.	Able to captures the pesticide peak concentration. Are necessary to capture peak concentrations. Available tools may not be perfectly developed, but relatively cheap.	Planning of time and expenses might be influenced by unpredictable parameters (e.g., weather). May underestimation of negative effects of short-term/ peak exposure due to dilution of collected samples over time (if composite sample). May have some technical constraints depending on the technology and timely resolution of choice.

On the other hand, prospective exposure assessment often relies on fate and transport prediction models. Different models for various types of environments can be calibrated with site-specific properties. Some examples of currently used exposure prediction models:

- FOCUS Pesticide Root Zone Model (PRZM) Surface water
- RICE Water Quality model (RICEWQ)
- Riverine Water Quality model (RIVWQ)
- World Integrated System for Pesticide Exposure (WISPE) - for Norway

The certainty of their predictions is influenced by the assumptions and scenarios used to run the prediction models. In Nordic countries, some source of uncertainty is related to the degradation rates. They are often overestimated since calibration studies are usually performed in more temperate regions (higher temperatures) where degradation is faster (Benoit et al., 2007; Stenrød et al., 2016; Stenrød et al., 2008).

In the first tier, effect assessment is often based on DR models. Uncertainties in these models are infrequently or not systematically reported, which is connected to either old habits or a lack of computer resources (in previous decades) (Larras et al., 2022). Other related uncertainties can be linked to the selection of data, data set size or extrapolation from laboratory to field or inter-intraspecies variation (EC, 2011; ECHA, 2012; EFSA, 2018; Gustavsson et al., 2017; Rai et al., 2002). The current effect assessment heavily relies on single-species and single-stressor toxicity tests and can hinder realistic ERA. It is questionable if the responses of a few species sufficiently represent the responses of many species in the ecosystem to exposure (Posthuma et al., 2001; Van den Brink et al., 2018). Other factors that influence the uncertainty in toxicity testing are the duration of exposure, modifying factors for toxicity (e.g., factors influencing toxicokinetics), dose metrics, and causality (e.g., often, why and how effects occur is not investigated) (McCarty et al., 2018).

Furthermore, Zijp et al. (2017) pointed out that the current decision criteria using risk ratios (e.g. PEC/PNEC) cannot be interpreted as reliable quantitative estimators of actual risk.
The basis of the effect assessment in which NOECs and No Observed Effect Level (NOELs) are applied is frequently and for a long time being criticised, for example "*A warning: NOECs are inappropriate for regulatory use*" by Chapman et al. (1996), or "*What level of effect is a no observed effect*?" by Crane and Newman (2000). Landis and Chapman (2011) stated that NOEC's similar endpoints reflect "*a poor application of environmental statistics and laboratory testing*". Some of their more vigorous criticism states that these no observed effect endpoints can be considered as "*merely exposures selected by those doing the testing and are inconsistent between studies*" (Landis & Chapman, 2011), these biotests and experimental designs lead to a failure of statistical significance (some more details can be found in Fox (2008), Nelder (1999), Suter (1996)). Other criticism is related to the usage of safety factors (e.g., AF) that are not based on scientific findings (Ahlers et al., 2006; Brühl & Zaller, 2019; Landis & Chapman, 2011; Malkiewicz et al., 2009; van Dijk et al., 2021).
Some uncertainties that are related to selecting a single effective or lethal dose from a DR model (e.g., lowest NOEC or EC_{50}) can be overcome by using an approach based on SSDs. As they are based on multiple (eco)toxicity tests of different species, they can reflect some interspecies differences in sensitivity to a chemical (Belanger et al., 2017; EC, 2011). Some uncertainties cannot be overcome when using SSDs that are partly related to technical prerequisites, such as the non-representativity or lack of data and limited taxa diversity (Belanger et al., 2017). Current effect assessments do not require a detailed and relevant site-specific assemblage of species which in cases of retrospective risk assessment may lead to a site-specific exposure concentration being compared with a generic SSD (Grist et al., 2009).

Uncertainties are also related to SDD model construction: in-transparent of model choices, the selection of appropriate confidence intervals and appropriate distribution shape (Forbes & Calow, 2002), and the level of protection (Forbes & Calow, 2002; Grist et al., 2009). Even though different species' sensitivity is accounted for, they are not weighted within the distribution (Forbes & Calow, 2002). There is a general discussion from an ecological point of view regarding the relevance of a single-chemical SSD with an incentive to address more possible pressures and consequently place the risk posed by pollutants into a more meaningful context (Belanger et al., 2017).

An improvement could be to extrapolate effects across different levels of the ecosystem and different life stages. This can be achieved by using mechanistic effect models that Larras et al. (2022) has divided in six main categories: Quantitative structure-activity Relationship ((Q)SAR), DR and TKTD, population, multi-species, landscape, and mixture models Table 2. These models could enable more in-depth knowledge about the interactions and effects in an ecosystem and may increase the availability of data for key protection goals for species (Van den Brink et al., 2018).

Table 2 Overview effect modelling for ERA of PPPs. (Q)SAR = Quantitative structure-activity Relationship, DR = Dose-Response model, TKTD = ToxicoKinetics-ToxicoDynamic, GUTS = General Unified Threshold models of Survival, DEBtox = Dynamic Energy Budget applied to ecotoxicology, BCF = Bioconcentration factor (adapted from Larras et al. (2022))

Categories	**Example models**	**Description**	**Usage of models**
(Q)SAR	(Q)SAR	Mathematical models that use statistical correlation based on molecular descriptors to predict the ecotoxic city of substance; currently divided into rule-based expert systems (SAR model), and statistical systems ((Q)SAR model)	Can be used to predict toxicokinetic parameters (e.g., bioconcentration factor (BCF)), describing the correlation between hydrophobicity and BCF e.g. $\log_{10}(K_{ow})$) or acute toxicodynamic parameters (predicting the dose that leads to toxic effect e.g., LD_{50}), classification of substances (determining the mechanism or mode of action)
DR or TKTD	DR models	Static DR - links a substance concentration to the (potential) effect (adverse effects e.g., survival, reproduction, growth) of an exposed organism	DR -used primarily to calculate effect or lethal concentrations (tier 1 assessment)
	TKTD models	Dynamic TKTD - convert the exposure to a chemical (even if time-variable) into the predicted effect on the adverse effects of organisms; allowing to link the dynamics of external exposure concentration to the prediction of impact over time,	Toxicokinetic models - calculation of bioconcentration, biota sediment accumulation or biomagnification factors (also proposed to use for binary mixtures), TKTD models - extrapolation of effects under tested exposure patterns to untested ones,
	GUTS (subcategory of TKTD)	Handle survival data	Describes the survival probability as a function of time and exposure concentration (which can vary in time)
	DEBtox (subcategory of TKTD)	Considers different mode of actions of (potentially) toxic chemical substances	Explain the effects on sublethal individual history traits

Categories	Example models	Description	Usage of models
Population	Agent-based models	Simulates a population depending on tested scenarios (e.g., change in population size)	Assessment of chemical effect that can be observed on individual to population level; assessment of recovery from individual to population level
Multi-species models	SSD	Cumulative Distribution Function (CDF) that uses single-substance or mixture toxicity to a set of species (viewed as community or assemblage)	Impact at the community level (with an SSD, e.g., potential affect fraction (PAF), RAC - regulatory acceptable concentration. PNEC - predicted no effect concentration)
	Food web models and community models	Community models consider various types of inter-species interaction; food-chain models consider dynamic of abiotic factors	The indirect effect of chemicals within communities (e.g., PERPEST model), bioaccumulation and biomagnification within food chains or webs
Landscape models	-	Assess landscape structure (e.g., temporal and spatial variability) to predict the chemical exposure or toxicity organisms or effect on the population (of non-target species)	Can provide information on pesticide contribution to the degradation of biodiversity
Mixture models	Simple interaction	Assumes that one substance in the mixture, at a non-toxic concentration, can influence the toxicity of other substance through an indirect mechanism	Used to assess the effect of multiple stressors/ chemical mixtures

In Europe, handling uncertainty is based on the precautionary principle to safeguard both human and environmental health. It is defined as "*Where there are threats of serious or irreversible damage, lack of full scientific certainty shall not be used as a reason for postponing cost-effective measures to prevent environmental degradation" (UNEP 1992*), or in other words "*better safe than sorry*" (EC, 2017). However, there is growing evidence lot of protection that goals are not met, even though worst-case-scenarios are used, and the current risk assessment schemes not being sufficient to assess realistic risks of chemicals (Brühl & Zaller, 2019; Schäfer et al., 2019; Weisner et al., 2021). The use of worst-case assumptions and applying assessment factors to account for uncertainty and extrapolation could lead to improbable and unrealistic assessments of the actual risk that have been criticized for not being efficient nor transparent (Jager et al., 2001; Landis & Chapman, 2011; Van den Brink et al., 2018). The risks posed to the environment by chemicals and other stressors are expected to increase and diversify, and some scientists have requested an adaptation of the current frameworks (Fairbrother et al., 2016; Topping et al., 2020).

3.3 The impacts of climate change on pesticide fate and integration into environmental risk assessment

Climate change is expected to affect weather conditions and land-use practices indirectly in the future. Through regularly carried out predictions and modelling efforts, one can inquire about the extent and variability of Climate change in plenty of the reports by the Intergovernmental Panel on Climate Change (IPCC), European Commission, and more regional-focused governmental reports. However, the extent of possible changes and their effect tends to be connected to uncertainty (Bloomfield et al., 2006). ERA is already challenged to predict actual risk posed to the and lacks accounting for the complexity of the environment; consideration of the climate change magnitude of uncertainty and variability is an additional challenge (Brühl et al., 2013; Di Guardo et al., 2018; Köhler & Triebskorn, 2013; Van den Brink et al., 2018). When focusing on pesticides, the exposure of an ecosystem is influenced and depends on various site-specific properties, e.g., topography, soil characteristics, agricultural practices, climate conditions, chemical properties, crop and pest type (Di Guardo & Hermens, 2013; Gagnon et al., 2016; Leonard, 1990; Wauchope, 1978). A good overview of expected changes in chemical exposure, agricultural responses and the identification of essential research needs are described in Hader et al. (2022) (or (Bloomfield et al., 2006; Delcour et al., 2015; EEA, 2019)). The most important impacts of climate change on agriculture for the two climate zones relevant to this project are described in Table 3.

Table 3 Overview of climate change impacts on the agriculture sector for Boreal and Mediterranean region (adapted from EEA (2019))

Climate region	Increase in	Decrease in
Boreal region (e.g., South-east Norway)	Heavy precipitation events	Snow, lake and river ice cover
	Precipitation and river flow	
	The potential for forest growth and risk of forest pests	
	Risk winter storm damage	
	Crop yield	
Mediterranean (e.g., Spain)	Heat extremes	Precipitation and river flow
	Risk of droughts	Crop yield
	Risk of Biodiversity loss	
	Risk of forest fires	
	Water demand and competition between water users	
	Risks for livestock production	

Climate change may result in changes in persistence and transformation of pesticides, which can respond to microbial ecology, soil moisture and their aerobic/ anaerobic status, and degradation pathways and kinetics. Furthermore, pesticide transport and fate may be shifted due to changes in climate conditions or agricultural practices and technology. That can lead to changes in the physiochemical properties of the soil, in runoff, and volatilizations (Hader et al., 2022). Still, the extent of expected changes is often unknown and can hinder modelling efforts and assumptions made for ERA (Di Guardo et al., 2018; Di Guardo & Hermens, 2013). Some efforts have been undertaken with catchment-based modelling studies that were carried out with a range of climate change scenarios, thereby providing insights into pesticide behaviour, fate, and transport in the future (Bloomfield et al., 2006; Bolli et al., 2013 ; Christen et al., 2006).

One of the indirect effects of climate change is the adaption in agricultural practices. The emission of agricultural chemicals will be influenced by dietary changes, diseases, and pest pressure, temperature and precipitations changes, technological and policy advances. These, in turn, will respond to a change in land use and crop type, pesticide type, and use agricultural technologies (Bloomfield et al., 2006; Hader et al., 2022; Kattwinkel et al., 2011; Noyes et al., 2009). The development of appropriate scenarios considering these possible changes need to be incorporated in such scenarios. For example, some studies suggest the use of regression-based analysis to derive more appropriate pesticide emission scenarios, which can be used to predict exposure concentrations (Chiu et al., 2017; Kattwinkel et al., 2011).

3.4 Communication of uncertainty

Overall, uncertainty is part of risk assessment as it needs to account for natural variability as well as complex relationships. This limitation in knowledge about risks may lead to conflicting interpretation of what happens and cause irritations about precision and claims of scientists in the field. Uncertainty can be interpreted in various ways by the public and can be viewed as a lack of evidence or an indicator of ignorance. Instead of seeing uncertainty as an

improvement in precision, frequently, it is understood as a sign of weakness (SAPEA, 2018). To quote Pariès (2017), "*A paradigm shift is needed. Another approach to safety is possible. Uncertainty is not necessarily bad. Actually we are immerged in uncertainty, we live with it, and we need it to deal with the world's complexity with our limited resources. We have inherited cognitive and social tools to manage it and deal with the associated unexpected variability. We need to better understand these tools and augment their efficiency in order to engineer resilience into our socio-technical systems*".

The communication of risks and uncertainty associated with pesticides is influenced by stakeholders' interpretation and opinion. Different opinions are derived from the differences in interest, views and understanding of environmental protection or underlying ideologies and values. Generally, for risks to be acceptable, it is vital to develop and carry out a relevant risk assessment for stakeholders. A shared vision is also important to improve policies that are excepted containing clear and well-defined views (EC, 2018). Zero risk is impossible to ensure, and therefore, only a high level of certainty can be achieved by risk assessors to hinder the occurrence of harmful effects and aid informed decision-making. However, minor adverse effects are accepted and considered sufficiently small (EC, 2018). Clear messages are needed to avoid confusion and ensure risks are communicated adequately. It is difficult for specialists to communicate the outcomes of laboratory and field studies in a way that the general public understands it (Van den Brink et al., 2018). Hence, the awareness and behaviour of the public, as well as stakeholder involvement, should be further studied and integrated into ERA (Artigas et al., 2012). Nevertheless, communication of risk should not ignore uncertainties and needs to be truthful to ensure trust in the risk assessment process. Otherwise, stakeholders' beliefs may shift even further toward mistrust in scientists and industry-paid studies.

Maertens et al. (2022) stated, "*As we will see, embracing uncertainty can free us to adopt a new toxicity testing paradigm*". The current ERA process is not perfect, and there is a high necessity to gain more knowledge. "*Availability and transparency of data is necessary to provide scientists and policy makers with all the information needed. Finally involvement of social scientists together with chemists and ecologists is also a key to the provision of a sound comprehensive knowledge to the policy makers.*" (Artigas et al., 2012).
Unfortunately, unanticipated catastrophic events can still occur due to the misuse of chemicals that potentially can threaten human and ecosystem health and can lead to mistrust in assessment and processes in place (SAPEA, 2017). For the current decision-making in regulatory ERA, safe concentrations need to be defined, so regulators can determine if the use of a chemical should be allowed. New development and assessment methods need to be adapted in ERA more rapidly to enable better protection of the environment and humans. Nevertheless, ERA is a valuable tool that helps to minimize threats caused by pesticides. The communication of uncertainty and risk can help earn the trust of involved stakeholders is one of the most challenging tasks for the future.

3.5 Probabilistic risk assessment

The traditional risk characterisation is usually referred to as "deterministic" and is primarily based on point estimates (Rai et al., 2002). In contrast, probabilistic approaches can enable risk assessors to include uncertainty estimates and stochastic properties in both exposure and effect assessments (Fairbrother et al., 2016; Solomon et al., 2000). Probabilistic risk assessment can quantify one or more sources of variability in effect and exposure and their resulting risk by using probabilities or probability distributions (EUFRAM, 2006). The EUFRAM project has defined probabilistic risk assessment as a *"term used in pesticide risk assessment to describe 'quantitative risk analysis' or 'uncertainty analysis'. In essence it is the use of probability theory to characterize both toxicity and exposure. It is usual to consider the description of toxicity and exposure in terms of distributions*." The challenges related to interpreting the outcome of probabilistic risk assessment can be one of the most influential factors of them not being more commonly used in legislation. As Jager et al. (2001) put it, *"Of course, there is always a discomfort in risk assessment when the scientific process meets the legal one; decision makers are usually not statisticians and may feel ill at home with probability distributions. Instead of focusing on the statistical technicalities for uncertainty analysis, due attention should be paid to transparency, presentation and interpretation of uncertain end results to allow the risk managers to make informed decisions.*"

In ERA, the risk estimation is often simplified to a single value that displays a simple "yes/no" message to the risk assessor. On the other hand, probabilistic approaches use distribution throughout the whole assessment process instead. Anyhow, some uncertainties can be better accounted for in exposure assessment through distributions when using probabilistic approaches (Regan et al., 2003; Verdonck, 2003). Traditional risk assessment-based approach that, to some extent, uses a probabilistic approach is the SSD. As mentioned, they are based on multiple toxicity tests of different species and therefore reflect interspecies differences in sensitivity to a chemical (Belanger et al., 2017; EC, 2011). Moreover, they can be used to develop a community threshold (Belanger et al., 2017). Some examples of probabilistic approaches are joint probability distribution, probabilistic risk quotient, quantitative overlap, and Bayesian regression modelling (see Table 4).

The following describes some of the probabilistic approaches, their strength, and weaknesses. Quantitative overlap characterises risk as the extent of overlap between two curves (e.g., exposure and effect distributions). In other words, the overlap indicates the probability of exceeding the exposure concentration, thereby allowing for the estimation of the likelihood of impact that is potentially posed on the ecosystem (Hall et al., 2000; Manz et al., 1999; Poletika et al., 2002; Solomon et al., 1996; Solomon et al., 2000). Another probabilistic approach is the joint probability curve. For any given concentration, an effect distribution's cumulative probability (ordinate) is usually plotted against an exposure distribution's cumulative probability (abscissa) (Verdonck, 2003). One of this method's advantages is that it is easy to construct while providing more information than a simple risk quotient. However, a downside commonly associated with this method is the difficulties for decision-makers and risk managers to interpret and understand its output (Cardwell et al., 1999; Dreier et al., 2020; Giddings et al., 2000).

An example of how to visualize the outcome of this probability approach is better presented by Fairbrother et al. (2016), displaying a colour-schemed joint probability distribution. Another probabilistic approach is the probabilistic risk quotient, which is basically an exposure distribution divided by an effect distribution (e.g. SSD or SSD point estimate). This

probabilistic approach is easy to calculate and considered helpful for estimating of risk ranking and establishing priorities between different risk scenarios. (Campbell et al., 2000; Duvall & Barron, 2000; Verdonck, 2003). Another probabilistic approach is Bayesian regression modelling, an example was displayed by Wolf and Tollefsen (2021), who fitted MECs of three monitoring campaigns to derive a PEC distribution. The distributional regression model can separate temporally and spatially specific variation from latent background concentration while incorporating LOQ and LOD.

Some arguments frequently used against probabilistic approaches are data requirements and their output, often deriving distributions that are hard to interpret for decision-making (or other stakeholders) (Dreier et al., 2020; Giddings et al., 2000). Also, few studies pay attention to the visualization of risk and uncertainties (Verdonck, 2003)

Table 4 Overview of some of the currently existing probabilistic risk assessment approaches. AUC = Area under curve, SSD = Species sensitivity distribution.)

Risk characterisation method	Methodology/ Procedure	Advantage	Disadvantage	References
SSD	A probabilistic model for the variation of the sensitivity of biological species for a particular toxicant/ a set of toxicants; A HC (5-10%) is derived from a log-normal or log-logistic function, a more conservative concentration can be estimated by also using a lower X % confidence limit	Can provide a statement of the probability of harm to the selected group of species	Debatable whether a quantity derivable from a fixed probability model can be called "probabilistic"; there is a possible inappropriateness of the level of protection and distribution shape; interaction between species is not weighted within the sensitivity distribution	EUFRAM (2006); Forbes and Calow (2002); Posthuma et al. (2001)
Quantitative overlap	The extent of overlap between two curves is used to characterise the risk; the overlap indicates the probability of exceeding the exposure concentration	Allows estimation of the likelihood of potential ecosystem impacts and their magnitude	Relative risk and does not make a quantitative prediction; as no exact quantification of magnitude and likelihood of potential effects is carried out	Hall et al. (2000); Manz et al. (1999); Poletika et al. (2002); Solomon et al. (1996); Solomon et al. (2000)
Joint probability curve (JPC)	Plotting the cumulative probability of effect distribution on the ordinate against a cumulative probability of an exposure distribution on the abscissa for any given concentration	Provides more information than a single estimate RQ; relatively easy to construct and calculate	Not useful as quantitative predictors of risk; AUC of a JPC contains insufficient information to account for environmental circumstances; sometimes difficult for decision-makers and risk managers to understand and interpret	Giddings et al. (2000); Verdonck (2003)

Risk characterisation method	Methodology/ Procedure	Advantage	Disadvantage	References
Probabilistic risk quotient	Exposure distribution divided by either SSD or SSD point estimate	Use of more available data for effect and exposure; more valuable to estimate ranking and establishing priorities among alternative risk scenarios; Provides sense risk estimates; easy to calculate	Organisms used to derive the distribution are usually not representative of the actual community or ecosystem, so the species' role in the structure is not considered	Regan et al. (2003) Campbell et al. (2000); Duvall and Barron (2000); Maund et al. (2001); Verdonck (2003)

3.6 Bayesian networks: introduction and application

During the previous decade, BNs have been recognized as an effective tool for dealing with environmental problems and decision-making under uncertainty, and recently their use has increased (Hamilton & Pollino, 2012; Kaikkonen et al., 2021; Landis et al., 2013; Moe et al., 2021; Sperotto et al., 2017).

BN can model a system as a directed acyclic graph (DAG) consisting of a set of random variables (nodes) and their interaction in a network (arcs) (Hamilton & Pollino, 2012; Kanes et al., 2017). Within the network, arcs represent unidirectional cause-effect links between nodes (Bromley, 2005; Norton, 2010). The node causing an effect is referred to as the parent node, and the node it affects is called the child node. Root nodes do not have parent nodes, and those without child nodes are leaf nodes (Figure 3). Each node contains states with assigned probabilities (degree of belief), also referred to as a prior probability *p(X)(Bromley, 2005)*.

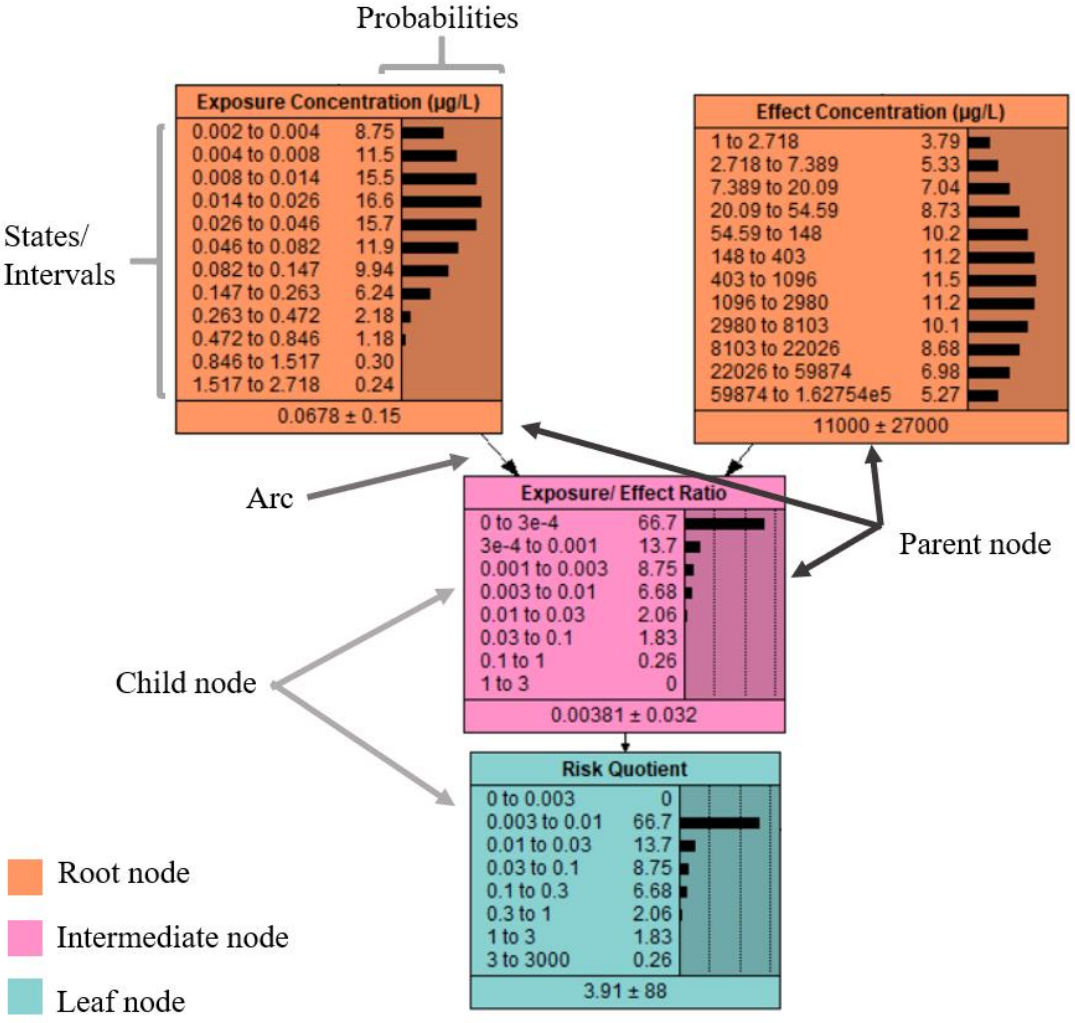

Figure 3 Example Bayesian network components (modified from Paper I)

The relationship between parent and child nodes is described by the conditional probability table (CPT), which contains each possible combination of parent node that are incorporated through a joint probability function based on conditional independence (Norton, 2010; Pollino & Henderson, 2010). According to Heckerman (1997), the joint probability distribution (in a direct graph-causal chain) is given by:

$$p(x) = \prod_{i=1}^{n} p(x_i | pa_i) \qquad [1]$$

The parent node is denoted by $\boldsymbol{Pa_i}$ and child node by $\boldsymbol{X_i}$. When new evidence becomes available, BNs implement the Bayes theorem, also referred to as Bayes' rule. It was founded and first published by Reverend Thomas Bayes in the essay "*Towards Solving a Problem in the Doctrine of Chances*" in 1764 (Pollino & Henderson, 2010; Uusitalo, 2007). The Bayes' rule describes how probabilities are combined to update the output probability distributions $\boldsymbol{p(X|E)}$, the posterior probability of $\boldsymbol{X}$ given an event $\boldsymbol{E}$ (Hamilton & Pollino, 2012; Molina et al., 2010; Norton, 2010; Pollino & Henderson, 2010):

$$p(X|E) = \frac{p(E|X)p(X)}{p(E)} \qquad [2]$$

BNs present results as a probability distribution instead of single values and can integrate different kinds of information, such as direct measurements, expert opinion, or model outputs. In ERA, limited data and knowledge often hinder more realistic modelling efforts as they require constraining to simpler model structures with more assumptions. As BNs can incorporate various sources of data input, they can be applied in cases where data is scarce while still addressing uncertainties and variabilities (Hamilton & Pollino, 2012; Pollino & Hart, 2006). One of their most beneficial features when it comes to the risk assessment cycle is the possibility to easily update data and gained knowledge (Pollino & Hart, 2006). This is particularly useful for pesticide risk assessment and management tasks as these require uncertainty characterisation and handle uncertainty evaluation in a transparent way (Carriger & Newman, 2012). Furthermore, BNs allow for the integration of various assessment endpoints within the same framework. Another advantage of BNs being casual models is that they can assist in risk prioritization, aiding better recognition of vulnerability relations and hazard pathways (Sperotto et al., 2017).

The construction of a BN consists of three steps: *Knowledge Acquisition*, *Design*, and *Application* (Figure 4). In the *Knowledge Acquisition* step, information about concepts, the system and its processes, and other information and data is gathered. Building conceptual models and defining all its network nodes is the starting point of the *Design step*. Usually, those are based on mind maps compiled in the first step. Identification of important nodes and their linkage is crucial in this part. Node prior probabilities are derived from distributions or equations fitted to in-situ data measurements or model outputs. After parameterisation the network is compiled. The *Application step* obtains model outputs for the leaf nodes. Once compiled, model validation, such as the sensitivity analysis carried out in Paper I, is highly recommended.

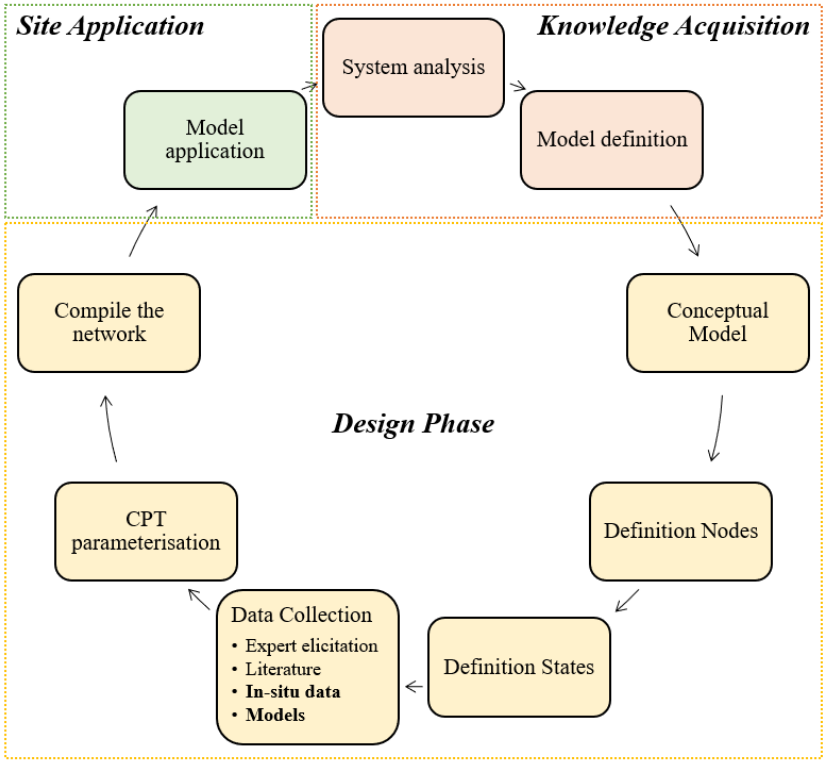

Figure 4 Generic methodology for the construction of a Bayesian network. Bold font are data sources used in the three papers of this synthesis (adapted from Pollino and Henderson (2010))

IV Data and method

4.1 Previous risk assessment approaches using Bayesian networks

BNs have not been commonly used even though they have been applied to many fields and can contribute to assessing ecological and contaminants risks (Kaikkonen et al., 2021). They can implement site-specific information within the model to calculate the risk of contaminants and other stressors to the endpoints while quantifying uncertainties. As Landis et al. (2013) pointed out, traditional ERA needs to better account for global climate changes. In this context, they presented seven principles of conducting an ecological risk assessment. The sixth principle states: "*Determine the major drivers of uncertainty, estimating and bounding stochastic uncertainty spatially and temporally, and continue the process as management*" (Landis et al., 2013). Troldborg et al. (2022) published an example of this, carrying out a probabilistic approach to assess the risk of pesticide exposure with the help of a spatial BN. Thereby, the developed BN can better inform about uncertainty for management interventions on a field level (Troldborg et al., 2022). Another advantage of BN is that various perspectives and endpoints can be integrated and considered within the same framework. An example of a published BN with toxicants, future climate projections, and some measures of ecological risks for polar bears is Atwood et al. (2016). Their model interlinks different sub-models such as "Marine prey and conditions" – an abundance of prey with "sea ice" - historical and predicted data from satellite observation (Atwood et al., 2016).

In a recent study, Carriger and Barron (2020) demonstrated how BNs could be used to estimate a probabilistic risk quotient for a single species (Puma concolor coryi) using an exposure and effect distribution. By this, they succeeded in including more uncertainty and variability influencing the risk estimation by expanding the traditional risk quotient (Carriger & Barron, 2020). Focusing on the aquatic environment for contaminated site management, Carriger and Parker (2021) explored and built a conceptual site model using BNs. Another study displayed how climate change variables and other anthropogenic or natural stressors can be integrated into a BN, as shown in Gaasland-Tatro (2016). A relative risk model was used to evaluate ecological parameters on a regional landscape scale (Gaasland-Tatro, 2016). In a paper by Landis et al. (2017), a BN relative risk model was presented that used biological and abiotic endpoints to calculate the ecological risk to various regions in the study area. Landis et al. (2017) developed a model that can assess changes in the risk on these biological endpoints depending on management activities. Furthermore, the multiple stressors effect can be evaluated over the regional spatial scale (Landis et al., 2017). The most recent review of BN in environmental risk assessment was carried out by Kaikkonen et al. (2021). It found that BNs have been applied to various environmental risk contexts and scopes in recent years, but there is still potential for improvements in their use in ERA (Kaikkonen et al., 2021).

4.2 Development of the Bayesian networks– from risk quotient to effect based approach

In this project, BNs were developed and explored to integrate various factors relevant to extend the current deterministic ERA methodology.
In the first step, a BN was developed closely following the traditional ERA procedure (Figure 5). The model shown in Paper I, was similar to the terrestrial approach by Carriger and Barron (2020), which derived a distributed risk quotient in this study as a ratio of exposure and effect distributions. In Paper I, a distributed risk quotient was derived by fitting an exposure distribution to monitoring data for a Norwegian case study area. In this study, an effect

distribution was fitted to toxicity data (multiple aquatic species, NOEC values) collected from NIVA Risk Assessment database (https://www.niva.no/en/projectweb/radb). In regular ERA, a PNEC value is derived by applying an AF to the most sensitive NOEC/ EC_{50} value or HC_5 of an SSD. In the developed BN model, a precautionary factor was applied after deriving an exposure: effect ratio to account for uncertainty related to the number of data points, species, taxonomic groups, and limitations in measured concentrations on the exposure part. Furthermore, a seasonal node was introduced to account for some temporal differences in the risk characterization. This way, an innovative approach was presented by carrying out probabilistic risk characterization with a BN (Paper I).

Paper II incorporated future scenarios for climate and land-use changes in probabilistic risk assessment for a Norwegian case study area. It used an exposure prediction model - World Integrated System for Pesticide Exposure (WISPE) (Bolli et al., 2013), to derive data for the exposure module. The WISPE model was run for the various developed scenario combinations containing specific time periods, global climate models, and application scenarios. Furthermore, this process-based exposure model was run for five pesticides (three herbicides and two fungicides), and its output predicted the exposure concentrations for a specific time since application. Due to the prediction model output, the BN structure was changed, now containing scenario nodes (climate model, application scenario, and scenario combination) and time-specifying nodes that determine the exposure concentration distribution for a specific time after pesticide application. After that, effect data was collected for NOEC or EC_{50} values for each pesticide from Ecotoxicology databases. Finally, the effect distributions were fitted to either NOEC or EC_{50} data sets. In this case, the risk characterisation was carried out with a distributed risk quotient (leaf node) (Paper II).

As was shown in Paper III, a BN model was developed that predicts the risk of various biological endpoints and the community level in a rice field. The study was carried out for a Spanish (Mediterranean) case study area. In Paper III, the exposure distribution was derived with a different process-based exposure model called autoRICEWQ (Fuentes-Edfuf & Martínez-Megías, 2022). It not only considered various applications, climate conditions, and crop types but also accounts for more spatial variability (ca. 550 rice field clusters in the Albufera national park) when predicting the exposure concentration in a rice field (Martínez-Megías et al., [in prep]). The effects on different biological endpoints were predicted with a case-based effect model (PERPEST) based on a database of micro- and mesocosm studies based on the mode of action (Larras et al., 2022; Van den Brink et al., 2006; Van den Brink et al., 2002). Different pesticide types of effects on the ecosystem could be compared by including additional endpoint group nodes and an effect on community nodes in the BN model. The shown innovative BN approach integrated semi-field data for a probabilistic risk assessment while using full probabilistic scenario-based exposure assessment (Paper III).

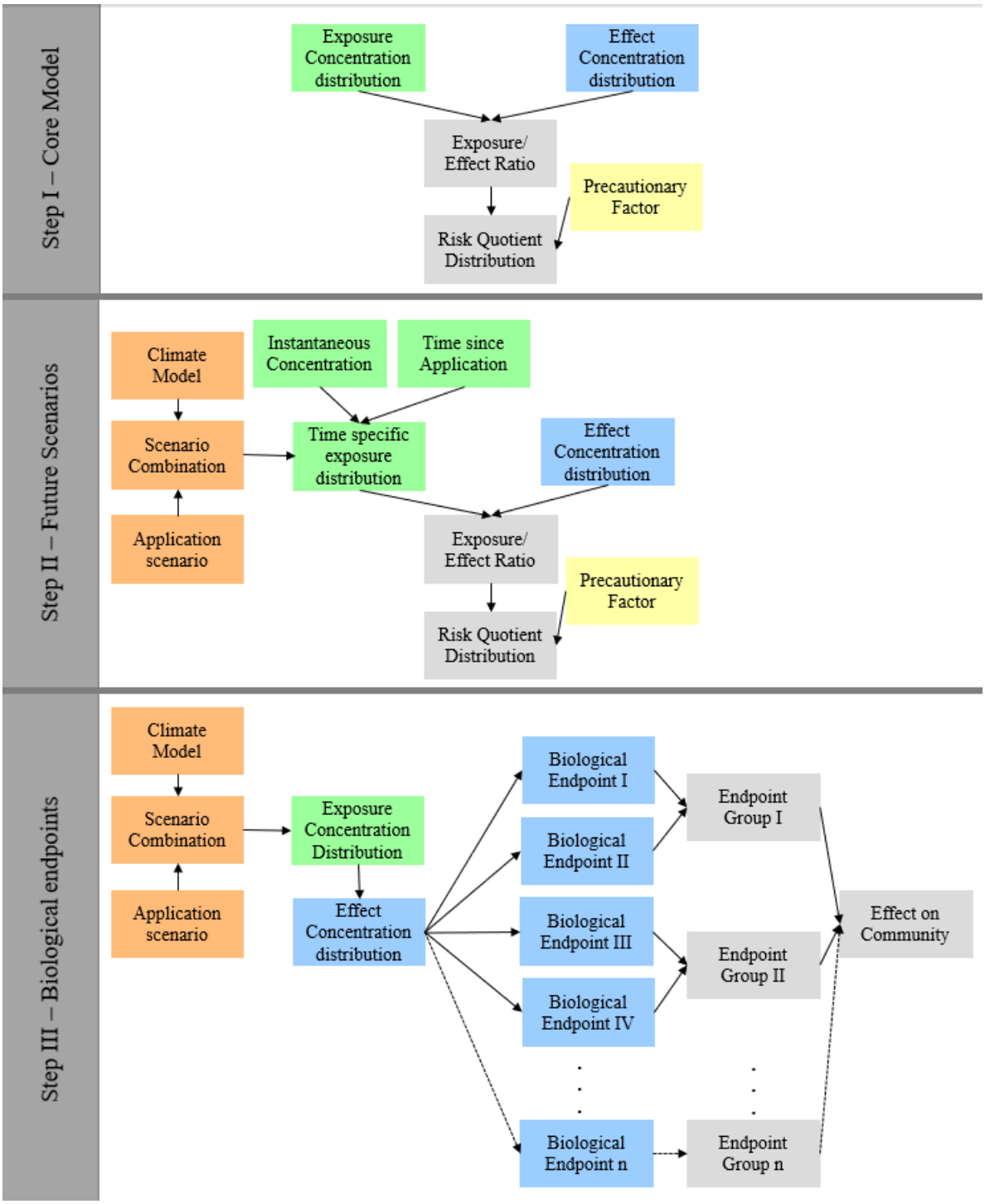

Figure 5 Development of conceptual models of the Bayesian network approaches used in Paper I – III.

V Results

5.1 Paper I – Using Bayesian networks for probabilistic risk assessment of pesticides

The communication of uncertainty for all components of risk characterisation and use of distributed risk quotient as output is still rare but relevant to carry out more appropriate and informative ERA. In Paper I, a BN was developed that incorporates a probabilistic approach to pesticide risk characterisation. As was shown in Paper I, the BN can be applied for fully probabilistic risk characterisation for retrospective assessment. The developed BNs predicted risk quotient distributions for three regularly detected pesticides in the study area: azoxystrobin, metribuzin, and imidacloprid. Furthermore, it demonstrated intermediate and fully probabilistic approaches for risk characterisation depending on data availability, see Figure 6.

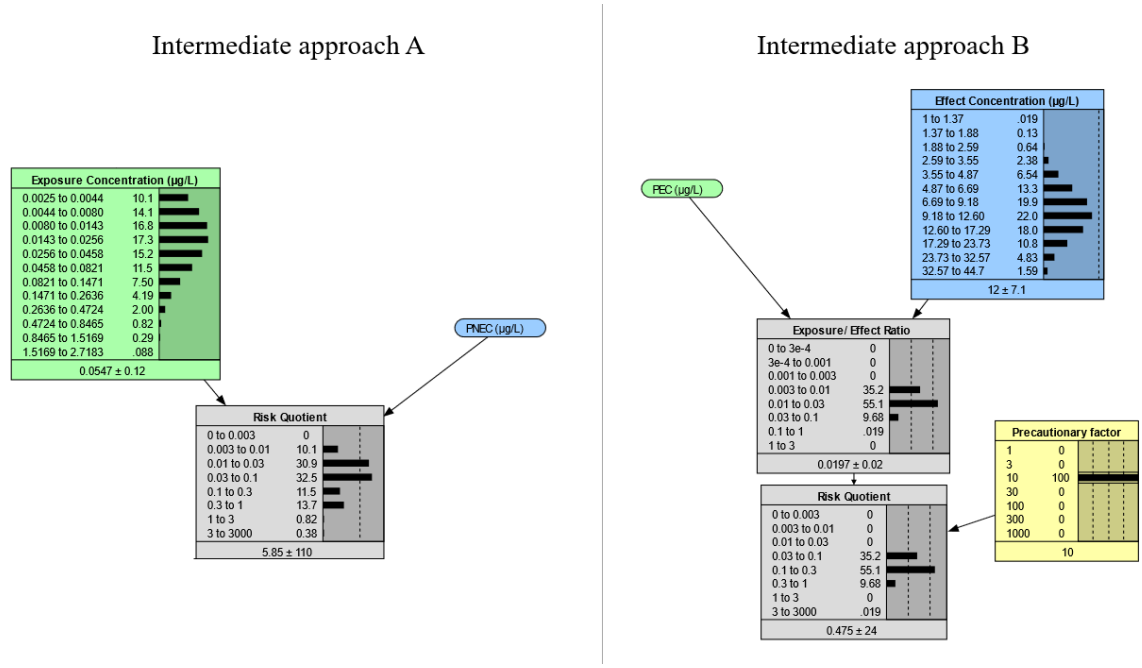

Figure 6 Intermediate probabilistic approaches. Approach A displays how to derive a risk quotient distribution from a exposure concentration distribution and a single value PNEC. Approach B shows how a risk quotient distribution is derived from a single vale PEC and an effect concentration distribution (adapted from Paper I).

In addition, a seasonal risk calculation was shown as a seasonal variable (node) was introduced into the core network structure. This enabled the comparison of different seasons and their risk to the aquatic environment, see Figure 7.

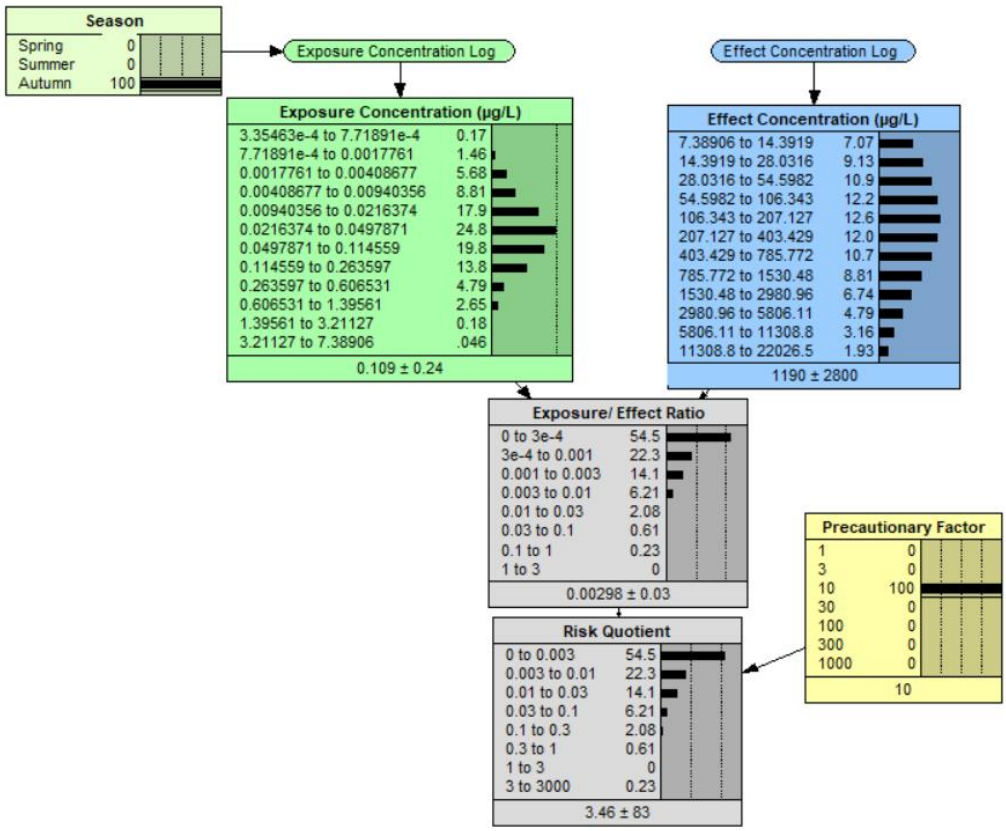

Figure 7 Example of a parameterized seasonal and fully probabilistic Bayesian network model for metribuzin. The risk quotient distribution was predicted for autumn season using a precautionary factor of 10 (adapted from Paper 1 Supplement material I)

In this paper, the results are displayed as bar plots, an alternative to cumulative probabilities often derived in other probabilistic approaches. Albeit, the BNs developed in Paper I enabled the quantification of uncertainty coherently and transparently for all components in the network and different levels of risk. At the same time, enabling easy-to-understand communication associated with model outputs (Paper I).

5.2 Paper II – Integrating exposure prediction model output into a Bayesian network

In Paper II a prospective risk assessment approach was shown for a Norwegian case study area. A probabilistic causal model was developed that assessed the environmental risk of pesticides under several future scenarios. The BN built on the core model of Paper I, while incorporating future climate and application scenarios. Various types of information were integrated into the BNs that acted as a meta-models. The BNs predicted risk quotient distributions using process-based exposure models (WISPE) inputs, toxicity tests, climate projections, and for five selected pesticides: clopyralid, fluroxypyr-meptyl, MCPA, prothioconazole, and trifloxystrobin. The model was able to show the general trend for risk change for this Norwegian region, as it predicted a slight increase toward higher risk levels for future periods (2000-2030, 2035-2065, 2070-2100), see Figure 8.

This goes along with the expected trends for this region in Norway, with increased precipitation and temperature. Increased precipitated is one of the main drivers of pesticide exposure to water bodies in Norway.

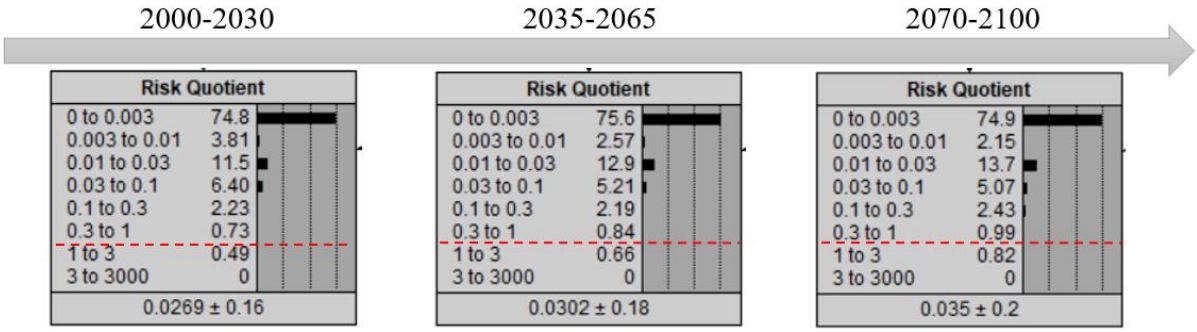

Figure 8 Example of risk quotient distribution shift from 2000 to 2100, for Fluroxypyr-meptyl. The BN predicted the risk quotient distribution for Climate model 1, the baseline+50% application scenario and for a precautionary factor of 10 in this example (adapted from Paper II).

Furthermore, application scenarios were predicted and able to be compared for the different pesticides. Generally, the risk quotient distribution shifted towards higher risk quotient levels the more pesticides were applied, see Figure 9.

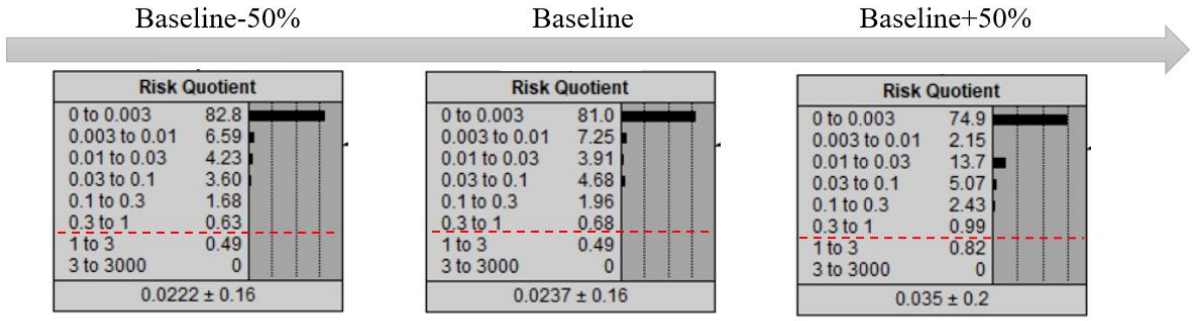

Figure 9 Example of risk quotient distribution shift due to increase in pesticide application, for Fluroxypyr-meptyl. The BN predicted the risk quotient distribution for Climate model 1, time-period 2070-2100 and for a precautionary factor of 10 in this example (adapted from Paper II).

Future scenarios are integrated into the exposure module. However, the process-based model was calibrated with historical data, so some uncertainty remains when it comes to changes in some of the environmental processes due to climate change. As toxicity tests are usually carried out under lab conditions, there is no direct link between the effect module of the BN. Quantified components' uncertainties were propagated and incorporated in the probabilistic risk characterization, which was again based on a distributed risk quotient.

5.3 Paper III – Integrating exposure and effect prediction model outputs into a Bayesian network

Paper III displayed a new BN approach to incorporate model outputs from a process-based exposure model (RICEWQ). The exposure model was run with future scenarios incorporated as exposure distribution in the BN (prospective assessment). Effect assessment was carried out by applying a case-based effect model (PERPEST) that predicted the effects on various biological endpoints. The BN model was able to estimate the effect on the various biological

endpoints, endpoint groups, and the aquatic community. The developed BN can be considered as a higher-tiered approach (tier 3 or tier 4) as it uses a model based on micro/mesocosm experiments. It predicted output for three pesticides: acetamiprid (insecticide), azoxystrobin (fungicide), and MCPA (herbicide). This study demonstrated the integration of a case-based effect model input in a BN. The BN model output can be used to compare different pesticide types and their effect on the community while visualising the uncertainty transparently for all model compartments see Figure 10. Based on currently available knowledge, the developed model incorporated various biological endpoints and enabled the quantification of uncertainty in the effect prediction on the community while indirectly accounting for some future scenarios through the exposure module.

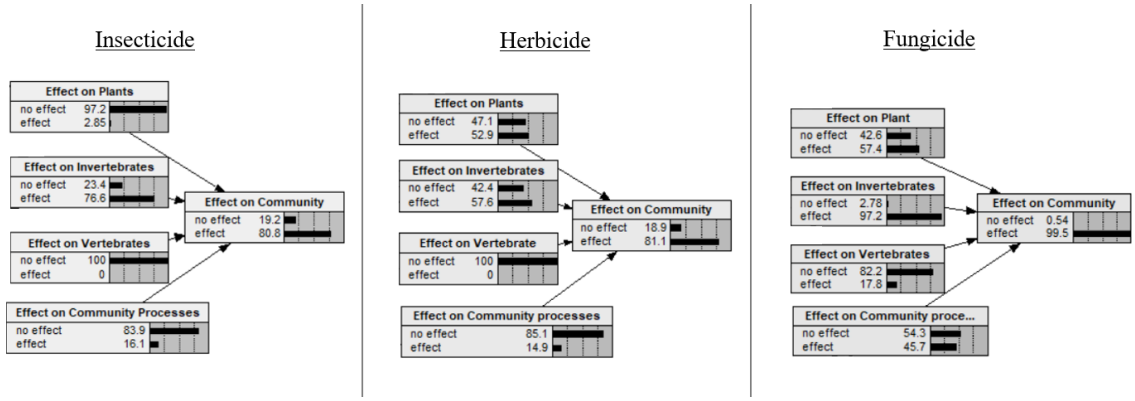

Figure 10 Example BN predictions of the effect on the aquatic community by the selected pesticides. The BN predicted the effect on any of the biological endpoints in the endpoint group and community for the climate conditions in 2050 with a baseline+50% application scenario (adapted from Paper III).

VI Discussion and future outlook

6.1 Implications of Bayesian networks use in environmental risk assessment

As aforementioned, traditional approaches in ERA usually favour single-point estimates (Moe et al., 2022). This deterministic approach hinders the realistic assessment of risk and lacks accounting for uncertainties appropriately, which can lead to overestimating or underestimating the predicted risk (Jager et al., 2001; Landis & Chapman, 2011; USEPA, 2014). Another often-mentioned limitation of ERA is the lack of certainty for input and output parameters (EUFRAM, 2006). The three papers presented in this synthesis address this by applying a probabilistic approach to the risk characterisation of pesticides. Consequently, uncertainties are treated explicitly throughout all compartments in the BNs (Kaikkonen et al., 2021), thereby they can overcome some of the limitations in traditional deterministic approaches (Carriger & Newman, 2012; EUFRAM, 2006; Solomon et al., 2000; Verdonck, 2003). Pariès (2017) and Maertens et al. (2022) have called for a shift toward embracing uncertainty in a risk paradigm. BNs allow uncertainties to be acknowledged and communicated in a transparent manner (e.g., Figure 7, Figure 8, and Figure 9), unlike single-estimate approaches that hide the underlying uncertainties (Moe et al., 2022).

Jager et al. (2001) pointed out that better and more informed decision-making depends on understanding and interpreting probabilistic model outputs. However, the output from commonly used probabilistic approaches is usually associated with difficulties when communicating their results to decision-makers (Dreier et al., 2020; Giddings et al., 2000). BNs, unlike other probabilistic methods, display outputs as probability density distributions rather than cumulative probability distributions. These outputs are more straightforward to interpret than many of the conventional probabilistic approaches (Moe et al., 2021) and enable better risk communication (Kaikkonen et al., 2021; Laurila-Pant et al., 2019). In addition, BNs having a graphical user interface makes them more accessible to stakeholders (Moe et al., 2022; Moe et al., 2021). This is supported by Moe et al. (2022), stating that BNs generally lower scientists' threshold starting to work with probabilistic methods.

One of the most advantageous features of BNs is being able to support a continuous learning process. Generally, this is achieved by adding new variables to the existing networks (Kaikkonen et al., 2021). This is also shown throughout the three papers presented in this thesis. First, the core BN model for probabilistic risk characterisation developed in Paper I, was extended to integrate future scenarios in Paper II (see Figure 5). This was then further adapted to predict the effect on various biological endpoints and the aquatic community in Paper III. In today's ERA, data limitation hinders more realistic risk estimation and could be overcome by BNs' ability to integrate knowledge from various sources (Kaikkonen et al., 2021). In the three presented papers, probability and probability distribution were integrated into the BNs from different sources, such as monitoring or predictions from process-based exposure for exposure modules and toxicity data or predictions from case-based effect models for the effect-related modules.

Furthermore, as shown in Paper II and Paper III, the developed BNs integrated future climate and land-use scenarios into a single model for pesticide exposure assessment. Today's frameworks need to be adapted to better account for multiple stressors, and future scenarios were requested by various scientists such as Fairbrother et al. (2016) and Topping et al. (2020). In addition, improved integration of climate change has been of interest for some

years now (Landis et al., 2014; Stahl et al., 2013). The presented innovative approaches used inputs from exposure prediction models, enabling the integration of future scenarios directly into exposure assessment and indirectly in effect assessment. The resulting improved assumptions made in ERA can aid the prevention of future damage to the aquatic environment (Topping et al., 2020).

6.2 Technical improvements for the developed Bayesian network

Even though BNs and other probabilistic approaches incorporated uncertainty better, some unquantifiable uncertainties remain. These are related to extrapolation or choice of distribution as used in Paper I, Paper II and Paper III. Refinement of exposure and effect modelling could be achieved through better fitting distributions or Bayesian distributional regression models (Wolf & Tollefsen, 2021). Another factor that might have cause some loss of information is the choice of discretisation (Kaikkonen et al., 2021; Nojavan et al., 2017), the discretisation of continuous variables simplifies the probability distributions (Kaikkonen et al., 2021; Uusitalo, 2007). This had also been a limitation in the developed BNs of the presented papers but was necessary and justified for their application.

For an adequate assessment of future scenarios and their effect on pesticide exposure and the ecosystem, it is recommended to use an ensemble of climate models, as mentioned by some experts, e.g., Steffens et al. (2014) and Moe et al. (2022). In addition, it is essential to account for the variability and uncertainty in future projections. The BN approach presented in Paper II has limited adjustability when running the exposure prediction model. The model used is somewhat manual and does not allow for a code line. Using a code line in Paper III allowed for more automatization in exposure modelling. This would empower running the process-based model with an ensemble of climate models, thereby reducing uncertainty in the exposure assessment. As mentioned earlier, BNs can easily be updated, so once new information and data are available, the network predictions certainty would be improved effortlessly. This means that risk assessment would be more realistic and better informed.

The application scenarios used in Paper II and Paper III, are based are fairly basic assumptions but could easily be updated if more realistic scenarios are available. For example, more informed and realistic risk and effect estimation could be carried out using application scenarios derived with regression-based analysis as described by Kattwinkel et al. (2011) and Chiu et al. (2017). Another option by Gagnon et al. (2016) presented another option, which used frameworks to assess climate change and pesticide transport impact presented. Again, through easily implementable updates of the BN, this new information could be integrated easily once the process-based model is run with these updated application scenarios.

Furthermore, the developed BN approach in Paper II and Paper III needed a more direct link between future scenarios and the effect modules. This means there was no appropriate representation of the direct effect of future changes on the biological endpoint, merely an indirect one through a change in exposure concentration. The effect distribution used in Paper II is based on laboratory condition toxicity tests that do not account for temperature or other environmental changes. Neither did the micro- and mesocosm study database that the case-based effect model uses for its prediction (Paper III). To properly assess multiple stressors and toxicity on the various species and the ecosystem, this link needs to be developed in the future. This could be achieved by integrating information and assumptions from research focused on multiple stressor scenarios, and some examples are Polazzo et al. (2022), focusing on multiple agricultural stressors' effect on freshwater ecosystems, or Arenas-Sánchez et al.

(2019), investigating multiple stressors effect on zooplankton community. Improved assumptions would enable better and more sound effect estimation by the BN. This might require restructuring of BN to some extent in order to incorporate assumptions and prior probabilities appropriately.

6.3 Further application of Bayesian network modelling for mixture risk assessment

BNs could also be used to explore mixture toxicity risk assessment, though it was beyond the scope of this project. An early idea of how mixture risk assessment could be carried out using a BN model is displayed in Figure 11. The conceptual model is based on a study by Backhaus and Faust (2012) and assumes CA, whereby a toxic unit is calculated as the PEC divided by the effect concentrations to organisms (EC_{50}). The sum of toxic units (STU) across pesticides can be calculated for each taxonomic group (e.g., algae, invertebrates, and fish). This can then be used to identify the taxonomic group with the highest STU. The conventional approach uses single values of exposure and effect to quantify the risk posed by chemical mixtures to the environment as a single risk quotient value (RQ_{STU}). When trying to implement a probabilistic approach, the exposure and effect concentration can be expressed as a probability distribution that derives STU and RQ_{STU} as probability distributions. The distribution and model development could be carried out similarly to what was presented in Paper I. The developed model can be a valuable tool to develop a fully probabilistic approach to mixture risk assessment while facilitating communication of uncertainties with stakeholders. Limited data availability could be overcome by using intermediate approaches, as displayed in Paper I. Though the usage of an intermediate approach might require some additional application of safety factors such as the mixture assessment factor to account for uncertainties in exposure and effect assessment.

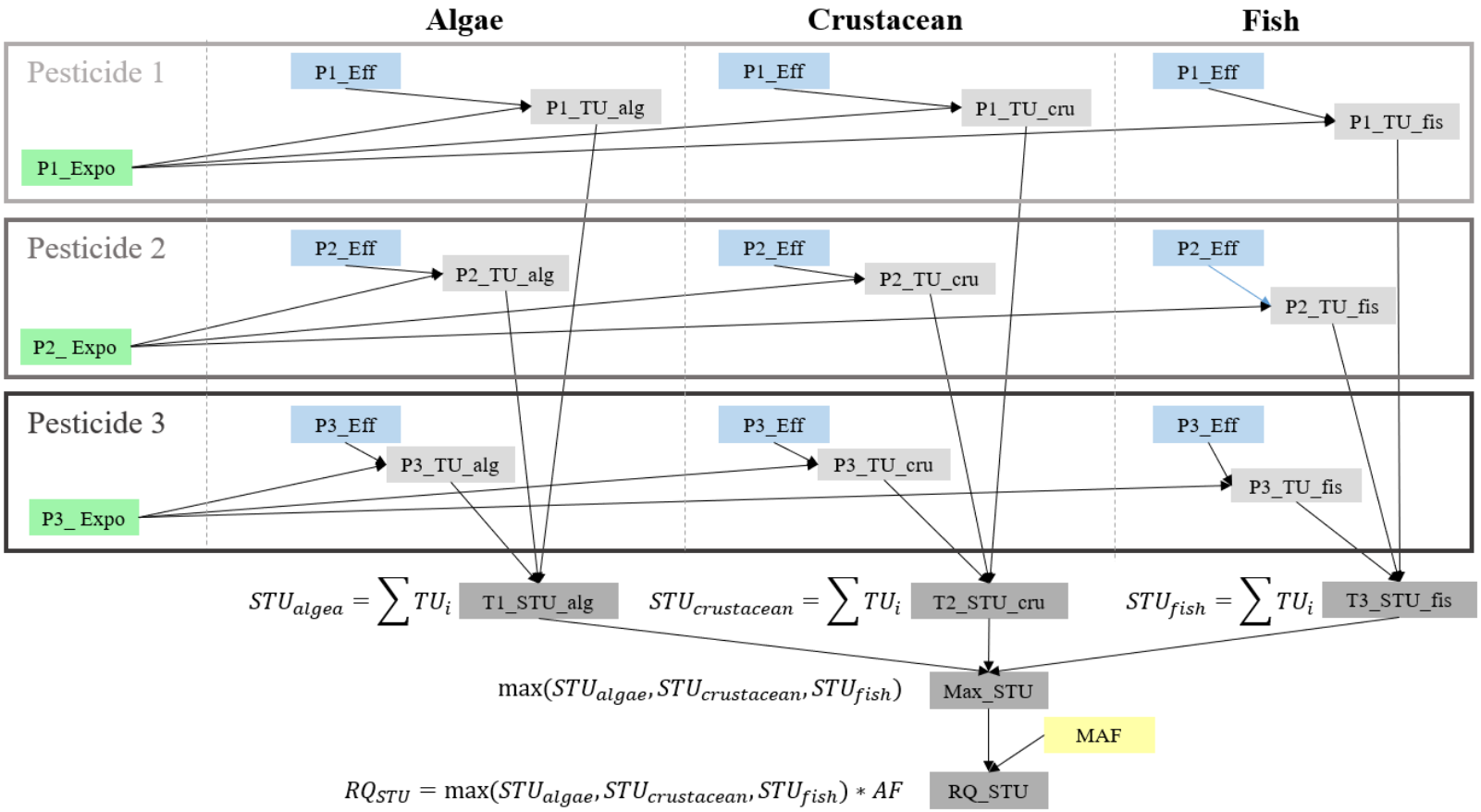

Figure 11 Conceptual model for mixture assessment for three chemicals and exemplary taxonomic groups. It displays how toxic units and sum of toxic units (TU) are derived, and possible applications for a Mixture Assessment factor (MAF). Expo = Exposure Concentration, Eff= effect concentration, TU = Toxic Unit, STU = Sum of toxic Unit, alg = Algae, crus = Crustacean, fish = Fish, P = Pesticide.

VII Conclusion

Throughout this PhD project, the primary aim was to develop a probabilistic approach using a Bayesian network that could be applied to pesticide risk assessment. A core structure was developed that enabled an alternative to a single-value risk quotient with the functionality to display uncertainty more transparently, communicate more information and be compatible with traditional risk assessment frameworks (Paper I). An example integrating different levels of data availability was shown for three selected pesticides for a Norwegian case study area, also considering intermediate approaches for situations where data is scarce.
After that, the core structure was extended to integrate future scenarios, thus, enabling risk characterisation using a risk quotient distribution for changes in climate conditions and agricultural practices. The network implementation of data and functionality was displayed for five selected pesticides and another Norwegian case study area. This developed BN enables risk prioritisation for specific times since application, time-periods in the future, application practices, and comparison of the different pesticides (Paper II). Additionally, BNs were constructed that estimate the effect of three pesticides on the different biological endpoints, and the aquatic community for a southern European case study. An innovative BN that predicts the pesticides' impact on various biological endpoints, endpoint groups and the community was developed. The network also enables the comparison of future scenarios directly on exposure assessment and indirectly on effect assessment (Paper III).

All developed BNs could be parameterised for different pesticides and study areas, with few adjustments necessary. As shown in all three Papers, the realism and certainty of all network predictions can be improved in a simple matter whenever more data and better assumptions are available, e.g., improved agricultural scenarios and ensembles of climate scenarios. Nonetheless, the developed networks enable a probabilistic approach to pesticide risk assessment while communicating the uncertainty of all model compartments and for different risk levels.

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Health & Ecological Risk Assessment

Development of a Bayesian network for probabilistic risk assessment of pesticides

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Abstract

Conventional environmental risk assessment of chemicals is based on a calculated risk quotient, representing the ratio of exposure to effects of the chemical, in combination with assessment factors to account for uncertainty. Probabilistic risk assessment approaches can offer more transparency by using probability distributions for exposure and/or effects to account for variability and uncertainty. In this study, a probabilistic approach using Bayesian network modeling is explored as an alternative to traditional risk calculation. Bayesian networks can serve as meta-models that link information from several sources and offer a transparent way of incorporating the required characterization of uncertainty for environmental risk assessment. To this end, a Bayesian network has been developed and parameterized for the pesticides azoxystrobin, metribuzin, and imidacloprid. We illustrate the development from deterministic (traditional) risk calculation, via intermediate versions, to fully probabilistic risk characterization using azoxystrobin as an example. We also demonstrate the seasonal risk calculation for the three pesticides. *Integr Environ Assess Manag* 2022;18:1072–1087. © 2021 The Authors. *Integrated Environmental Assessment and Management* published by Wiley Periodicals LLC on behalf of Society of Environmental Toxicology & Chemistry (SETAC).

KEYWORDS: Bayesian network, Pesticide, Probabilistic risk assessment, Risk quotient, Uncertainty

INTRODUCTION

Pesticides play an important role in food production by maintaining or enhancing crop yields and quality in arable farming. However, they can also lead to harmful effects in the environment and pose risks to human health. There is now a widespread concern about regular emissions of such substances designed to control specific target organisms and their effects on ecosystems (Boye et al., 2019; Bradley et al., 2017; Mohaupt et al., 2020; Szöcs et al., 2017; Van den Brink et al., 2018).

In spite of strict regulations of pesticide use (e.g., Directive 2009/128/EC; Regulation (EC) No 1107/2009), there are still knowledge gaps for the potential environmental impact of these pesticides and their mixtures (Bradley et al., 2017; Mohaupt et al., 2020; Szöcs et al., 2017). Current risk assessment methods use conservative assumptions to avoid underestimating the risk (F. A. M. Verdonck et al., 2003), and decision makers rely on large safety margins for protective decision making (Fairbrother et al., 2015).

In general, risk assessment of pesticides is carried out to protect human health as well as the health and biodiversity of ecosystems (Schäfer et al., 2019). The purpose is to assess the probability that adverse effects of regulatory concern occurs in ecosystems due to the exposure to one or several chemicals. This can be done as a prospective assessment for the registration of substances before products enter the market, or as a retrospective assessment for potentially harmful substances that are already in use (Forbes & Calow, 2002). The environmental risk assessment process usually incorporates exposure and effect assessments as well as risk characterization (Figure 1). Exposure assessment covers the estimation of the predicted or measured environmental concentration (PEC) of the compound in the environment (van Leeuwen & Vermeire, 2007). Predicted environmental concentration is usually calculated as the maximum environmental exposure concentration (Finizio & Villa, 2002). Effect assessment is typically based on the response of species that are exposed to a chemical in toxicity tests, such as data for toxicity endpoints (e.g., mortality, reproduction, and growth) after short-term exposure (acute) or long-term (chronic) exposure (van Leeuwen & Vermeire, 2007).

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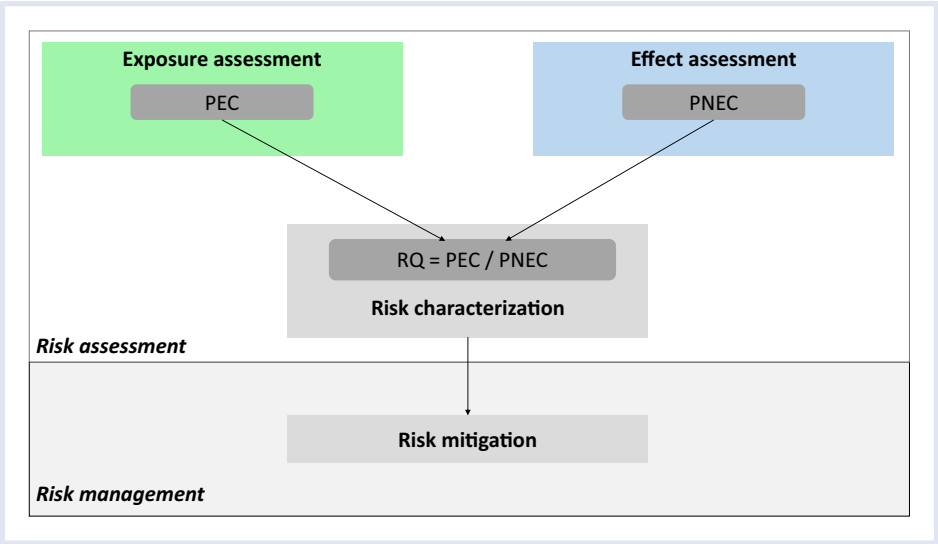

FIGURE 1 General ecological risk assessment process. AF, assessment factor; HC5, hazardous concentration for 5% of the species derived from SSD (species sensitivity distribution); PEC, predicted or measured environmental concentration; PNEC, predicted no effect concentration; RQ, risk quotient

Usually, a predicted no-effect concentration (PNEC) is obtained from the most sensitive no-observed-effect concentration (NOEC). Alternatively, the PNEC can be calculated from the hazardous concentration for 5% of the species (HC5) based on the species sensitivity distribution (SSD) (Bruijn et al., 2002). To account for uncertainty, the lowest NOEC (alternatively the HC5) is divided by an assessment factor (AF) to derive the PNEC, so it can be considered a safe concentration for non-target organisms (Schäfer et al., 2019). Risk characterization includes a risk estimation by comparing effect (hazard identification and characterization) and exposure assessment; some of the metrics used are margin of exposure, hazard, or risk quotient (More et al., 2019). To ensure low risk, it is required that the PEC is lower than the PNEC (Bruijn et al., 2002; Schäfer et al., 2019), so when using a risk quotient (RQ), it is derived by the PEC/PNEC ratio. Usually, in EU frameworks, if the risk quotient exceeds 1, a risk of harmful effects to the environment is indicated (Bruijn et al., 2002). Risk is usually considered an estimation of the likelihood that an adverse effect occurs on a biological target when being exposed to a chemical (Fairbrother et al., 2015; Finizio & Villa, 2002; Moe, Carriger, et al., 2021). Nevertheless, in the commonly used framework for environmental risk assessment, the output of risk characterization tends to be a single value (the risk quotient) from which the conclusion is a "yes/no" statement (Fairbrother et al., 2015). It has been argued that such single-value estimates cannot stand alone as a scientifically defensible characterization of ecological risk (Campbell et al., 2000). The analysis and quantification of uncertainty are a vital part of risk assessment of the environmental impacts of pesticides, which is not reflected in the single-value risk estimate (Fairbrother et al., 2015; USEPA, 2014). Based on this, a concerted action was established to develop a European framework for probabilistic risk assessment of the environmental impacts of pesticides (EUFRAM). The consortium named several shortcomings of conventional ERA (EUFRAM, 2006). For example, there is no indication of the level of certainty associated with the risk assessment; no quantification of the risk is carried out; the uncertainty calculation is not transparent but hidden in assessment factors; and it is difficult to follow all steps of the risk assessment. Various recommendations were given for development toward probabilistic risk assessment, mainly based on the use of cumulative probability distributions (EUFRAM, 2006). Also, Jager et al. (2001) recommend the use of probabilistic risk assessment for the European Union (EU). In recent years, EFSA has published a Guidance document on Uncertainty analysis where they mention not only Bayesian inference but also Bayesian graphical models as a way to use probability distribution to analyze variability and uncertainty (EFSA et al., 2018) Nevertheless, non-probabilistic methods are still more commonly used (Fairbrother et al., 2015). During the "International conference on uncertainty in risk analysis" held in 2018 by the European Food Safety Authority (EFSA) and the German Federal Institute for Risk Assessment (BfR), three conclusions were drawn highlighting that training is important to improve the understanding of uncertainty, that there is an ethical responsibility of scientists to communicate uncertainties, and that active steps need to be taken by risk assessors to avoid undetected sources of uncertainty (EFSA & BfR, 2019).

The aim of this study was to explore Bayesian network modeling as a tool to combine probability distributions of pesticide exposure and effects, to facilitate the calculation of the risk quotient as a probability distribution instead of a single number. We aimed to align the developed model to the EU regulatory requirements and current risk assessment procedures (Figure 1). Although a Bayesian network model could also have incorporated more advanced components such as effect modeling, we chose a simpler model structure to facilitate the comparison of the Bayesian network approach with the more traditional existing approaches

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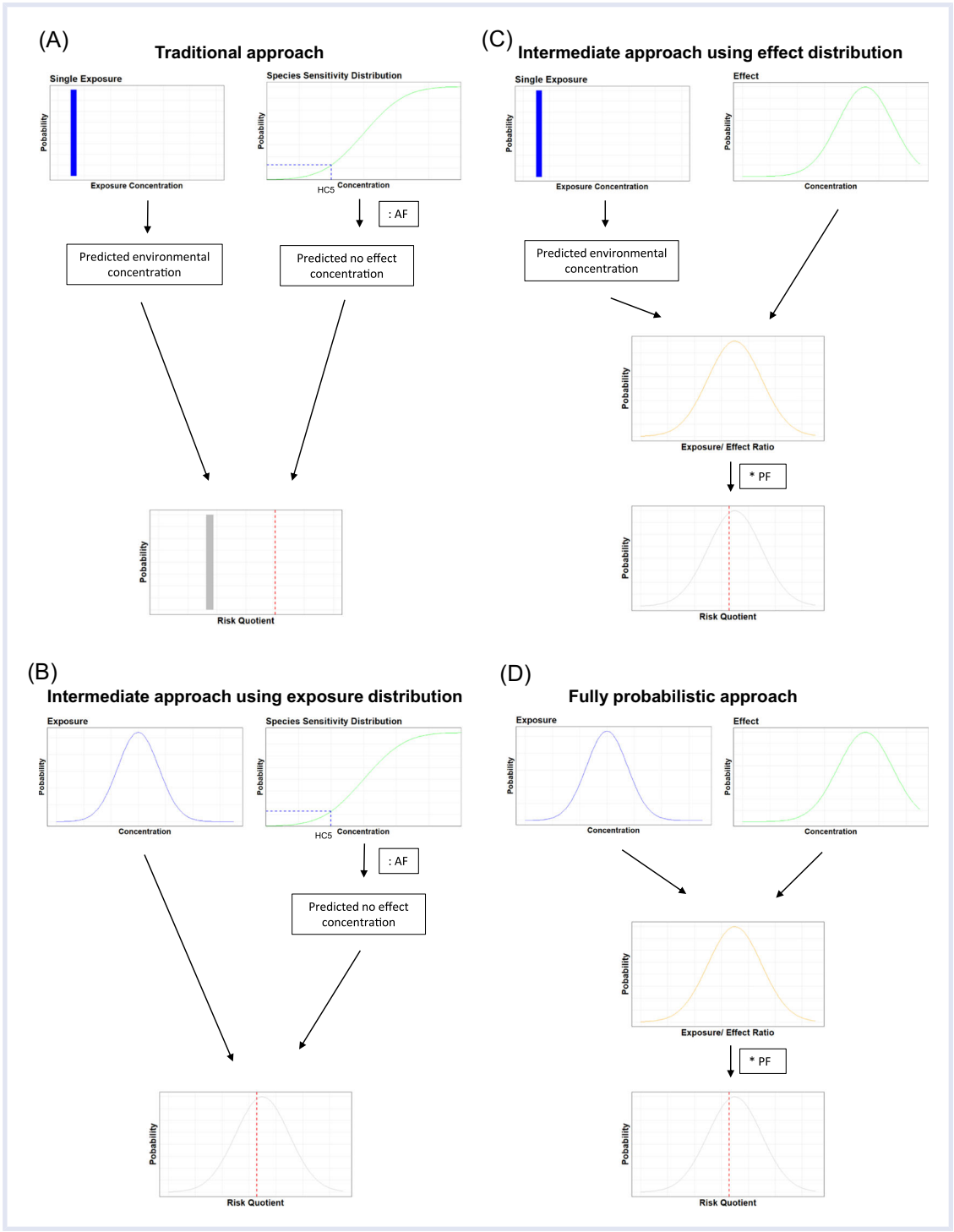

FIGURE 2 Systematic overview of the traditional approach to derive a risk quotient (A), compared with two intermediate probabilistic options that contain single values and a distribution (B and C), and a fully probabilistic option that derives a risk quotient distribution (D). Option B has a single exposure value and an effect distribution, and Option C has an exposure distribution and a single effect value. AF, assessment factor; HC5, hazardous concentration for 5% of the species derived from SSD (species sensitivity distribution); PF, precautionary factor

(Figure 2). To this end, we present the development from a deterministic toward a fully probabilistic Bayesian network approach to risk characterization for a case study representing a small agricultural catchment in Norway. The model application is demonstrated for three examples of pesticides and for different seasons of the year.

APPROACHES TO PROBABILISTIC RISK ASSESSMENT

Proposed methods for probabilistic risk assessment

Probabilistic risk assessment has been defined as using "probabilities or probability distributions to quantify one or

more sources of variability and/or uncertainty in exposure and/or effects and the resulting risk" (EUFRAM, 2006). This allows the inclusion of estimates of uncertainty and stochastic properties (Solomon et al., 2000). There are now several probabilistic methods in use for risk characterization. The species sensitivity distribution (SSD) (Posthuma et al., 2001) is a probabilistic model for the variation in the sensitivity of biological species to a single or a set of toxicants, which is used in several frameworks (Belanger & Carr, 2020). Guidance on modeling and data requirements can be found in the "Technical Guidance for Deriving Environmental Quality Standards" (TGD) (SCHEER, 2017). Many of the probabilistic methods currently at hand also incorporate a distribution for the exposure part. Methods such as quantitative overlap and joint probability curves are relatively easy to construct (Campbell et al., 2000; F. A. M. Verdonck, 2003) and use more available data for exposure and effect compared with traditional approaches (Campbell et al., 2000). They also allow for an estimation of the likelihood of potential ecosystem impact and their magnitude (Solomon et al., 1996). Recently, an "Ecotoxicity Risk Calculator" was presented by Dreier et al. (2020) that uses joint probability curves. It is able to provide more information than a single-value risk quotient, as it depicts the relationship between cumulative probability and magnitude of effect. The use of both effect and exposure distributions enables a more powerful approach for risk assessment and communication (Dreier et al., 2020). However, most of these probabilistic methods derive a distribution that can be a challenge for decision makers to understand and interpret (F. A. M. Verdonck et al., 2003).

From deterministic to probabilistic risk quotient

Another method more consistent with the probabilistic definition of risk is the calculation of probabilistic risk quotients. It can be useful for ranking of different scenarios as well as prioritizing among alternative risk scenarios (Campbell et al., 2000). A fully probabilistic risk quotient calculation requires the quantification of a probability distribution for both exposure and effect. In cases where exposure or effect data are too limited, an alternative "intermediate" probabilistic approach could be applied using a distribution for either the exposure or effect component (Figure 1). This will allow for some variability to be taken into account when deriving a distribution for the risk quotient. For example, an intermediate approach could be applied when an effect concentration distribution can be quantified by a species sensitivity distribution, although few exposure measurements are available. An overview of the underlying concepts for the traditional deterministic approach, and the intermediate and fully probabilistic approaches is shown in Figure 2. The traditional deterministic approach (Figure 2A) uses single-value PEC and PNEC to calculate a single-value risk quotient. The second option (Figure 2B) used an exposure distribution together with a single-value PNEC, derived the same way as in the traditional approach. However, unlike the traditional approach, here, a risk quotient distribution is derived. The third option (Figure 2C) uses the probability distribution of effects (corresponding to an SSD). Instead of using the SSD to extract a single-value HC5 as a basis for a single-value PNEC in combination with an assessment factor, in this case, a precautionary factor (PF) is applied to the calculated risk quotient distribution. The precautionary factor plays a similar role as an assessment factor by adjusting the predicted risk to account for uncertainties, for example, associated with extrapolation from laboratory toxicity tests to environmental effects. However, we chose to use the slightly different term "precautionary factor" to avoid misusing the more well-established term "assessment factor." The principle of avoiding the use of assessment factors as a prudential measure in the calculation of the exposure/effect ratio, and instead applying a precautionary factor more transparently in the subsequent step, is inspired by the recommendations of F. Verdonck et al. (2005). The fourth option (Figure 2D), uses effect and exposure probability distributions to derive the exposure/effect ratio distribution. Again, no PNEC is derived, so after calculating the exposure/effect ratio distribution, the precautionary factor is applied to derive the risk quotient distribution.

Probabilistic risk assessment using Bayesian networks

The early efforts of probabilistic risk assessment for pesticides, which were usually visualized by cumulative distribution curves, were sometimes difficult to interpret for both for advanced users and the general public (EUFRAM, 2006). As an alternative, Bayesian networks may provide a way to overcome the limitations associated with visualization of risk estimations while accounting for uncertainties when using probabilistic approaches. They have been recognized as a tool to analyze complex environmental problems and support decision making while considering uncertainty (Sperotto et al., 2017), and have recently been increasingly used for environmental risk assessments (Moe, Carriger, et al., 2021). A Bayesian network can characterize a system by showing its interactions between variables in a network (Chen & Pollino, 2012) through a directed acyclic graph (Kanes et al., 2017). They are probabilistic graphical models implementing Bayes' rule for updating probability distributions based on evidence. The nodes (variables) have discrete states (e.g., intervals), quantified by discrete probability distributions. The causal links (arrows) represent the conditional probability table (CPT), which can be based on equations. The causal links (arrows) represent conditional probability tables (CPT), which can be based on equations of several methods, empirical frequency distributions, information from the literature, or expert opinion. The degree of belief (probability) that a node will be in a particular state given the state of the node are specified by conditional probability table (Chen & Pollino, 2012) and by using Bayes' rule probability distributions are updated based on new evidence (Molina et al., 2010). In this project, Bayesian network construction largely followed the

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guidelines provided by Marcot et al. (2006) and Pollino and Henderson (2010).

Bayesian networks have an integral feature suitable for risk estimation as they present results in the probability distribution form instead of point estimates. They can accommodate different kinds of data; their sources can include both direct measurements and output from models. Also, if data are limited or non-existent, it is possible to include expert opinions instead (Pitchforth & Mengersen, 2013). The models can be updated with new information on pesticide exposure and effects whenever it becomes available. Model updates are carried out by combining prior probabilities and new data so that an update of the network posterior probabilities can take place as a response to the added observational information (Franco et al., 2016). Bayesian networks are especially useful for pesticide risk assessment and management tasks as these require characterization of the uncertainties (Carriger and Newman (2012)). Focusing on a terrestrial species (puma), Carriger and Barron (2020) reported a process of mapping cause–effect relations into a quantitative model. This is supported by Catenacci and Giupponi (2013), who found that the Bayesian network approach can examine different phenomena due to its flexibility for interdisciplinary integration, e.g., climatic, physical, ecological, and socio-economic. They also have the ability to perform predictive (forward), diagnostic (backward), and mixed (forward and backward) inferences (Carriger & Barron, 2020).

METHODS

Study area

The model was developed based on monitoring data from a catchment within the Norwegian Agricultural Environmental Monitoring Program (JOVA) located in South-East Norway (Heia, location: 59°21′29″N, 10°47′52″E). The monitoring catchment has a total area of 1.7 km^2, of which 62% is cropland. As the catchment is located in a coastal climate, winters are mild and the growing season starts relatively early as compared to Norwegian conditions in general. The catchment has an annual rainfall of 829 mm and a mean annual temperature of 5.6 °C (in 2016). The crop production in the catchment is mostly grain (up to 75%). Potato and vegetable production made up about 40% until 2007 and had decreased to about 25% in 2015. The catchment's use of plant protection products and exposure data are recorded in the JOVA program (Bechmann et al., 2017). Flow-proportional composite sampling of stream water at the catchment outlet was performed in the JOVA program throughout the spraying season and the analyses of concentrations of a wide range of current and previously used pesticides were included. Based on these data, exceedances of environmental safety thresholds are identified for different agricultural management practices for key agricultural production systems in various catchments in Norway (Stenrød, 2015). The JOVA monitoring data for pesticides have been collected over 25 years (1995 onward) and thus also support the retrospective assessment of ecological risk and temporal trends (Bechmann et al., 2017).

Pesticides—exposure and effect data

The chemicals selected for analysis in this study are most frequently occurring pesticides and the highest in concentration in the study catchment (Table 1). Azoxystrobin and metribuzin are approved chemicals for use in the EU and Norway. Since 2013, the use and sale of imidacloprid are prohibited in the EU (EC, 2013). Of the selected chemicals, only the fungicide azoxystrobin has low solubility in water at 20 °C (6.7 mg L^{-1}), whereas metribuzin and imidacloprid have high solubility in water. All pesticides form metabolites primarily in soil (for more information, see the Supporting Information, Chemical properties of selected pesticides). The data used in this study were obtained from the NIVA Risk Assessment database (NIVA RAdb, www.niva.no/radb), which hosts exposure and effect data from a wide variety of sources. Moreover, this database provides transparent and harmonized cumulative risk predictions according to international recommendations for harmonized approaches for human and ecological risk assessments (Tollefsen, 2021). Exposure data for the period from 11.05.2011 to 06.12.2016 from the JOVA monitoring program and effect data (NOECs) for the different compounds originating from the ECOTOXicology Knowledgebase (ECOTOX) (https://cfpub.epa.gov/ecotox/index.cfm) were extracted from the NIVA RAdb database.

The total number of measured environmental concentrations was 55 for azoxystrobin and 59 for metribuzin and imidacloprid. There is a large variation in the measured concentration levels during the season and years for each of the pesticides. The percentages of the detection frequencies were 47.4%, 76.3, and 81.4 for azoxystrobin, metribuzin, and imidacloprid, respectively. In general, sampling of pesticides varied markedly between the years and months. The highest concentrations were recorded in summer and autumn, and lower concentrations were recorded in spring and winter. Due to the sampling method and frequency (i.e., an approx. 20-day sampling period of composite flow proportional sampling), the measured exposure concentrations can reflect chronic exposure to the ecosystem, but maximum and/or peak exposure concentrations are unlikely to be reflected (see the Supporting Information.

The exposure data for the three pesticides showed that 22%–50% of the measured values were below the respective limit of quantification (LOQ) (Supporting Information Tables S4, S6, S7, and S8). In the case of non-detected values (below LOQ), new values were generated as follows (see Supporting Information, Figure 4). First, the non-quantified records were temporarily assigned the value LOQ/2. Use of the LOQ/2 value has been common practice in assessing the potential risks of non-detected residues (Loos et al., 2018), but has been criticized for overestimating the risks of chemicals with PNEC below LOQ (von der Ohe

TABLE 1 Overview of the selected pesticides, their Chemical Abstract Service (CAS), pesticide type, mode of action, and common application crop adapted from Lewis et al. (2016), PubChem (2021a, 2021b, 2021c)

Substance	CAS	Type	Mode of action	Approved use (crop)
Azoxystrobin	131860-33-8	Fungicide	Systemic translaminar and protectant action with additional curative and eradicant properties. Respiration inhibitor	Wheat; fruit (grapes, citrus, strawberries, peaches); sunflowers; vegetables (onions, brassicas, curcubits); potatoes; cotton; pecans; canola; soybeans; peanuts; turf; ornamentals
Metribuzin	21087-64-9	Herbicide	Selective, systemic with contact and residual activity. Inhibits photosynthesis (photosystem II).	Soybeans; potatoes; barley, wheat; asparagus; sugarcane; tomatoes; peas; lentils
Imidacloprid	138261-41-3	Insecticide, veterinary substance	Systemic with contact and stomach action. Acetylcholine receptor (nAChR) agonist.	Lawns and turf; domestic pets; rice, cereals; maize; potatoes; sugar beet

et al., 2011). Second, this intermediate data set was used to derive a mean and standard deviation in ln scale. Third, the resulting log-normal distribution was used to simulate new values in the range from 0 to LOD to replace the non-detected values. The discretized version of this distribution was used as the prior probability distribution of the Exposure node.

For the selected pesticides, data on toxic effects for several freshwater species representing various taxonomic groups were extracted from the NIVA RAdb and represent data from the ECOTOX data repository. The data set consisted of NOECs (no observed effect concentration) for adverse effects such as growth, reproduction, and population. For each chemical, multiple NOEC values from the same species were used in our analysis that represent different species, test durations, and time for effect observation (see Table 2). In traditional effect assessments, only the most sensitive value per species is often chosen to derive an SSD, although, in some cases, an average is also used. In cases where multiple NOEC values of the same species were present, the mean NOEC was used. The fitted distribution corresponds to a species sensitivity distribution (SDD), which is often fitted as a log-normal distribution (Belanger & Carr, 2020).

Data processing

Data preparation was carried out using R version 4.0.2 (Team, 2020) using packages including *tidyverse* (version 1.3.0) (Wickham et al., 2019), *dplyr* (version 1.0.2) (Wickham et al., 2020), and *readxl* (version 1.3.1) (Wickham & Bryan, 2019). To obtain probability distributions for the BN model from the exposure and effects data, log-normal distribution models were fitted to the data using the *R* package *MASS* (version 7.3-51.6) (Venables & Ripley, 2002).

In the case of exposure data below the LOQ, new values in the range from 0 to LOQ were simulated using the mean and standard deviation from the fitted log-normal

TABLE 2 Overview of the collected toxicity data of the selected pesticides, also showing their adverse effect endpoint, and number (*n*) of means used to fit the distribution and species with multiple NOECs for the same substance

Substance	Endpoints	*n*
Metribuzin	Growth	11
	Population	
Azoxystrobin	Growth	13
	Population	
Imidacloprid	Growth	11
	Population	
	Reproduction	

Abbreviation: NOEC, no observed effect concentration.

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distribution. To take into account the seasonal variation in pesticide exposure, a separate probability distribution was estimated for each season, defined as follows: Winter = Dec–Feb; Spring = Mar–May; Summer = Jun–Aug; and Autumn = Sep–Nov.

For the effect distribution, likewise, a log-normal distribution was fitted to the NOEC values available for each pesticide. However, while SSDs are traditionally used to derive a single PNEC value (Figure 1), we used the whole probability distribution of effects data in this study. For comparison with the traditional risk quotient calculation based on a PNEC, as described in the introduction, an HC5 was derived from a species sensitivity distribution using the package *ssdtools* (Thorley & Schwarz, 2018) (see the Supporting Information).

Parameterization of the Bayesian networks

The Bayesian networks were built in Netica (Norsys Software Corp., www.norsys.com). For each pesticide, a BN was built with an identical structure, for both exposure and effects nodes, the range was defined by the observed values of the given pesticide, and the intervals were discretized into 12 equidistant bins in a log10-scale. The fitted log-normal distributions were used to parameterize the parent nodes. The individual node description is shown in Table 3; further detailed information is shown in the Supporting Information—IV. Netica discretization and equation syntax).

All conditional probability tables of the BNs (Figure 3) were generated from equations, by the function "Equation to Table" in Netica (see the Supporting Information). The probability distribution of the nodes "Exposure Concentration (µg/L)" and "Effects Concentration (µg/L)" was calculated from their respective parent nodes by exp-transformation. The node "Exposure/Effect Ratio" was discretized into eight equidistant bins and calculated using the equation [Exposure Concentration (µg/L)]/[Effects Concentration (µg/L)]. Thereafter, the risk quotient distribution was derived by multiplying the "Exposure/Effect Ratio" with a precautionary factor. The precautionary factor can be applied to account for uncertainties in the effect assessment, similar to the use of an assessment factor in traditional risk assessment (Figure 1). This factor can be transparent and standardized in a simple manner by considering the information used during the effect assessment, for example, number of data points, species, taxonomic groups, and region-specific species. In our model (Figure 1), the node "precautionary factor" has alternative levels that can be selected by the risk assessor, depending on the sources of uncertainty to be accounted for in the risk assessment. We describe diagnostic inference in more detail and how we used it to derive an appropriate precautionary factor (see Figure 3) in the results, as we used the parameterized Bayesian network for this.

After the Bayesian network was constructed and parameterized, a sensitivity analysis was carried out in Netica. The report showed that the risk quotient distribution is dominated by the exposure side over the effect side, which is most likely due to the wider range of concentrations.

In this way, a Bayesian network model is intended as a tool for calculating the risk quotient as a probability distribution, to account for, for example, temporal variability in exposure, taxonomic variability in effects, and other types of uncertainties.

TABLE 3 Node description for the example of Option D, the fully probabilistic approaches (see Figure 4D), also describing the discretization type, number of states, conditional probability table input, and parent relation

Node/variable	Type of discretization	States
Exposure concentration distribution	C	10
Effect concentration distribution	C	10
Exposure–effect–ratio distribution	C	8
Uncertainty factor	D	7
Risk quotient distribution	C	8

Abbreviations: C, discretized continuous; continuous variables were binned into the states; D, discretized discrete; States, number of intervals of each node.

RESULTS AND DISCUSSION

Diagnostic inference to derive an appropriate precautionary factor used in the Bayesian network

This section describes the parameterized version of the Bayesian network for each of the three pesticides, illustrated with azoxystrobin as an example. For comparison, the risk quotient was also calculated using the traditional single-values method (Figure 2A) as well as by the two intermediate options (Figure 2B,C). For the single-value exposure versions (Options A and C), the minimum (0.01 µg/L), mean (0.129 µg/L), and maximum (0.660 µg/L) of the measured concentrations were selected as alternative PEC values. The highest exposure concentration is usually used as the more conservative or protective choice. To be able to compare traditional and probabilistic outputs better, we have decided to use the mean PEC instead. For the single-value effect version (Options A and B), the PNEC values were derived from an HC5 of 3.87 µg/L divided by an assessment factor of 10, 5, 3, and 1 (Table 5). The Technical Guidance Document recommends the use of an assessment factor of 1–5 when deriving the PNEC from an SSD. We also applied an additional and more conservative assessment factor of 10, as the data set that we used does not fulfil all the requirements of the TGD with at least 10 NOECs and at least 8 taxonomic groups. The Technical Guidance Document also states that the assessment factor should be decided on a case-by-case basis "through consideration of sensitive endpoints, sensitive species, mode of toxic action and/or knowledge from structure-activity considerations"

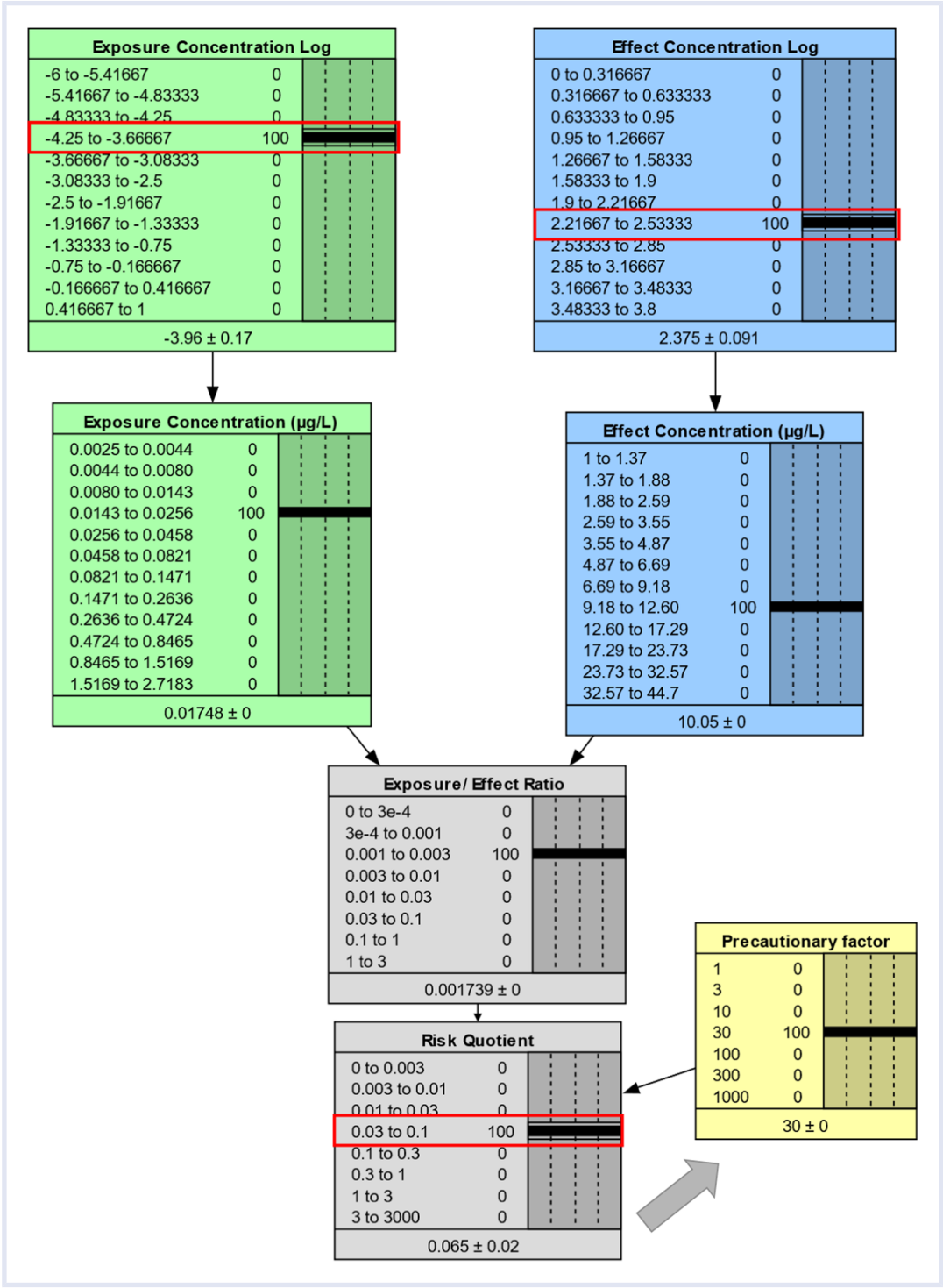

FIGURE 3 Example of diagnostic inference for a mean exposure and effect interval. The precautionary factor was explored for a Risk quotient interval of "0.03 to 0.1" of azoxystrobin. The initiated nodes are visualized by the line above and below the interval probability bar (also the red outline)

(Bruijn et al., 2002). Therefore, in this study, we present several assessment factors but primarily focus on an assessment factor of 5.

The probability distributions of exposure and/or effects data in Options B, C, and D were based on the fitted log-normal distribution with mean and standard deviation. The exposure distribution had a mean of −4.148 (ln µg/L), with a standard deviation of 1.484 (ln µg/L). The effect distribution had a mean of 2.322 (ln µg/L), with a standard deviation of 0.56 (ln µg/L).

The seasonal version of the Bayesian network was parameterized with exposure distributions based on seasonal mean values for the three pesticides. Winter season for all chemicals and spring season for azoxystrobin had

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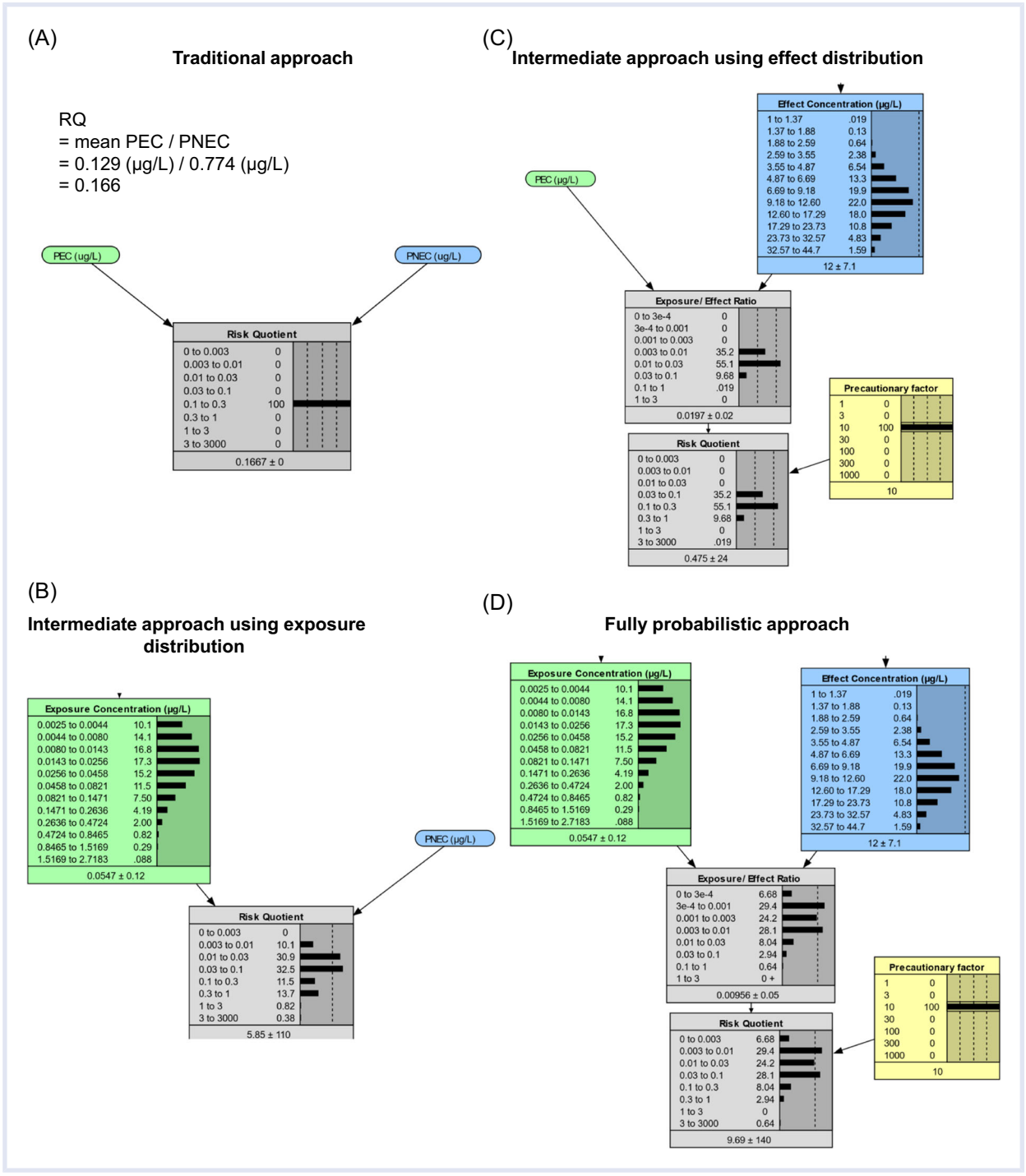

FIGURE 4 Example of Bayesian network representation of the four alternative options shown in Figure 2, parameters for the fungicide azoxystrobin. A single-value risk quotient is calculated from a mean predicted environmental concentration (PEC) and predicted no effect concentration (PNEC) derived with an assessment factor of 5 (A); the risk quotient distribution is calculated for the an exposure distribution and a PNEC derived with an assessment factor of 5 (B), the risk quotient distribution is calculated for a mean predicted environmental concentration and an effect distribution, with a precautionary factor of 30 (C), and the risk quotient distribution is calculated for exposure and effect distributions, with a precautionary factor of 30 (D)

too few detected concentrations to derive a distribution and were therefore excluded from further analysis. In general, the mean concentrations in summer were higher than in spring and intermediate in autumn (Table 4). The exception was Imidacloprid, which had higher concentrations in autumn.

Before the parameterized Bayesian network model can be used to calculate the risk quotient, an appropriate precautionary factor should be set by the risk assessor. In our example, to follow a regulatory accepted method as closely as possible, we selected a precautionary factor that would yield a similar risk quotient as the SSD-based

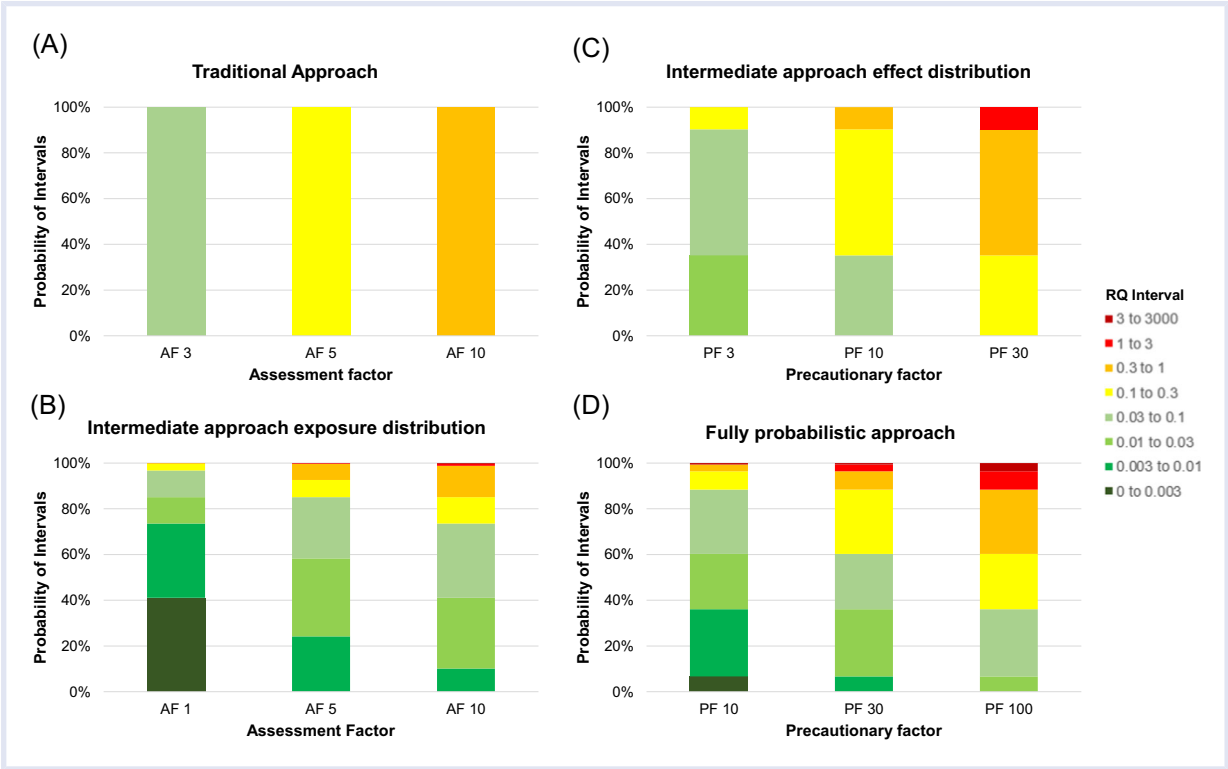

FIGURE 5 Risk quotient values calculated with three alternative assessment factor values (AF = 1, 5, or 10) and corresponding precautionary factor values (PF = 3, 10, 30, or 100) from the traditional approach using the single mean predicted environmental concentration (PEC) and predicted no effect concentration (PNEC) values (A), from the intermediate approaches with exposure distribution and PNEC (B) or mean PEC and effect distribution (C), and a fully probabilistic approach with exposure and effect distribution (D). There are eight risk quotient intervals ranging from 0 to 3000. The color scheme ranges from dark red (high-risk quotient interval) to dark green (low-risk quotient interval). AF, assessment factor; PF, precautionary factor; RQ, risk quotient

approach (Figure 2A). The derived ranges of risk quotients are shown in Table 5. The values of the precautionary factor corresponding to selected assessment factor values of 1, 5, and 10 were derived by diagnostic inference by instantiating the nodes for exposure, effect concentration, and risk quotient nodes (Figure 3). For the exposure and effect concentrations, the intervals were set according to the mean of the observed values. The intervals for the risk quotient were set according to Table 5. An example is shown in Figure 3, where the risk quotient was 0.0999 (see Table 5), showing that the risk quotient node interval is set to "0.03 to 0.1." In this example, the resulting precautionary factor is 30. The appropriate precautionary factors found corresponding to the assessment factors are shown in Table 6. To explore the role of the assessment factor and the precautionary factor and their effect on the risk quotient, we chose precautionary factors of 3, 10, and 30 for Option C and 10, 30, and a 100 for Option D for the first example with azoxystrobin (Figure 5). For all the seasonal versions of the Bayesian network, only one precautionary factor (100) was chosen to focus more on the exploration of the seasonal effects.

TABLE 4 Estimated mean and standard deviation of the exposure by season and effect distributions, which are used as input for the nodes in the Bayesian network

	Exposure			
Compound	Spring ln (μg/L)	Summer ln (μg/L)	Autumn ln (μg/L)	Effect ln (μg/L)
Azoxystrobin				
Mean		−3.939	−4.018	2.322
SD		1.529	1.541	0.568
Metribuzin				
Mean	−4.357	−2.794	−3.292	4.946
SD	0.966	1.416	1.363	2.432
Imidacloprid				
Mean	−3.902	−3.404	−1.783	6.484
SD	1.481	1.116	1.743	4.004

Risk quotient distributions predicted by the Bayesian network

The Bayesian networks for the different options for the risk quotient calculation (Figure 2) were carried out for azoxystrobin and are shown in Figure 4. The posterior probability distribution of the risk quotient node output was shown for the different approaches (Figure 2) and for alternative values

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TABLE 5 Alternative risk quotient calculated for the combinations of minimum, average, and maximum predicted environmental concentration (PEC), respectively, and alternative predicted no effect concentration (PNEC)

AF	PNEC	PEC minimum 0.01	PEC average 0.129	PEC maximum 0.66
10	0.387	0.0258	0.3333	1.7041
5	0.775	0.0129	0.1665	0.8521
3	1.291	0.0077	0.0999	0.5112
1	3.873	0.0026	0.0333	0.1704

Note: The alternative PNECs are derived from the HC5 (see Figure 2A) with an assessment factor (AF) of 1, 3, 5, and 10.

of the assessment factor or precautionary factor, respectively. The colors range from green (no risk) to red (posing a risk) (Figure 5). The risk quotient distribution for the approaches ranged from 0 to 3000. Higher assessment factor and precautionary factor increase the probability of the risk quotient exceeding 1.

An example using a Bayesian network approach for the different approaches for Options A–D (Figure 2) is shown in Figure 4. The assessment factor used in a risk assessment is usually decided by the risk assessor depending on the available toxicity test data. In this study, we have explored the resulting risk quotient when using three alternative plausible assessment factor values for Options (A) and (B), and three corresponding precautionary factor values (see Table 6) for Options (C) and (D). In this example, the risk quotient was calculated using the following evidence: a mean PEC and a PNEC with an applied assessment factor of 5 (Options A and B) and a precautionary factor of 10 (Options C and D). Using the deterministic method, the risk quotient distribution is estimated to be within the interval "0.01 to 0.3" with 100% probability (Figure 4A). On the other hand, Options B–D show a wider distributed risk quotient and probabilities distributed over several risk levels. Options B and D have the highest probabilities in the intervals of "0.003 to 0.01," "0.01 to 0.03," and "0.03 to 0.1." Option C has the highest probability in the interval of "0.1 to 0.3." A bar charts displaying vizualising the results for the different Options A/D and selected assessment and precautionary factor of the Bayesian network risk quotient node are shown in Figure 5. When using an assessment factor of 1, 5, or 10, the deterministic option (Figure 5A) results in 100% probability of the risk quotient being in the intervals of "0.01 to 0.03," "0.1 to 0.3," or 0.3 to 1, respectively. Option B uses an exposure distribution and the same assessment factors as in Option A to calculate the risk quotient, which is distributed over the intervals "0 to 0.0003" and "1 to 3." For an assessment factor of 1, the probability for the risk quotient to be in an interval higher than 0.1 is about 3.2%, whereas for an assessment factor of 5, it is 26.4%. Option C in this example uses the precautionary factor calculated in Table 6a. For the events of a mean PEC with a precautionary factor of 30, the interval of "0.3 to 1" has the highest probability. If a precautionary factor of 10 is chosen, however, the interval of "0.1 to 0.3" has the highest probability (Figure 5C). The probability for the risk quotient to be above 0.1 with a precautionary factor of 3 is less than 10%; with one of 10, it is about 65% and with one of 30, it is about 100%. The fully probabilistic approach—Option D uses distributions for both exposure and effect, when using precautionary factors of 10, 30, and 100, Table 6b. The probability for the risk quotient to be above 0.3 is about 4% with a precautionary factor of 10, 12% with PF = 30, and about 40 with PF = 100 (Figure 5D).

As can be seen in Figure 5, the probabilistic approaches yield a distributed risk quotient. The general tendency is that the calculated risk quotient is similar in all of the approaches; nevertheless, the Bayesian network yields a more nuanced risk estimation and offers some uncertainty related to the different risk quotient intervals. In other words, instead of having a single risk quotient (e.g., RQ > 1), uncertainties for various risk levels (e.g., RQ > 0.1, RQ > 0.001, RQ < 1) can be derived. The intermediate approaches using a distribution for only exposure or effect also results in a more informative risk quotient compared to the traditional approach, but include more variability and/or uncertainty, respectively, in effect or exposure. Therefore, options b and c could be used whenever data are lacking for the fully probabilistic approach. The assessment and precautionary factor applied have a major impact on the risk quotient exceeding 1 and with that being an unacceptable effect for non-target organisms and aquatic organisms (Bruijn et al., 2002). In this example, fully

TABLE 6 Precautionary factor resulting from diagnostic inference (see Figure 3)

(a)	PEC min	PEC avg	PEC max
AF	0.01	0.129	0.66
10	30	**30**	30
5	30	**10**	10
3	10	3	10
1	1	**3**	3
(b)	**PEC min**	**PEC avg**	**PEC max**
AF	0.01	0.129	0.66
10	10	**300**	1000
5	10	**100**	300
3	3	30	300
1	1	**30**	100

Note: For each alternative risk quotient in Table 5, the related RQ interval was selected as evidence to derive the corresponding precautionary factor for Option C—the intermediate approach using effect distribution (a) and Option D—the fully probabilistic approach (b). The bold values are the ones used in the examples of the result section. AF, assessment factor; PEC, predicted environmental concentration.

FIGURE 6 Risk quotient values calculated for three seasons spring, summer, and autumn for a precautionary factor of 100 for (A) azoxystrobin, (B) metribuzin, and (C) imidacloprid

probabilistic approaches only show the risk quotient exceeding 1 for high assessment and precautionary factors (Options B–D) (Figure 5).

Seasonal variation in risk quotients

A more temporally refined version of the Bayesian network was developed and used for calculating seasonal risk quotients for all three pesticides (see the Supporting Information). The precautionary factor was set to 100 as this was found to be the most appropriate in comparison with the deterministic method (Table 6). According to this model (Figure 6), the probability of the risk quotient for azoxystrobin exceeding 0.1 during summer is about 72%, while the probability of the risk quotient exceeding 1 is about 15%.

In comparison with the other two pesticides, azoxystrobin clearly showed a higher probability of exceeding the risk quotient levels of 0.1 to 0.3 in summer and autumn (Figure 6). Metribuzin and imidacloprid have a wider distribution for the risk quotient, mainly ranging from 0.0001 to 0.001. Spring and autumn distributions of probability in the case of imidacloprid are more similar, unlike metribuzin, where summer and autumn distributions appear to be more similar, with higher probabilities of the risk quotient

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exceeding 1 than the spring season. This analysis illustrates how the Bayesian network approach can be used to identify periods with a high risk of environmental effects of individual pesticides. This outcome can in turn be used to assess the combined risk of multiple pesticides in specific periods.

Evaluation of the Bayesian networks approach for risk characterization

This study has demonstrated that Bayesian networks can account for quantified uncertainties and variabilities in a more coherent and transparent way than traditional risk characterization. When developing this Bayesian network approach, we aimed to follow important recommendations for probabilistic risk estimation given by EUFRAM (2006). We tried to accomplish these by combining the new methods with the conventional "deterministic" assessment to enable the end user (e.g., regulators) to become familiar with the new methodology. Furthermore, the developed models follow well-known concepts described in the TGD whenever it was possible and logical. The TGD, for example, describes what an appropriate assessment factor is depending on the available data and mentions requirements for the used data for a minimum amount of taxonomic and species used for SSD modeling (More et al., 2019). In addition, the Bayesian network methodology provides a simple display of the results in bar plots (histograms) instead of cumulative probability. This was also pointed out by EUFRAM (2006), which mentioned stakeholders being more likely to take up results if they and the concepts used are as simple as possible and aligned with existing frameworks (EUFRAM, 2006).

Bayesian networks are increasingly being used in environmental risk assessment (Moe, Wolf, et al., 2021). They can offer a transparent way of evaluating the required characterization of uncertainty for pesticide risk assessment as well as for ecological risk assessment in general (Carriger & Newman, 2012). Moreover, their application is not only carried out for risk estimation (e.g., risk quotient) but also used to predict ecological effect from stressors more directly (e.g., decline in species abundance [Mitchell et al., 2021]) and to develop quantitative Adverse Outcome Pathways (Moe, Wolf, et al., 2021). Dreier et al. (2020) pointed out that the use of effect and exposure distribution allows for a competent risk assessment and communication approach. In their "ecotoxicity risk calculator," they used joint probability curves or a risk curve-based approach that are able to show the connection between cumulative probability and magnitude of effect (Dreier et al., 2020). Although this might be an advantage of using joint probability curves, probabilistic risk quotients can provide a better sense of the risk estimates and are useful for ranking of different scenarios as well as prioritizing among alternative risk scenarios (Campbell et al., 2000). Another probabilistic alternative to the risk quotient was introduced by van Straalen (2001) and has also been applied by Aldenberg et al. (2001); it defines the ecological risk (δ) as the probability that the environmental concentration exceeds the no effect concentrations, while making use of the whole probability distributions. This method does not make use of an assessment factor; therefore, the δ would correspond to the probability of our calculated Exposure/Effect ratio >1 (e.g., Figure 3), or a risk quotient with the UF set to 1. However, this method does not allow for the calculation of different levels of risk.

Especially in ecological systems, limited data and knowledge can hinder modeling efforts, as they constrain it to simpler model structures that involve more assumptions. In these cases, Bayesian network models can still be applied by making better use of different sources of information, including expert judgment (Hamilton & Pollino, 2012). Also, Bayesian networks can be developed as casual models, which can help understand pathways of hazard and vulnerability relations better and thereby be used to assist risk prioritization (Sperotto et al., 2017).

Carriger and Barron (2020) recently showed how the Bayesian network estimated a probabilistic risk quotient for a single species by calculating the probability of an exposure distribution exceeding an effect distribution. Their Bayesian network estimated the risk by expanding the standard risk equation to include more uncertainties and variables that influence the risk (Carriger & Barron, 2020). The networks that we have created used similar risk quotient calculations, though instead of focusing on one terrestrial species, we have included toxicity data for multiple aquatic species using a species sensitivity distribution. Also, Carriger and Barron (2020) stated that "the capabilities for performing diagnostic, mixed, and predictive inference make Bayesian networks especially useful for examining the causal factor that could lead to higher or lower risk outcomes." The influence of different causal factors on the predicted risk in our case study will be further explored later by including different scenarios of climate and pesticide application.

The networks that we developed use discretization of continuous variables and, due to this, lose some of the initial precision and information. This is commonly considered a shortcoming of Bayesian network models (Marcot, 2017). Nevertheless, a possible improvement can be to use dynamic discretization to enable higher resolution and lower uncertainty associated with the predictions (Carriger & Barron, 2020).

Furthermore, F. A. M. Verdonck (2003) pointed out that there are some unquantifiable uncertainties such as the choice of distribution, model, and extrapolation uncertainties that remain difficult to quantify, some of which may be overcome by using distribution models other than the ones used in this study. An alternative to the exposure modeling that we have carried out in this study was presented by Wolf and Tollefsen (2021), showing how Bayesian distributional regression models could be used to better include spatiotemporal conditional variances in exposure assessment and still allow for a distributed PEC (Wolf & Tollefsen, 2021). Further refinement of the Bayesian Network model presented here can make use of such statistical

modeling for better estimation of the pesticide exposure distributions.

There are many possibilities for further development of the models presented here, for example, to better account for spatial and temporal variations in exposure and inter- versus intra-species variation in sensitivity in effect assessment. Nevertheless, we have demonstrated that this approach can offer a transparent way of evaluating the required characterization of uncertainty for pesticide risk assessment (Benford et al., 2018) as well as for ecological risk assessment in general (Carriger & Newman, 2012).

CONCLUSION AND OUTLOOK

This study demonstrates that Bayesian network modeling is a promising tool for probabilistic calculation of a risk quotient to carry out risk assessment of pesticides. A probabilistic risk quotient is a more informative alternative to the traditional single-value risk quotient, which is often interpreted as a binary outcome. The Bayesian network approach provides more opportunities for interpretation, such as the probability of the risk quotient that exceeds not only the conventional threshold of 1 but also other specified threshold values. The model presented here can easily be mapped to the main steps of traditional risk characterization frameworks. The Bayesian network approach can still apply a precautionary factor to account for additional uncertainties that are not captured by the exposure and effects distributions, corresponding to the assessment factor used in traditional risk assessment. Thus, Bayesian networks can offer a transparent way of evaluating the characterization of uncertainty required for pesticide risk assessment as well as for ecological risk assessment in general.

Our planned further development of this Bayesian network includes extending the model for cumulative risk assessment of pesticide mixtures in the aquatic ecosystem. Furthermore, we intend to incorporate climate and agricultural scenarios to predict the environmental risk of pesticides under alternative future conditions.

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DISCLAIMER

The peer review for this article was managed by the Editorial Board without the involvement of S. Jannicke Moe.

DATA AVAILABILITY STATEMENT

This work resides on the bioRxiv Preprint Server (bioRxiv.org; BIORXIV/2021/444913). The R scripts developed for data preparation and data used are available in the Supporting Information.

SOFTWARE AVAILABILITY

Bayesian network modeling was carried out using Netica 6.05 (www.norsys.com/). Files are added as supplementary information.

SUPPORTING INFORMATION

The Supporting Information file contains:

- Chemical properties of selected pesticides
- Netica discretization and equation syntax used in the developed model
- Conditional probability tables and output/posterior probability tables of the exposure/effect ratio and risk quotient distribution node.

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Paper I Supplement material

Supporting Information

Contents

I. Chemical properties of selected pesticides

Table S. 1 Overview of the chemical properties of the selected pesticides: azoxystrobin, metribuzin and imidacloprid (Lewis et al., 2016)

Substance	Solubility In water at 20ºC (mg l-1)	Water phase only DT50 (days)	Water-sediment DT50 (days)	Freundlich Kf	Freundlich 1/n	Threshold of Toxicological Concern (Cramer Class)	Toxicity to …
Azoxystrobin	low (6.7)	moderately fast (6.1)	slow (205)	moderately mobile 7.350	0.850	high (class III)	toxic to birds, most aquatic life, honeybees and earthworms.
Metribuzin	high (10700)	stable (41)	moderately fast (50)	mobile 0.874	0.922	high (class III)	Moderately toxic to primary producers, birds, fish, earthworms and aquatic invertebrates. Highly toxic to some mammals. Low toxicity to honeybees.
Imidacloprid	high (610)	stable (30)	slow (129)	moderately mobile 2.230	0.802	high (class III)	highly toxic to birds and honeybees, Moderately toxic to mammals and earthworms. It is non-toxic to fish.

II. Derivation of exposure distribution

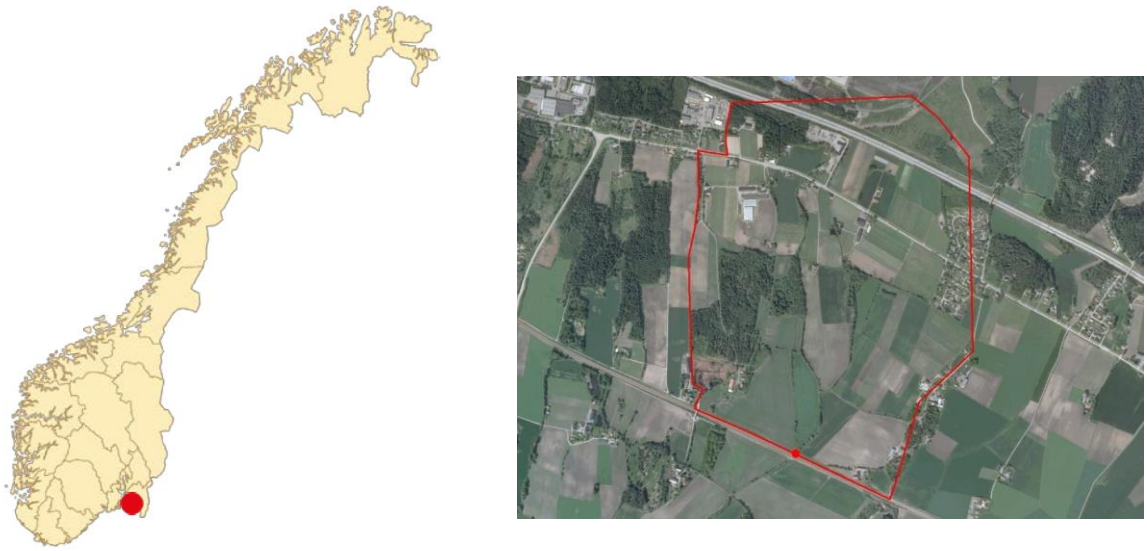

Figure S. 1 The location of the Heia catchment (red line) in Norway (left) and a detailed picture of the catchment area with the measuring station (red dot)

The Norwegian Agricultural Environmental Monitoring Program (JOVA) aims to record concentrations of different pesticides and identify exceedance above environmental safety thresholds for different agricultural management practices for key agricultural production systems in Norway. Its data spans for more than two decades and continuously record water-flow and samples for analysis of nutrients and pesticides (Bechmann et al., 2017). The JOVA data is especial useful as it is collected over a long period of time. Raw exposure data can be found in the attached excel file (Raw_data.zip – JOVA_Data.xlsx).

The JOVA monitoring sampling intervals varied from 10 to 35 days between analysis of the composite sample. The sampling is carried out with flow-event triggered composite sampling. There is are 20.7 days averages with a standard deviation of about 5.2 between the sampling dates. Also, some additional samples to the composite sample were taken on some occasions (days appear twice and are indicated with a time difference of 0) for detailed information of the sampling dates (see Supporting files Raw_data.zip – JOVA_Data.xlsx).

In general, it can be assumed that non-frequent sampling combined with storage before analysis means that peak concentrations will not be captured. This inappropriate capture of exposure of pesticides to the ecosystems is due to peak concentrations occurring stochastically. They can occur following major rainfall events or after their application (Bundschuh et al., 2014). Another factor, that's leads to the underestimation of negative effects of peak exposure that dilution occurs when collection takes place over an extend periods of times (Bundschuh et al., 2014). Another factor influencing and possibly minimizing the detection of contaminants is based on their aquatic half-life (Morrison et al 2016). In Morrison et al. 2016 it was also stated that regardless of sampling methodology better estimates of the actual peak 96-h time-weighted average were obtained when sampling frequencies were high.

Table S. 2 Overview of the collected exposure data for the Heia catchment, showing the detected concentrations for the selected pesticides, their detection frequency, total amount of data points, the limit of quantification (LOQ), and mean of the detected concentrations.

Substance	Number of detected concentration (n)	Detection frequency (%)	Total	LOQ (µg/L)	Mean detected concentrations (µg/L)	Standard deviation detected concentrations
Azoxystrobin	26	47.7	55	0.01	0.129	0.178
Metribuzin	45	76.3	59	0.01	0.175	0.515
Imidacloprid	48	81.4	59	0.01	0.342	0.492

Table S. 3 Overview of derived single value predicted environmental concentrations (PEC) for the detected exposure concentrations of azoxystrobin (see Figure 2a).

Measured Concentration	PEC (µg/L)
Minimum	0.010
Mean	0.129
Maximum	0.660

Table S. 4 Azoxystrobin, metribuzin and Imidacloprid exposure data with number of detected concentrations, detection frequency, mean and standard deviation of detected concentration, and maximum and minimum value collected.

Pesticide	Season	Number of detected concentration (n)	Detection frequency (%)	Mean (µg/L)	sd	Maximum (µg/L)	Minimum (µg/L)
Azoxystrobin	Spring	8	12.5	0.043	-	0.04	-
	Summer	28	53.6	0.131	0.187	0.66	0.010
	Autumn	18	55.6	0.134	0.181	0.43	0.012
	Winter	1	0.0	-	-	>0.01	-
Metribuzin	Spring	8	50.0	0.035	0.013	0.05	0.022
	Summer	32	84.4	0.023	0.656	3.50	0.022
	Autumn	18	77.8	0.108	0.137	0.55	0.015
	Winter	1	0.0	-	-	>0.01	-
Imidacloprid	Spring	8	50.0	0.103	0.075	0.20	0.032
	Summer	32	87.5	0.529	0.571	1.90	0.023
	Autumn	18	83.4	0.079	0.129	0.54	0.016
	Winter	1	100	0.018	-	0.02	-

To explore and select a suitable probability distribution for the exposure concentrations, we have carried out some exploratory Kaplan Meier failure estimation for the selected pesticides as described by Gillespie et al. (2010) and Shoari and Dubé (2018). For all three the LOQ was set to 0.01 as a censoring data, with two columns containing 0 and LOQ for the non-detected values using JMP statistical software (v. 16.0.0). It tested the three available

estimations for exponential, Weibull and lognormal distribution. In all cases the lognormal fitted best as judged from the QQ plots (not shown).

Simulated LOQ

The following figure shows an example for the generation of the value below limit of quantification (see Figure S. 2).

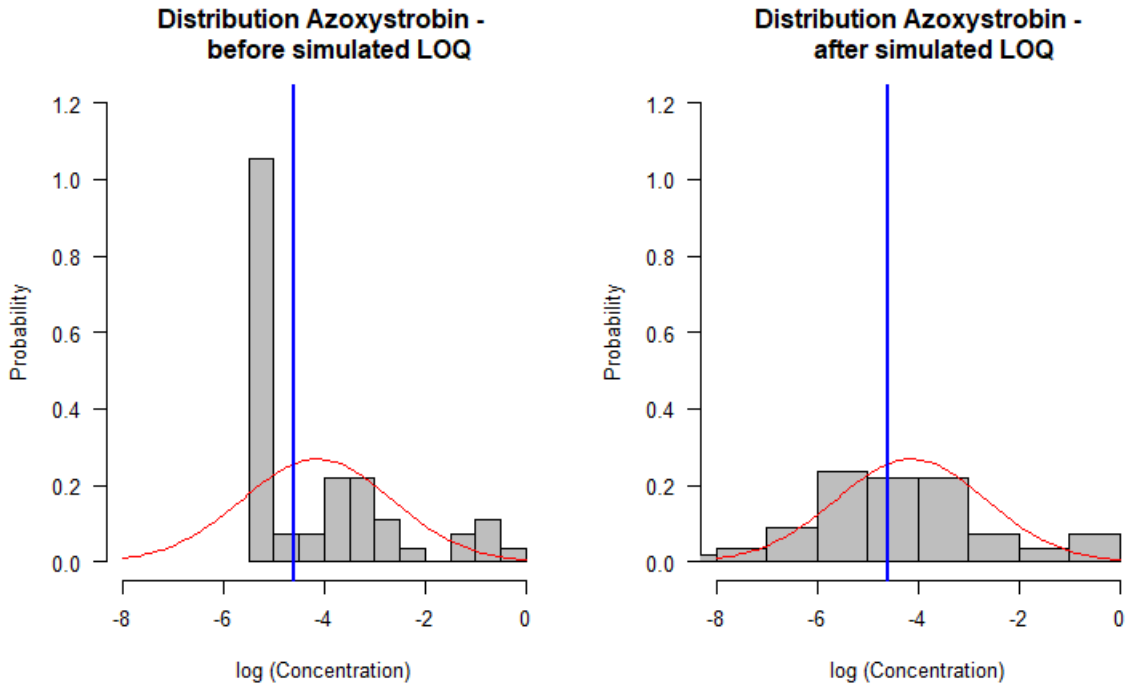

Figure S. 2 Generation of values below limit of quantification (LOQ) before simulation (left) and after simulation (right) for the example of azoxystrobin. (distribution = red curve, LOQ value = blue line)

III. Derivation of effect distribution

Raw effect data can be found in the attached excel file (Raw_data.zip . - EXTRACT_ECOTOX_V13_Chronic_Growth_Population_Reproduction.xlsx). It contains information about the species group, common name, endpoint, test type, target type (effect), measured value and unit collected for this pesticide.

Table S. 5 Species sensitivity distribution for azoxystrobin based on means for multiple of the same species values. The dotted line indicates the derived 5% hazard concentration (HC5) used to derive the PNEC concentration in this study. The R package 'ssdtools' was used to derive/ calculate the HC5 and model this distribution.

Substance	Mean (µg/L)	sd
Azoxystrobin	12.39	9.13
Metribuzin	3804.44	8779.10
Imidacloprid	16671.03	53202.28

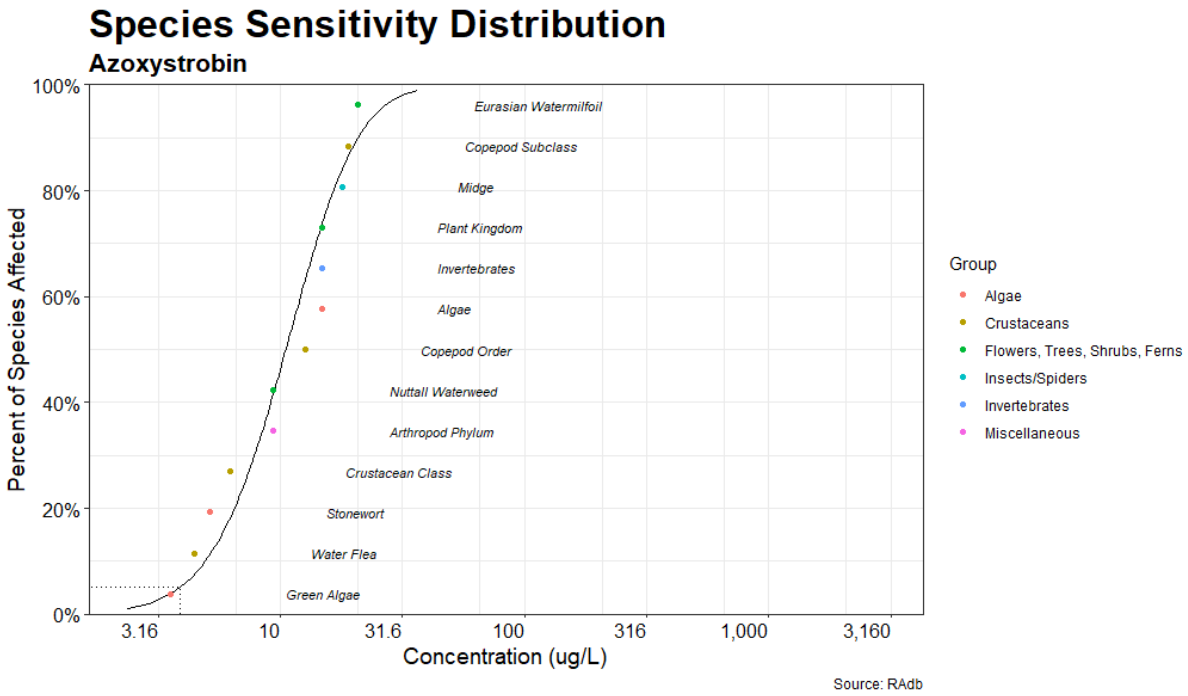

Figure S. 3 Species sensitivity distribution for azoxystrobin based on means for multiple of the same species values. The dotted line indicates the derived 5% hazard concentration (HC5) used to derive the PNEC concentration in this study. The R package 'ssdtools' was used to derive/ calculate the HC5 and model this distribution.

Table S. 6 Overview of the derived predicted no effect concentration (PNEC) for azoxystrobin with a used Assessment factor (AF) of 1, 3, 5 and 10.

Determined by assessment factor	PNEC (µg/L)
1	3.87
3	1.29
5	0.77
10	0.39

The effect data set received and used for this study are compiled from NIVA RAdb database and represent data from the ECOTOXicology Knowledgebase (ECOTOX) database (https://cfpub.epa.gov/ecotox), a comprehensive, publicly available Knowledgebase providing single chemical environmental toxicity data on aquatic life, terrestrial plants and wildlife. The database contains a number of data and metadata, including information about the tested chemicals, bioassay species, endpoints, effect type, bioassay-specific information and effect concentrations (NOEC, LOEC, ECx etc.). The database assembly have undergone a certain level of quality assurance, but some data redundancy may be expected due to presence of data representing different observation times from the same test and potential duplication of data entries due to erroneous taxonomic identifiers. No additional effort was undertaken to remove such redundancy as effect data was merely used for demonstration of the Bayesian modelling approach.

IV. Netica discretization and equations syntax

In the following, the node discretization is described in more detail.

For the Precautionary factor, we chose integers of 1,3, 10, 30, 100, 300, and 1000 as alternatives.

For the Exposure/Effect ratio and risk quotient distribution, the intervals were discretized into 8 approximately equidistant bins in log10 scale (see Table S. 7).

Table S. 7 Discretizaion of the Exposure/Effect ratio and Risk Quotient nodes.

Node title	States
Exposure: effect - ratio distribution	0 to 3e-4
	3e-4to 0.001
	0.001 to 0.003
	0.003 to 0.01
	0.01 to 0.03
	0.03 to 0.1
	0.1 to 1
	1 to 3
Risk Quotient distribution	0 to 0.003
	0.003 to 0.01
	0.01 to 0.03
	0.03 to 0.1
	0.1 to 0.3
	0.3 to 1
	1 to 3
	3 to 3000

For the exposure and effect concentration nodes, the discretization was carried out with the multi-purpose box described at Norsys (1995c). The following shortcuts were used:

1. $[b, e]\ /\ n$
2. $[b, e]\ /L\ n$

With the interval beginning with “b” and ending with “e”, the number of intervals is decided by “n”, “L” divides the list logarithmically. The first shortcut was used to discretize the nodes “Exposure concentration Log” and “Effect concentration Log”, whereas the second shortcut was used for the nodes “Exposure concentration distribution (µg/L)” and “Effect concentration distribution (µg/L)”. These concentration nodes have equidistant intervals given (see Table S. 8)

Table S. 8 Discretization of the exposure and effect concentration nodes.

Node title	Discretization syntax		
	Azoxystrobin	Metribuzin	Imidacloprid
Effect Concentration distribution Log	[0, 3.8]/ 12	[2, 10]/ 12	[0, 12]/ 12

Effect concentration Distribution	[1, 44.7]/L 12	[7.38, 22026.5]/L 12	[1, 1.62755e5]/L 12
Exposure Concentration distribution Log	[-6, 1]/ 12	[-8, 2]/ 12	[-6, 1]/ 12
Exposure/Effect ratio distribution	[0.0025, 2.71828] /L 12	[3.35463e-4, 7.38906] /L 12	[0.00247875, 2.71828] /L 12

For these exposure and effect concentration nodes, the following distribution was used to quantify the conditional probability table:

NormalDist (x, μ, σ)

With "x" indicating the node, "μ" being the mean of the normal distribution, and "σ" being the standard deviation of the distribution (Norsys, 1995d). In our case we used ln-transformed values.

For the season Bayesian another equation was used to implement conditions (for the different seasons).

$p(X|B) =$
$(B == Spring)?\ NormalDist\ (x, \mu, \sigma):$
$(B == Summer)?\ NormalDist\ (x, \mu, \sigma):$
$(B == Autumn)\ ?\ NormalDist\ (x, \mu, \sigma)\ :\ 0$

The parent of "X" (Exp_Log) in this network is "B" (Sea = Season). The formula describes the way to condition states of a discrete node and each condition has a distribution assigned (Norsys, 1995a)) Other common mathematical operators used in the model were exp (x) for exponential (e ^ x) (Norsys, 1995b). An example can be found in Table S. 10 – Source or CPT for the Exposure concentration distribution Log node.

V. Conditional probability tables and posterior probabilities for the example of azoxystrobin

a) Bayesian network for the traditional approach

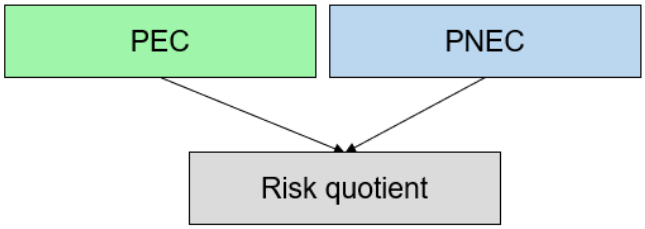

Figure S. 4 Node overview for the traditional Bayesian network option a. (PEC = Predicted environmental concentration, PNEC = Predicted no effect concentration)

Data input:

- Exposure concentration max value from exposure data set

- Predicted no effect concentration derived by applying an assessment factor to the an HC5 of a NOEC based Species sensitivity distribution

Table S. 9 Node description title, name, number of states per node and source of conditional probability table (CPT) of the traditional Bayesian network option a. (PEC = predicted environmental concentration, PNEC = predicted no effect concentration)

Node title	Netica node name	Number of States	Description of states	Source of CPT
PEC (µg/L)	Exp_Norm	3	(ref to Table S. 3)	(root node)
PNEC (µg/L)	Eff_Norm	4	(ref to Table S. 6)	(root node)
Risk quotient	RQ	8	(ref to Figure 4)	RQ (Exp_Norm, Eff_Norm) = Exp_Norm/ Eff_Norm

b) Bayesian network for the intermediate approach using exposure distribution

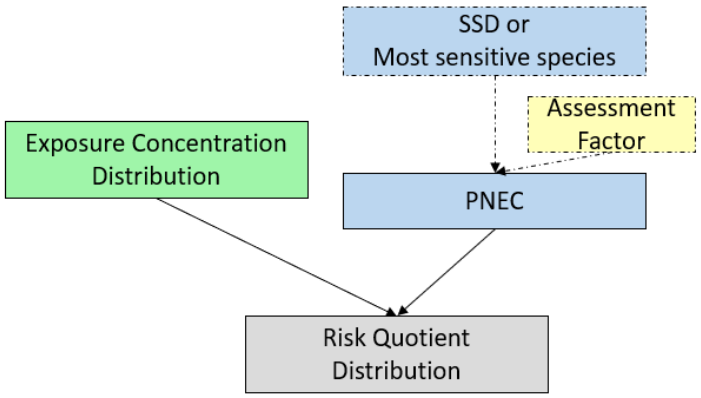

Figure S. 5 Node overview for the intermediate Bayesian network option b using an exposure distribution. (PNEC = predicted no effect concentration, SSD = species sensitivity distribution)

Data input:

- Exposure distribution derived from exposure data set
- Predicted no effect concentration derived by applying an assessment factor to the an HC5 of a NOEC based Species sensitivity distribution

Table S. 10 Node description title and name, type of node, number of states per node and used source of conditional probability table (CPT) generating the conditional probability table of the intermediate Bayesian network option b using exposure distribution for azoxystrobin.

Node title	Netica node name	Number of States	Source of CPT
Exposure concentration distribution Log	Exp_Log	10	P (Exp_Log|) = NormalDist (Exp_Log, -4.148, 1.484)
Exposure concentration distribution (µg/L)	Exp_Norm	10	Exp_Norm (Exp_Log) = exp(Exp_Log)
PNEC (µg/L)	PNEC	1	root node (ref to Table S. 6)
Risk quotient distribution	RQ	7	RQ (Exp_Norm, PNEC) = (Exp_Norm/PNEC)

Table S. 11 Posterior risk quotient probability distribution of the Bayesian network option b for azoxystrobin. The table contains the calculated probabilities for each interval of the risk quotient node depending on the selected assessment factor (AF).

	Interval/ states	Posterior probability given alternative evidence			
Node title		AF1	AF3	AF5	AF10
Risk quotient probability distribution	0 to 0.003	0.410	0.101	0.000	0.000
	0.003 to 0.01	0.325	0.141	0.242	0.101
	0.01 to 0.03	0.115	0.341	0.341	0.309
	0.03 to 0.1	0.117	0.343	0.268	0.325
	0.1 to 0.3	0.028	0.042	0.075	0.115
	0.3 to 1	0.004	0.031	0.070	0.137
	1 to 3	0.000	0.001	0.003	0.008
	3 to 3000	0.000	0.000	0.001	0.004

c) Bayesian network the intermediate approach using effect distribution

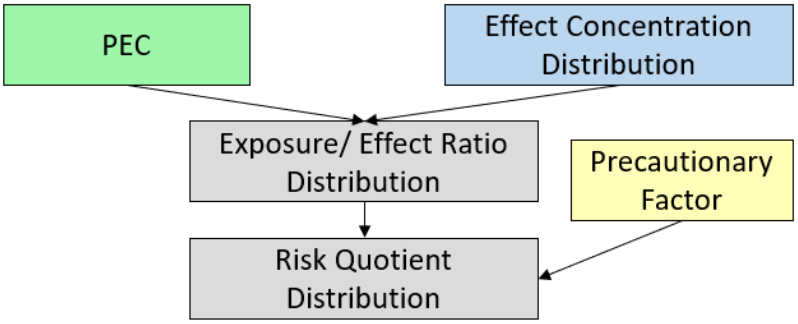

Figure S. 6 Node overview for the intermediate Bayesian network option c using an effect distribution. (PEC = Predicted environmental concentration)

Data input:

- Effect distribution from collected NOEC values
- Exposure concentration max, min and mean value from exposure data set

Table S. 12 Node description title and name, number of states per node and source of conditional probability table (CPT) generating the conditional probability table of the intermediate Bayesian network option c using effect distribution for azoxystrobin. (PEC = Predicted environmental concentration)

Node title	Netica node name	Number of States	Source of CPT
PEC (µg/L)	PEC	2	Root node (ref to Table S. 3)
Effect Concentration distribution Log	Eff_Log	10	P(Eff_Log|) = NormalDist(Eff_Log, 2.3224782, 0.5680065)
Effect concentration distribution (µg/L)	Eff_Norm	10	Eff_Norm (Eff_Log) = exp(Eff_Log)
Exposure/ effect - ratio distribution (µg/L)	Exp_Eff_Ra	8	Exp_Eff_Ra (Exp_Norm, Eff_Norm) = (Exp_Norm/Eff_Norm)
Precautionary factor (PF)	PF	8	-
Risk quotient distribution	RQ	8	RQ (PF, Exp_Eff_Ra) = (PF*Exp_Eff_Ra)

Table S. 13 Posterior risk quotient distribution of the Bayesian network option c for azoxystrobin. The table contains the calculated probabilities for each interval of the Exposure – effect ratio and, and risk quotient node depending on the selected Precautionary (PF), for the event of a mean (a) and maximum (b) predicted environmental concentration (PEC).

a) Mean PEC

States	Posterior probability given alternative evidence				
	Exposure/ effect - ratio distribution	Risk Quotient			
		PF 10	PF 30	PF 100	PF 300
0 to 3e-4	0.000	-	-	-	-
3e-4to 0.001	0.000	0.000	0.000	0.000	0.000
0.001 to 0.003	0.000	0.000	0.000	0.000	0.000
0.003 to 0.01	0.352	0.000	0.000	0.000	0.000
0.01 to 0.03	0.551	0.352	0.000	0.000	0.000
0.03 to 0.1	0.097	0.551	0.352	0.000	0.000
0.1 to 1	0.000	0.097	0.551	0.352	0.000
1 to 3	0.000	0.000	0.097	0.551	0.352
3 to 3000	-	0.000	0.000	0.097	0.648

b) Maximum PEC

States	Posterior probability given alternative evidence				
	Exposure/ effect - ratio distribution	Risk Quotient			
		PF 10	PF 30	PF 100	PF 300
0 to 3e-4	0.000	-	-	-	-
3e-4to 0.001	0.000	0.000	0.000	0.000	0.000
0.001 to 0.003	0.000	0.000	0.000	0.000	0.000
0.003 to 0.01	0.000	0.000	0.000	0.000	0.000
0.01 to 0.03	0.064	0.000	0.000	0.000	0.000
0.03 to 0.1	0.706	0.064	0.000	0.000	0.000
0.1 to 1	0.230	0.706	0.064	0.000	0.000
1 to 3	0.000	0.000	0.706	0.064	0.000
3 to 3000	-	0.230	0.230	0.936	1.000

d) Bayesian network for the fully probabilistic approach

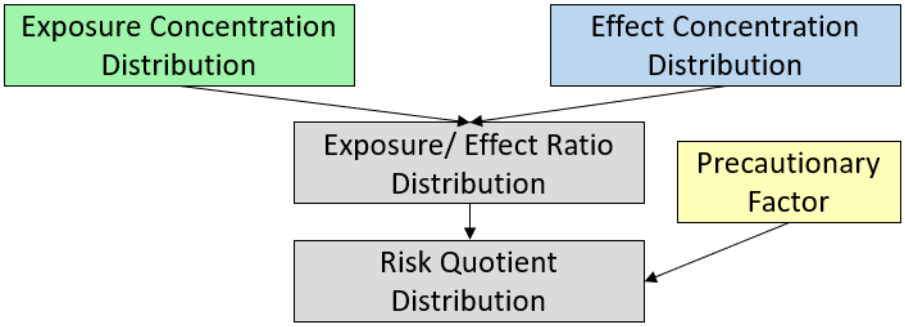

Figure S. 7 Node overview for the fully probabilistic Bayesian network option d.

Data input:

- Effect distribution from collected NOEC values
- Exposure distribution derived from exposure data set

Table S. 14 Node description title and name, number of states per node and used Netica equation generating the conditional probability table of the fully probabilistic Bayesian network option d for azoxystrobin.

Node title	Netica node name	Number of States	Netica equation
Exposure concentration distribution log	Exp_Log	10	P(Exp_Log) = NormalDist(Exp_Log, -4.148, 1.484)
Effect concentration distribution log	Eff_Log	10	P(Eff_Log|) = NormalDist(Eff_Log, 2.3224782, 0.5680065)
Exposure concentration distribution (µg/L)	Exp_Norm	10	Exp_Norm (Exp_Log) = exp(Exp_Log)
Effect concentration distribution (µg/L)	Eff_Norm	10	Eff_Norm (Eff_Log) = exp(Eff_Log)
Exposure/ effect - ratio distribution	Exp_Eff_Ra	8	Exp_Eff_Ra (Exp_Norm, Eff_Norm) = (Exp_Norm/Eff_Norm)
Precautionary factor	PF	8	-
Risk quotient distribution	RQ	8	RQ (PF, Exp_Eff_Ra) = (PF*Exp_Eff_Ra)

Table S. 15 Posterior risk quotient distribution of the Bayesian network option d for azoxystrobin. The table contains the calculated probabilities for each interval of the risk quotient node depending on the selected Precautionary factor (PF).

Risk Quotient distribution	Posterior probability given alternative evidence			
Interval/ states	PF 10	PF 30	PF 100	PF 300
0 to 0.003	0.067	0.000	0.000	0.000
0.003 to 0.01	0.294	0.067	0.000	0.000
0.01 to 0.03	0.242	0.294	0.067	0.000
0.03 to 0.1	0.281	0.242	0.294	0.067
0.1 to 0.3	0.080	0.281	0.242	0.294
0.3 to 1	0.029	0.080	0.281	0.242
1 to 3	0.000	0.029	0.080	0.281
3 to 3000	0.006	0.006	0.036	0.116

VI. Conditional probability tables and posterior probabilities for the seasonal Bayesian network approach for azoxystrobin, metribuzin, and imidacloprid

a) Azoxystrobin

Table S. 16 Node description title and name, number of states per node and used Netica equation generating the conditional probability table of the seasonal fully probabilistic Bayesian network approach for azoxystrobin.

Node title	Netica node name	Number of States	Netica equation
Season	Sea	2	-
Exposure concentration distribution Log	Exp_Log	10	P(Exp_Log| Sea) =Sea == Summer? NormalDist(Exp_Log, -3.939194, 1.528558): Sea == Autumn? NormalDist(Exp_Log, -4.017832, 1.540513):0
Effect concentration distribution Log	Eff_Log	10	P(Eff_Log|) = NormalDist(Eff_Log, 2.3224782, 0.5680065)
Exposure concentration distribution	Exp_Norm	10	Exp_Norm (Exp_Log) = exp(Exp_Log)
Effect concentration distribution	Eff_Norm	10	Eff_Norm (Eff_Log) = exp(Eff_Log)
Exposure/ effect - ratio distribution	Exp_Eff_Ra	8	Exp_Eff_Ra (Exp_Norm, Eff_Norm) = (Exp_Norm/Eff_Norm)
Precautionary factor	PF	8	-
Risk quotient distribution	RQ	8	RQ (PF, Exp_Eff_Ra) = (PF*Exp_Eff_Ra)

Table S. 17 Posterior risk quotient distribution of the seasonal fully probabilistic Bayesian network approach for azoxystrobin. The table contains the calculated probabilities for each interval of the Exposure – effect ratio, and risk quotient node depending on the selected Precautionary factor (PF) of 10, 30, 100, 300 and 3000, for summer (a) and autumn (b) season.

a) Summer

States	Posterior probability given alternative evidence					
	Exposure/ effect - ratio distribution	Risk Quotient				
		PF 10	PF 30	PF 100	PF 300	PF 1000
0 to 3e-4	0.039	-	-	-	-	-
3e-4to 0.001	0.237	0.039	0.000	0.000	0.000	0.000
0.001 to 0.003	0.319	0.237	0.039	0.000	0.000	0.000
0.003 to 0.01	0.255	0.319	0.237	0.039	0.000	0.000
0.01 to 0.03	0.093	0.255	0.319	0.237	0.039	0.039
0.03 to 0.1	0.051	0.093	0.255	0.319	0.237	0.000
0.1 to 1	0.007	0.051	0.093	0.255	0.319	0.237
1 to 3	0.000	0.000	0.051	0.093	0.255	0.319
3 to 3000	-	0.007	0.007	0.058	0.150	0.405

b) Autumn

States	Posterior probability given alternative evidence					
	Exposure/ effect - ratio distribution	Risk Quotient				
		PF 10	PF 30	PF 100	PF 300	PF 1000
0 to 3e-4	0.045	-	-	-	-	-
3e-4to 0.001	0.246	0.045	0.000	0.000	0.000	0.000
0.001 to 0.003	0.298	0.246	0.045	0.000	0.000	0.000
0.003 to 0.01	0.244	0.298	0.246	0.045	0.000	0.000
0.01 to 0.03	0.100	0.244	0.298	0.246	0.045	0.045
0.03 to 0.1	0.060	0.100	0.244	0.298	0.246	0.000
0.1 to 1	0.008	0.060	0.100	0.244	0.298	0.246
1 to 3	0.000	0.000	0.060	0.100	0.244	0.298
3 to 3000	-	0.045	0.008	0.068	0.167	0.411

b) Metribuzin

Table S. 18 Node description title and name, number of states per node and used Netica equation generating the conditional probability table of the seasonal fully probabilistic Bayesian network approach for metribuzin.

Node title	Netica node name	Number of States	Netica equation
Season	Sea	3	-
Exposure concentration distribution Log	Exp_Log	10	P(Exp_Log| Sea) = Sea == Spring? NormalDist(Exp_Log, -4.3568058, 0.9664787): Sea == Summer? NormalDist(Exp_Log, -2.793568, 1.415767): Sea == Autumn? NormalDist(Exp_Log, -3.292422, 1.363139): 0
Effect concentration distribution Log	Eff_Log	10	p(Eff_Log|) = NormalDist(Eff_Log, 4.946324, 2.431668)
Exposure concentration distribution (ug/L)	Exp_Norm	10	Exp_Norm (Exp_Log) = exp(Exp_Log)
Effect concentration Distribution (ug/L)	Eff_Norm	10	Eff_Norm (Eff_Log) = exp(Eff_Log)
Exposure/ effect - ratio distribution	Exp_Eff_Ra	8	Exp_Eff_Ra (Exp_Norm, Eff_Norm) = (Exp_Norm/Eff_Norm)
Precautionary factor	PF	8	-
Risk quotient distribution	RQ	8	RQ (PF, Exp_Eff_Ra) = (PF*Exp_Eff_Ra)

Table S. 19 Posterior risk quotient distribution of the seasonal fully probabilistic Bayesian network approach for metribuzin. The table contains the calculated probabilities for each interval of the Exposure – effect ratio, and risk quotient node depending on the selected Precautionary factor (PF) of 10, 30, 100, 300 and 3000, for spring (a), summer (b) and autumn (c) season

a) Spring

States	Posterior probability given alternative evidence					
	Exposure/ effect - ratio distribution	Risk Quotient				
		PF 10	PF 30	PF 100	PF 300	PF 1000
0 to 3e-4	0.764	-	-	-	-	-
3e-4to 0.001	0.167	0.764	0.000	0.000	0.764	0.000
0.001 to 0.003	0.052	0.167	0.764	0.000	0.000	0.000
0.003 to 0.01	0.016	0.052	0.167	0.764	0.000	0.000
0.01 to 0.03	0.001	0.016	0.052	0.167	0.000	0.764
0.03 to 0.1	0.000	0.001	0.016	0.052	0.167	0.000
0.1 to 1	0.000	0.000	0.001	0.016	0.052	0.167
1 to 3	0.000	0.000	0.000	0.001	0.016	0.052
3 to 3000	-	0.000	0.000	0.000	0.001	0.017

b) Summer

States	Posterior probability given alternative evidence					
	Exposure/ effect - ratio distribution	Risk Quotient				
		PF 10	PF 30	PF 100	PF 300	PF 1000
0 to 3e-4	0.476	-	-	-	-	-
3e-4to 0.001	0.238	0.476	0.000	0.000	0.476	0.000
0.001 to 0.003	0.166	0.238	0.476	0.000	0.000	0.000
0.003 to 0.01	0.077	0.166	0.238	0.476	0.000	0.000
0.01 to 0.03	0.029	0.077	0.166	0.238	0.000	0.476
0.03 to 0.1	0.010	0.029	0.077	0.166	0.238	0.000
0.1 to 1	0.003	0.010	0.029	0.077	0.166	0.238
1 to 3	0.000	0.000	0.010	0.029	0.077	0.166
3 to 3000	-	0.003	0.003	0.014	0.042	0.119

c) Autumn

States	Posterior probability given alternative evidence					
	Exposure/ effect - ratio distribution	Risk Quotient				
		PF 10	PF 30	PF 100	PF 300	PF 1000
0 to 3e-4	0.545	-	-	-	-	-
3e-4to 0.001	0.223	0.545	0.000	0.000	0.545	0.000
0.001 to 0.003	0.141	0.223	0.545	0.000	0.000	0.000
0.003 to 0.01	0.062	0.141	0.223	0.545	0.000	0.000
0.01 to 0.03	0.021	0.062	0.141	0.223	0.000	0.545
0.03 to 0.1	0.006	0.021	0.062	0.141	0.223	0.000
0.1 to 1	0.002	0.006	0.021	0.062	0.141	0.223
1 to 3	0.000	0.000	0.006	0.021	0.062	0.141
3 to 3000	-	0.002	0.002	0.008	0.029	0.091

a) Imidacloprid

Table S. 20 Node description title and name, number of states per node and used Netica equation generating the conditional probability table of the seasonal fully probabilistic Bayesian network approach for imidacloprid.

Node title	Netica node name	Number of States	Netica equation
Season	Sea	3	-
Exposure concentration distribution Log	Exp_Log	10	P(Exp_Log| Sea) = Sea == Spring? NormalDist(Exp_Log, -3.901538, 1.481266): Sea == Summer? NormalDist(Exp_Log, -1.783072, 1.742699): Sea == Autumn? NormalDist(Exp_Log, -3.403673, 1.115896): 0
Effect concentration distribution Log	Eff_Log	10	P(Eff_Log|) = NormalDist(Eff_Log, 6.483570, 4.003579)
Exposure concentration distribution (µg/L)	Exp_Norm	10	Exp_Norm (Exp_Log) = exp(Exp_Log)
Effect concentration Distribution (µg/L)	Eff_Norm	10	Eff_Norm (Eff_Log) = exp(Eff_Log)
Exposure/ Effect ratio distribution	Exp_Eff_Ra	8	Exp_Eff_Ra (Exp_Norm, Eff_Norm) = (Exp_Norm/Eff_Norm)
Precautionary factor	PF	8	1, 3, 10, 30, 100, 300, 1000
Risk quotient distribution	RQ	8	RQ (PF, Exp_Eff_Ra) = (PF*Exp_Eff_Ra)

Table S. 21 Posterior risk quotient distribution of the seasonal fully probabilistic Bayesian network approach for imidacloprid. The table contains the calculated probabilities for each interval of the Exposure/Effect ratio, and risk quotient node depending on the selected Precautionary factor (PF) of 10, 30, 100, 300 and 3000, for spring (a), summer (b) and autumn (c) season.

a) Spring

States	Posterior probability given alternative evidence					
	Exposure/ Effect ratio distribution	Risk Quotient				
		PF 10	PF 30	PF 100	PF 300	PF 1000
0 to 3e-4	0.704	-	-	-	-	-
3e-4to 0.001	0.109	0.704	0.000	0.000	0.000	0.000
0.001 to 0.003	0.072	0.109	0.704	0.704	0.000	0.000
0.003 to 0.01	0.065	0.072	0.109	0.000	0.000	0.000
0.01 to 0.03	0.030	0.065	0.072	0.109	0.704	0.000
0.03 to 0.1	0.017	0.030	0.065	0.072	0.109	0.704
0.1 to 1	0.004	0.017	0.030	0.065	0.072	0.109
1 to 3	0.000	0.000	0.017	0.030	0.065	0.072
3 to 3000	-	0.004	0.004	0.021	0.051	0.116

b) Summer

States	Posterior probability given alternative evidence					
	Exposure/ Effect ratio distribution	Risk Quotient				
		PF 10	PF 30	PF 100	PF 300	PF 1000
0 to 3e-4	0.517	-	-	-	-	-
3e-4to 0.001	0.154	0.517	0.000	0.000	0.000	0.000
0.001 to 0.003	0.091	0.154	0.517	0.517	0.000	0.000
0.003 to 0.01	0.097	0.091	0.154	0.000	0.000	0.000
0.01 to 0.03	0.052	0.097	0.091	0.154	0.517	0.000
0.03 to 0.1	0.058	0.052	0.097	0.091	0.154	0.517
0.1 to 1	0.032	0.058	0.052	0.097	0.091	0.154
1 to 3	0.000	0.000	0.058	0.052	0.097	0.091
3 to 3000	-	0.032	0.032	0.090	0.141	0.238

c) Autumn

States	Posterior probability given alternative evidence					
	Exposure/ Effect ratio distribution	Risk Quotient				
		PF 10	PF 30	PF 100	PF 300	PF 1000
0 to 3e-4	0.683	-	-	-	-	-
3e-4to 0.001	0.114	0.683	0.000	0.000	0.000	0.000
0.001 to 0.003	0.076	0.114	0.683	0.683	0.000	0.000
0.003 to 0.01	0.072	0.076	0.114	0.000	0.000	0.000
0.01 to 0.03	0.036	0.072	0.076	0.114	0.683	0.000
0.03 to 0.1	0.018	0.036	0.072	0.076	0.114	0.683
0.1 to 1	0.002	0.018	0.036	0.072	0.076	0.114
1 to 3	0.000	0.000	0.018	0.036	0.072	0.076
3 to 3000	-	0.002	0.002	0.019	0.055	0.127

b) Example of seasonal Bayesian network

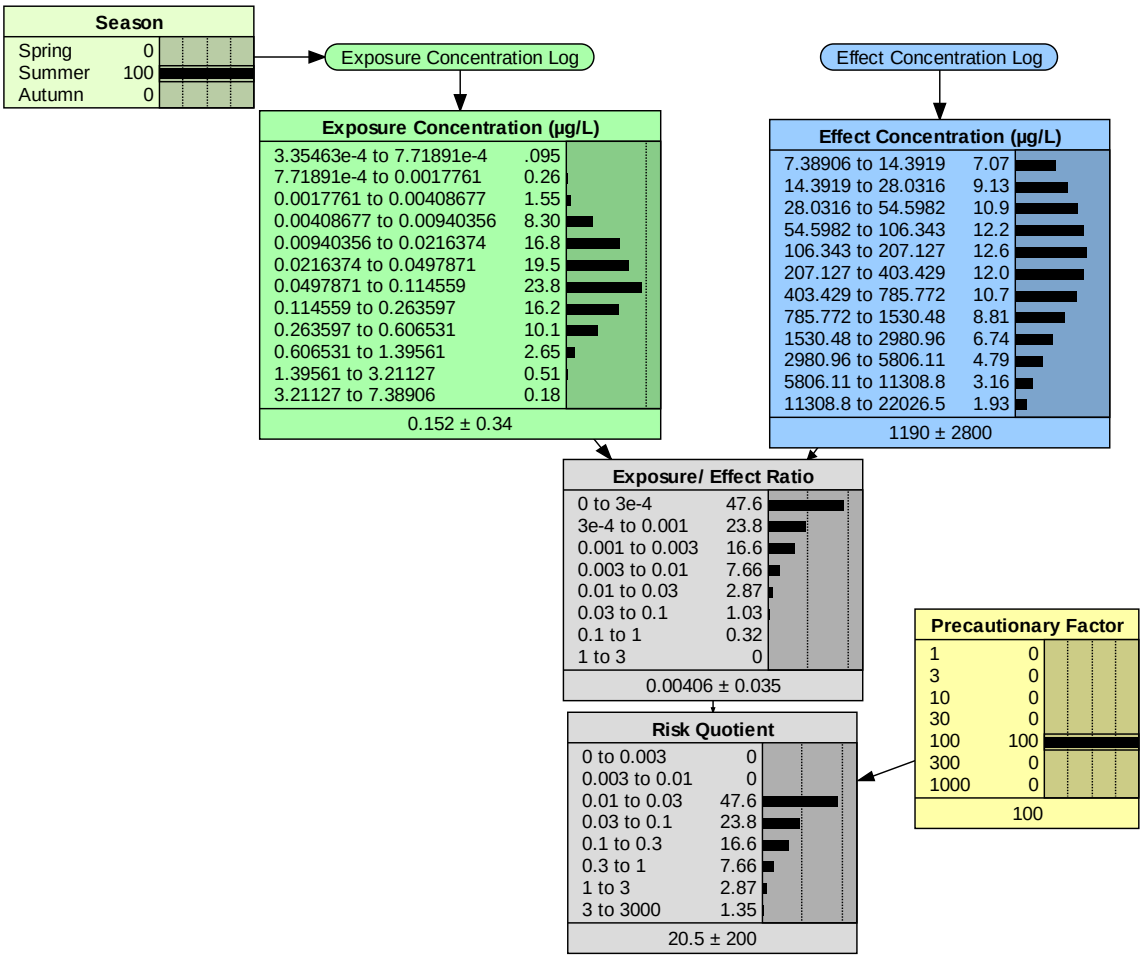

Figure S. 8 Example of parameterized seasonal fully probabilistic Bayesian network model for metribuzin, with a selected Precautionary factor of 100 and for the summer season.

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Probabilistic risk assessment of pesticides under future agricultural and climate scenarios using a bayesian network

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The use of Bayesian networks (BN) for environmental risk assessment has increased in recent years as they offer a more transparent way to characterize risk and evaluate uncertainty than the traditional risk assessment paradigms. In this study, a novel probabilistic approach applying a BN for risk calculation was further developed and explored by linking the calculation a risk quotient to alternative future scenarios. This extended version of the BN model uses predictions from a process-based pesticide exposure model (World Integrated System for Pesticide Exposure - WISPE) in the exposure characterization and toxicity test data in the effect characterization. The probability distributions for exposure and effect are combined into a risk characterization (i.e. the probability distribution of a risk quotient), a common measure of the exceedance of an environmentally safe exposure threshold. The BN model was used to account for variabilities of the predicted pesticide exposure in agricultural streams, and inter-species variability in sensitivity to the pesticide among freshwater species. In Northern Europe, future climate scenarios typically predict increased temperature and precipitation, which can be expected to cause an increase in weed infestations, plant disease and insect pests. Such climate-related changes in pest pressure in turn can give rise to altered agricultural practices, such as increased pesticide application rates, as an adaptation to climate change. The WISPE model was used to link a set of scenarios consisting of two climate models, three pesticide application scenarios and three periods (year ranges), for a case study in South-East Norway. The model was set up for the case study by specifying environmental factors such as soil properties and field slope together with chemical properties of pesticides to predict the pesticide exposure in streams adjacent to the agricultural fields. The model was parameterized and evaluated for five selected pesticides: the three herbicides clopyralid, fluroxypyr-meptyl, and 2-(4-chloro-2-methylphenoxy) acetic acid (MCPA), and the two fungicides prothiocanzole and trifloxystrobin. This approach enabled the calculation and visualization of probability distribution of the risk quotients for the future time horizons 2050 and

2085. The risk posed by the pesticides were in general low for this case study, with highest probability of the risk quotient exceeding 1 for the two herbicides fluroxypyr-meptyl and MCPA. The future climate projections used here resulted in only minor changes in predicted exposure concentrations and thereby future risk. However, a stronger increase in risk was predicted for the scenarios with increased pesticide application, which can represent an adaptation to a future climate with higher pest pressures. In the current study, the specific BN model predictions were constrained by an existing set of climate projections which represented only one IPCC scenario (A1B) and two climate models. Further advancement of the BN modelling demonstrated herein, including more recent climate scenarios and a larger set of climate models, is anticipated to result in more relevant risk characterization also for future climate conditions. This probabilistic approach will have the potential to aid targeted management of ecological risks in support of future research, industry and regulatory needs.

KEYWORDS

bayesian network models, exposure modelling, environmental risk assessment, pesticides, uncertainty

1 Introduction

Climate change (CC) is expected to shift weather patterns, and consequently can alter the way water and food resources are obtained and managed worldwide. Already today, European assessment for rivers and lakes report that 5–15% of the monitoring stations show exceedances of environmental quality standards by herbicides, and 3–8% by insecticides over the period 2007–2017 (Mohaupt et al., 2020). Nevertheless, in future pesticides will be extensively used as they will continue to play a vital role in the food production process and food security (Popp et al., 2013). Despite thorough regulation of pesticides, large knowledge gaps continue to hinder risk assessment, especially when it comes to potential environmental impact of pesticide mixtures and impacts of climate and regional factors (Topping et al., 2020; Weisner et al., 2021). In Northern Europe, predicted increase in plant diseases and insect pests may consequently lead to higher pesticide use and thereby occurring concentration of pesticides in the environment (Kattwinkel et al., 2011; Sutherst et al., 2011; Delcour et al., 2015). As pesticide environmental fate and exposure scenarios for Norway and the Nordic countries deviate from EU predictions due to spatial (regional) or temporal differences (Stenrød et al., 2008; Holten et al., 2018), the pesticide use, emissions, exposure and fate are not adequately represented by the standardized EU model scenarios (Stenrød et al., 2016). To safeguard environment health better, there is a need to improve the integration of trend connected to CC into environmental risk assessments of pesticides, considering both direct effects such as the shifts in climate conditions and indirect effects such as changes in pesticide application patterns. This should subsequently enable better informed risk management.

Current paradigms for environmental risk assessment (ERA) of pesticides typically aim to take into account the variability of species sensitivities by estimating a proportion of affected species in a community, which is used to define a predicted no-effect concentration (PNEC) of the pesticide (More et al., 2019). The traditional risk characterization of pesticides usually uses single-value e.g., toxic exposure ratio derived from the PNEC divided by the predicted environmental concentration (PEC) to assess whether a chemical substance poses a risk to the environment (EC, 2011). In this study, a more general approach was applied using a risk quotient (RQ) that is calculated as PEC/PNEC, where a potential risk to the environment is assumed whenever the PEC exceeds the safe concentration (PNEC) (Bruijn et al., 2002; More et al., 2019). These derived point estimates may convey an unjustified sense of accuracy (Rai et al., 2002), as they ignore many sources of uncertainty such as the variability of pesticides concentrations in the environment or other factors that influence the exposure of biota to these chemicals. Especially in Europe, these traditional methods seek to avoid underestimating risk by using conservative assumptions (i.e., assessment factors) to account for various sources of uncertainty (Verdonck, 2003). This way, protective decision making relies on precautionary safety margins (Fairbrother et al., 2015). Spatial and temporal variations in exposure are caused by many factors, including changing environmental characteristics and contamination sources (Artigas et al., 2012) that can cause uncertainty. There is therefore a need for risk assessment methodology to better account for uncertainty and variability in chemical exposure (Belanger and Carr, 2020).

Probabilistic risk assessment make use of probability distributions to characterize uncertainty in all parts of the risk characterization (EUFRAM, 2006; Mentzel et al., 2021). Ergo, fully probabilistic risk characterization can better account for spatial and temporal variability of both chemical concentrations and species sensitivity (Solomon et al., 2000; Verdonck, 2003; EUFRAM, 2006; Fairbrother et al., 2015). Several probabilistic

methods have been proposed to characterize risk while including estimation of stochastic properties and uncertainty (Maertens et al., 2022). The general responsibility of scientists to communicate uncertainties has also been highlighted by the EU (EFSA BFR, 2019). Already 2 decades ago, the use of probabilistic risk assessment has been recommended for the European Union (EU) (Jager et al., 2001) but is still not commonly applied in regulatory risk assessment (Fairbrother et al., 2015). Probabilistic methods that incorporate distributions for exposure and effect are e.g., joint probability curves and quantitative overlap. Generally, probabilistic methods require more data for calculation of distributions compared to traditional ERA, but on the other hand probabilistic methods make better use of available data as well as other sources of information (Campbell et al., 2000; Verdonck, 2003). However, some of the results are difficult to communicate and thereby challenging for decision-makers to interpret and understand (Verdonck, 2003; FOCUS, 2007), possibly because they are often based on cumulative distribution curves (EUFRAM, 2006). A Bayesian network (BN) model has therefore been proposed as a more user-friendly and intuitive method for supporting probabilistic risk assessment of pesticides (Mentzel et al., 2021).

In this study, the BN model developed by Mentzel et al. (2021) was further extended and explored to assess environmental risk of pesticides under future scenarios. The extended BN model presented here includes the output of a pesticide exposure prediction platform for a representative Northern European area (WISPE; Bolli et al. (2013)) under different climate and pesticide application scenarios. The main objective of this study was to develop an approach for incorporating alternative climate change and pesticide application scenarios into a probabilistic approach to risk characterization, based on the available data and information for a Norwegian case study.

2 Materials and methods

2.1 Approach

2.1.1 Bayesian network model, structure and implementation

Bayesian methods have been recommended by the European Food Safety Authority (EFSA et al., 2017) for uncertainty analysis in the process of identifying limitations in scientific knowledge and evaluating their implications for scientific conclusion. Bayesian networks (BNs) are a branch of Bayesian approaches that have been increasingly used in environmental risk assessment and management (Aguilera et al., 2011; Moe et al., 2021b; Kaikkonen et al., 2021). BNs are probabilistic and graphical models, more specifically directed acyclic graphs (DAG) (Kanes et al., 2017) that have no feedback loops. The nodes (variables) are connected through links (potentially causal relationships) shown as arcs representing conditional probability tables (CPTs) (Kjærulff and Madsen, 2013). Each node has a set of alternative states (typically intervals) that are quantified by probability distributions. To update probability distributions of the network, the Bayes' rule is implemented to combine prior probabilities with new evidence (Carriger et al., 2016). One of the main benefits of BNs is that all components can be quantified by probability distributions, which facilitates a probabilistic risk calculation. Along these lines, BNs can incorporate various sources of information such as expert opinion, literature and model outputs, enabling a greater use of available data and knowledge (Carriger and Newman, 2012; Carriger et al., 2016). An example of the application of spatial BNs for probabilistic assessment of pesticide exposure on a field level has been carried out by Troldborg et al. (2021). Carriger and Barron (2020) combined probabilistic exposure and effect characterization into calculation of a probabilistic risk quotient (RQ) of Mercury for the Florida panther. This approach to a probabilistic calculation of RQ and associated uncertainties was further developed by Mentzel et al. (2021), by using species sensitivity data for the effect characterization to represent risk to aquatic ecosystems.

The BN conceptual model developed here is based on Mentzel et al. (2021) and consist of four modules (Figure 1): 1) future scenarios (orange), 2) pesticide exposure (blue), 3) toxic effect (green) and 4) risk characterization (grey). The scenario module contains a scenario node that is based on the climate and pesticide application. These scenarios determine the instantaneous pesticide concentration and its probability distribution (pesticide exposure module). This instantaneous concentration node together with the set time since application (node) determines the distribution of the time-specific concentration node, via a log-linear equation. The risk characterization module composes the exposure/effect ratio node that together with an appropriate precautionary factor predicts the probabilities of the RQ intervals. The finalized BN can be instantiated by selecting a scenario and specifying the time since application of interest as evidence. Given this evidence, probability distributions will be updated throughout the network. The four modules are described in more detail in Section 2.2.

2.1.2 Exposure sampling and modelling

Measured pesticide exposure concentrations, their distribution and associated uncertainties are highly influenced by sampling method, time and rate (Spycher et al., 2018). Data derived from monitoring has a wide range of uncertainties through sampling constraints and limited representativeness (FOCUS, 2017). Yet, a realistic environmental concentration is vital for reliable environmental risk assessment. This is especially significant whenever a single number is used without accounting for uncertainty, but is also influential when trying to derive a representative exposure distribution as uncertain estimations can

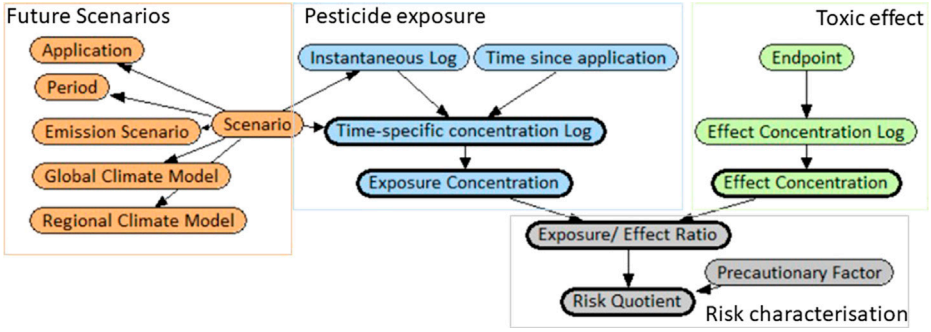

FIGURE 1
Conceptual model for the risk estimation of a pesticide. Pesticide exposure derives input from the WISPE platform and is determined by the associated future scenarios. The toxic effect nodes together with the exposure concentration derives the risk quotient under risk characterization.

hinder appropriate decision-making (Wolf and Tollefsen, 2021). Thence, the EU (Directive 2009/128/EC (EC, 2009a) and REGULATION (EC) No 1107/2009 (EC, 2009b)) offers the option to use models to predict environmental concentrations (PECs) in surface waters. Even if monitoring data are available, the use of modeling approaches for exposure assessment is encouraged by EFSA (2017). They have developed the FOCUS (FOrum for the Co-ordination of pesticide fate models and their Use) surface water scenarios using the model tool SWASH, a GUI for the models PRZM (Pesticide Root Zone Model), MACRO and TOXSWA (TOXic substances in Surface Waters). PRZM and MACRO are models frequently used to simulate pesticide transport in soil while TOXWA simulates the dilution at the edge of field or drain water concentration from the other two models in different surface water body types. SWASH takes agricultural management practices, climate, crops, topography, and soil types into account (Adriaanse et al., 2017).

For this study, we used the World Integrated System for Pesticide Exposure (WISPE) platform, which was developed to evaluate the potential for pesticide exposure to surface waters and groundwaters (Bolli et al., 2013). The WISPE platform was configured with scenarios containing crop, soil, and weather conditions for representative agricultural areas among others in the EU, USA and Norway. This modelling platform interlinks the pesticide root zone model (PRZM), an exposure analysis modeling system (EXAM) (Burns, 2004) and the aquifer dilution assessment model (ADAM) (Williams, 2010) similar to TOXWA. The PRZM model simulates the movement of chemicals within and below the root zone (in unsaturated soil systems). EXAM is a hydraulic model combined with a chemical fate and transport model simulating processes in aquatic environments. It simulates various processes in the aquatic environment. ADAM is an integrated model which predicts the chemical dilution, partitioning and persistence to a water body. EXAM and PRZM are standard models used by USEPA, and the latter model is also used in European pesticide registration and risk assessment (REGULATION (EC) No 1107/2009 (EC, 2009b)). In a previous study, the transport of particles and particle bound pesticides was calibrated for two field sites representative for Norwegian agricultural areas by Bolli et al. (2013). The study found that in this northern region the erosion and transport of particle-bound pesticides are heavily dependent on the weather conditions such as precipitation shortly after application or melting-freezing episodes, which take place in spring and winter. The WISPE platform is based on many of the FOCUS default setting but was specifically tailored for northern European conditions and contains e.g. major Norwegian crops, and plant growth effected by climate conditions, therefore being better suited as a exposure prediction tool in this study.

2.2 Bayesian network modules

In the following, the information sources and assumptions for the four modules of the BN model and the model runs are described. The software Netica (Norsys Software Corp, www.norsys.com) was used to construct the BN model. The BN was constructed with identical node structure and number of states for all of the selected pesticides, but with different discretization of the concentration nodes. For each pesticide, the range of the exposure and effect concentration nodes was adapted to the distributions derived from the data used for exposure and effect assessment, respectively. We chose a relatively high number (10) of intervals to obtain a high resolution of the model. The concentration nodes were discretized by equidistant intervals in the log-scale.

The exposure model platform WISPE was run for each selected pesticide, for three application scenarios and for two climate models. In the selected case study area, environmental

TABLE 1 Bayesian network node description detailing the type of node, the number of states and the method used to parameterize the network.

Node name (Variable)	Type	Number of states	Explanation and information source
Climate model	Categories	2	Scenario component (parent node)
Period	Ranked categories	3	Scenario component (parent node)
Application	Ranked categories	3	Scenario component (parent node)
Scenario	Integers	18	Combination of the scenario components: Scenario = climate scenario + pesticide application scenario + period scenario
Intercept Log	Intervals	5	Maximum environmental concentration (log-transformed), scenario-specific probability distribution
Time since application	Integers	5	Day 1, 2, 5, 21 or 60 for WISPE model prediction (parent node)
Time-specific concentration Log	Intervals	10	Time-specific environmental concentration (log-transformed), function with scenario-specific slope: [Intercept Log] + ([slope] x [Time since application]))
Endpoint	Categories	2	EC50 (day 1)
			NOEC (day 1–61)
Effect concentration Log	Intervals	10	EC50: NormalDistribution (mean, sd) or NOEC: NormalDistribution (mean, sd)
Exposure concentration	Intervals	10	exp ([Time specific concentration Log])
Effect concentration	Intervals	10	exp ([Effect concentration Log])
Exposure/effect ratio	Intervals	7	Ratio [Exposure concentration]/[Effect concentration]
Precautionary factor	Integers	7	A scaling factor for deriving the risk quotient (parent node)
			1, 3, 10, 30, 100, 300, or 1000
Risk quotient	Intervals	7	[Exposure/effect ratio] x [Precautionary factor]

factors such as soil and site parameters together with chemical properties and climate scenarios were linked to the exposure of a pesticide by using the WISPE platform. The probability distribution of pesticide exposure was obtained from predicted concentrations for multiple years, which enabled accounting for variability over a longer time period (FOCUS, 2017). Correspondingly, for the probability distribution of effects, the range of species sensitivities was determined from available toxicity data. The RQ node was discretize with a high number of states, this enabled exploring the differences between scenarios. A more detailed node description and model assumptions are given in the following Table 1.

2.2.1 Future scenarios

The agricultural sector manages 3.5% of Norway's land area pr. 2021. Being part of northern Europe, Norway has lower temperatures and a shorter growing season than central and southern Europe. These climate conditions restrict the area suitable for grain cultivation. Until the year 2060, the annual average temperature is expected to increase by approx. 2°C, with the largest increase in temperature in winter, and the lowest in summer in Norway. Consequently, the meteorological growing season will be longer than the current, with a predicted increase in growing season of up to 2 months towards the end of the century (Fuglestvedt, 2016). This may lead to earlier sowing, ripening and harvest for spring cereals and growing of crop types that mature later but offer a higher yield potential. CC is also expected to lead to significant changes in precipitation with an increase of 8% for annual precipitation at the end of the century, but with large variation between the cropping regions in Norway (Olesen and Bindi, 2002). For the cultivation of grain, not only the amount and intensity of rainfall is of interest, also its frequency and distribution throughout the growing season. Other expected CC impacts are the introduction of new plant pathogens and pests from southern countries to northern areas while existing will be able to take advantage of a longer growing season and multiply faster than before. Also, changes in crop composition may lead to a change in the occurrence of the diseases and possibly new host-parasite interactions (Fuglestvedt, 2016). Furthermore, pesticides efficacy is affected by environmental factors such as temperature, precipitation and wind (Olesen and Bindi, 2002). In Norway, a longer growing season and more frequent pest infestations may require the use of more pesticides. A warmer climate is expected to result in increased production of winter wheat. The milder cold season may provide better overwintering conditions for plant pathogens, which might entail early and more severe infestation of the crop the following season. The most relevant measure apart from using resistant crop types is spraying of fungicides. In addition, early infestations require spraying both

earlier and more frequently during the growing season (Fuglestvedt, 2016). Based on these considerations, winter wheat was chosen as the model crop for this study.

A more detailed description of the expected CC for this region is given by Hanssen-Bauer et al. (2015). In the following, the future scenarios used to run the WISPE platform are described.

2.2.1.1 Climate scenarios

In this study, two sets of climate projections were used originally developed for the site Grue in the south east of Norway (ca 160 km North-east of Syverud/Ås) under the GENESIS project (2009–2014, https://cordis.europa.eu/project/id/226536). Both were derived from the greenhouse gas emission scenario "A1B" (IPCC, 2000), which was developed to represent a future world of very rapid economic growth, low population growth and rapid introduction of new and more efficient technology, for a spatial resolution of 50 km. The two sets of climate projections were derived by two global climate models (GCM) which will be referred to as Climate Model 1 (C1) and Climate Model 2 (C2). The GCM of C1, "ECHAM5-r3" (Roeckner et al., 2004), was developed by the Max Planck Institute for Meteorology, and the GCM for C2, "HADCM3-Q0" (Gordon et al., 2000), was developed at the Hadley Centre. Regional climate models (RCMs) are commonly applied to downscale from the global to more local levels (Jones et al., 2011; Samuelsson et al., 2011). Here, the same RCM called RCA3 was used, developed by the Rossby Center at SMHI (the Swedish Meteorological and Hydrological Institute). Thereby, C1 represents the regional climate model "ECHAM5-r3 A1B-SMHI-RCA3" and C2 represents "HADCM3-Q0 A1B-SMHI-RCA3".

The climate projections used in this study has several limitations: the emission scenario and the two climate models are rather old, and they have not been bias-corrected for the study area. Moreover, climate projections should ideally be obtained from a larger ensemble of climate models rather than one or a few models (Moe et al., 2022). However, generating a new and more appropriate set of climate projections was beyond the scope of this study. Therefore, the climate projections that were already derived for the WISPE platform were considered sufficient for the purpose of demonstrating this BN approach to linking climate projections, pesticide exposure and risk characterization.

Projections from the two climate models (C1 and C2) differed in precipitation, temperature, evapotranspiration, solar radiation and wind. For example, they had different projected changes in number of days with snow cover and changes of annual rainfall (Kjellstöm et al., 2011). The differences between the two climate models are especially of interest for the chosen days and months of pesticides application. Based on Mann-Kendall (MK) trend analysis, C1 showed a positive trend in temperature, evapotranspiration and precipitation for a 3-days average before the day of pesticide application. When comparing climate conditions for 10-days average before day 21 after application, a positive trend was detected for temperature and evapotranspiration (i.e. the process of water evaporation from soil and other surfaces through transpiration from plants). In general, C2 showed no trend for May, and even a negative trend for October for a 3-days average before the day of application (see Supplementary Table S2). The projections from C1 were more consistent with more recent climate projections for Norway, which show that an increase in temperature and precipitation can be expected (Hanssen-Bauer et al., 2015). Consequently, in this paper we decided to focus mainly on predicted exposure concentration based on C1.

2.2.1.2 Pesticide application scenarios

The first pesticide application scenario is based on the current common practice dosage and is referred to as the "baseline" scenario (see Table 2). The second scenario, referred to as "baseline-50%", is inspired by the European Green Deal, which aim for a 50% reduction of the pesticide use by 2030 (EC, 2020). The third scenario represents a potentially increased use of pesticides in the future, for example due to changing climate conditions and increased pest pressures (Fuglestvedt, 2016) and is referred to as "baseline+50%".

We selected active pesticide ingredients that are all approved in Norway for crop protection in winter wheat. Two plant protection products, a herbicide containing MCPA (CAS nr. 94–74-6), fluroxypyr-meptyl (CAS nr. 81,406–37-3) and clopyralid (CAS nr. 1702–17-6), and a fungicide composed of trifloxystrobin (CAS nr. 141,517–21-7) and prothioconazole (CAS nr. 178,928–70-6), were chosen for the purpose of demonstrating the approach. Inherent properties such as molecular weight, water solubility, sorption properties (Koc), degradation half-life (DT50 soil), and vapor pressure, and Freundlich exponent (1/n), and systemic property e.g. plant uptake factor, were collected and included in the data asset (see Supplementary Table S1).

The associated application rate and time of spraying were used to define the application scenario for the WISPE platform runs. It was assumed that the herbicide is applied once in the first half of May (crop growth stage BBCH 13–14; cf. label for Ariane ™ S, Corteva Agriscience), and that the fungicide is applied once in the first half of October (after sowing and germination of the winter wheat; cf. label for Delaro SC 325, Bayer Crop Science). For the calibration of the WISPE platform no tillage was assumed. Some of the combinations chosen for pesticide application, e.g. the choice of no soil tilling in combination with winter cereals, may not be the most common/optimal agronomic practice and can hence add to some of the uncertainty in the modelling.

TABLE 2 Description of application scenarios used in this case study for the five selected pesticides.

Active substance	Baseline-50%	Baseline	Baseline+50%
	Dose active substance (kg/ha)	Dose active substance (kg/ha)	Dose active substance (kg/ha)
Clopyralid	0.025	0.05	0.075
Fluroxypyr-meptyl	0.05	0.1	0.15
MCPA	0.25	0.5	0.75
Prothioconazole	0.0875	0.175	0.2625
Trifloxystrobin	0.075	0.15	0.225

2.2.2 Pesticide exposure

The scenarios described above were used as input information for the WISPE platform. Additional settings used to run the platform are described in the succeeding section. The exposure distributions used as input for the pesticide exposure module were based on the predicted exposure concentration from the WISPE platform.

2.2.2.1 WISPE platform settings

When the WISPE platform was first developed as a tool to estimate pesticide exposure in ground- and surface water for Norwegian conditions, two study areas were chosen as representative field sites to generate data for calibration and validation of the model (Bolli et al., 2013). In this study, the Syverud was used as a site scenario, which was developed to represent larger agricultural areas in South East Norway. The study site is located on the grounds of the Norwegian University of Life Sciences (NMBU) in Ås (Supplementary Table S1). The soil in this study area is classified as loam/silt loam, with 26% clay, 49% silt, and 25% sand content. The area was formerly used as a meadow which resulted in a soil structure with high infiltration capacity, aggregate stability and saturated hydraulic conductivity (Bolli et al., 2013). For the model simulations the site was assumed to be ploughed in autumn, with a ploughing depth of 20 cm. The platform predicts output concentrations for a stream, pond and ditch with parameters adapted originally from TOXSWA into the EXAM model.

We have only considered the predicted output for the stream environment, with the following water body parameters: 1 m width, 100 m total length, 0.3 m average water depth, 15 mg/L concentration of suspended solids, 5% organic carbon content, and 800 kg/m3 dry bulk density (FOCUS, 2015). WISPE was calibrated for the model crop winter wheat.

2.2.2.2 Exposure prediction platform implementation

The WISPE platform was run according to the previously mentioned future scenarios and platform settings such as the selected representative field site, crop type and for the various time-periods of C1 and C2. The WISPE platform predicted exposure concentration for 26 years, corresponding to the 26 years over which the model runs. The concentrations were predicted for instantaneous, 24 h, 96 h, 21, 60 and 90 days.

In the further process, the time-periods were changed into three periods (year 2000–2030, 2035–2065, 2070–2100) to derive the distributions (BN input) representing inter-annual variation within each of the 30-year period. The platform simulated pesticides to specified unique application conditions for the two climate models. In total, 18 scenarios were used in the developed BN per pesticide (Table 3). The following example shows the log-transformed pesticide concentration against time since application predicted by WISPE for scenario 11 (Figure 2). A log-linear equation was fitted to each of the predicted concentrations time series. Data processing and analysis was carried out in R (version 4.1.0), using the tidyverse package (Wickham et al., 2019) and some base R functions (R Core Team, 2020). Within each scenario the slope did not differ significantly among the years (see Figure 2), therefore the average slope across years was used to calculate the time-specific concentration for each scenario (see Supplementary Information SII). The probability distribution of the instantaneous concentration (representing inter-annual variation) was used as input in the conditional probability table (CPT) of the instantaneous concentration node. This distribution was combined with the slope to derive the distribution of the time-specific concentration node (see Supplementary Information SII). In general, the instantaneous node interval range differed for each selected pesticide: clopyralid 0.0025–0.6065 μg/L, fluroxypyr-meptyl 0.0111–4.4817 μg/L, MCPA 0.0821–12.1825 μg/L, prothioconazole 0.0302–0.2231 μg/L, trifloxystrobin 0.0235–0.1653 μg/L.

2.2.3 Pesticide effects

Uncertainties related to current effect assessment are often associated with extrapolation from laboratory to field and inter-intraspecies variation (Rai et al., 2002) and can also be linked to the data set size. In traditional regulatory effect assessment, these uncertainties are usually accounted for by assessment factors to increase the assumed safe concentration threshold (PNEC). In this study, two types of effect distribution were derived and used

TABLE 3 Overview of scenarios used in the Bayesian network model combining the three scenario components Climate model, Period and Application scenario. For description of the climate models, see Section 2.2.1.1. For definition of the pesticide application scenarios, see Table 2.

Scenario	Climate model	Period (years)	Application scenario
1	C1	2000–2030	baseline
2	C1	2000–2030	baseline+50
3	C1	2000–2030	baseline-50
4	C1	2035–2065	baseline
5	C1	2035–2065	baseline+50
6	C1	2035–2065	baseline-50
7	C1	2070–2100	baseline
8	C1	2070–2100	baseline+50
9	C1	2070–2100	baseline-50
10	C2	2000–2030	baseline
11	C2	2000–2030	baseline+50
12	C2	2000–2030	baseline-50
13	C2	2035–2065	baseline
14	C2	2035–2065	baseline+50
15	C2	2035–2065	baseline-50
16	C2	2070–2100	baseline
17	C2	2070–2100	baseline+50
18	C2	2070–2100	baseline-50

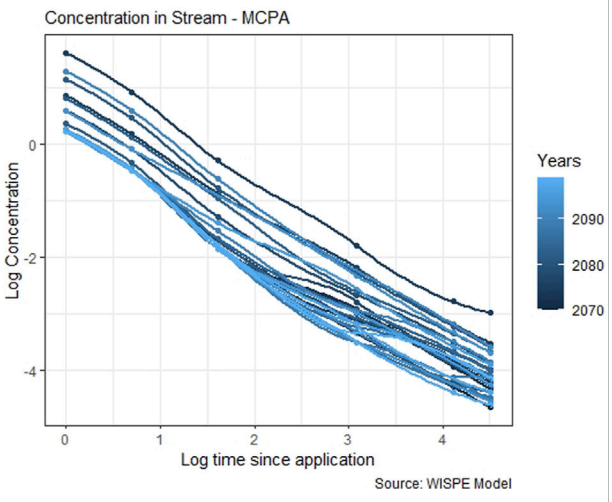

FIGURE 2
Example log-linear regression of the concentration in the stream predicted by the WISPE platform for MCPA with an application baseline scenario for the C1 and the time interval 2070–2100.

as input in the pesticide effect module. They were based on either NOEC (no-observed effect concentrations) values or on EC50 (effect concentration for 50% of the test population) values and collected for each of the selected pesticides. The derived effect distribution is similar to a species sensitivity distribution (SSD), representing inter-specific variation in sensitivity to toxicants, which is used extensively in ecotoxicology (Belanger and Carr, 2020). SSDs are now commonly used as an alternative to the conservative approach on the basis of the most sensitive species (lowest NOEC value). They are based on multiple toxicity tests of different species and thereby reflect interspecies differences in sensitivity to a chemical. Subsequently, SSDs can be used to develop a community level threshold (Belanger et al., 2017). However, SSDs are usually used to derive a single threshold value such as the HC5 (hazardous concentration to 5% of the species), as a basis for the PNEC. Here we follow the approach presented by (Mentzel et al., 2021), to use the whole species sensitivity distribution in the calculation of the exposure/effect ratio distribution (Section 2.2.4). Toxicity data were mainly collected and used from the US EPA ECOTOX Knowledgebase (https://cfpub.epa.gov/ecotox/search.cfm) and supplemented with data from Middle Tennessee State University EnviroTox Database (https://envirotoxdatabase.org). The EC50 effect distribution was derived from EC50 and LC50 (lethal dose for 50% of the test population) toxicity data (Table 4). The NOEC distribution is based on NOEC and NOEL (no-observed effect level) values, apart from Clopyralid for which only NOEC toxicity data was available. If multiple values for the same species occurred in the data set, the mean was used as a data point to derive the distribution (Mentzel et al., 2021). The number of observations for this study varied depending on the chemical, and whether it was an EC50 or NOEC toxicity test. In this study, we only considered adverse effects such as

TABLE 4 Effect (toxicity) data collected for this study, detailing the effect types per pesticides and the derived EC50 and NOEC natural log(ln) mean and standard deviation for the natural log distributions.

Pesticide	Number of values		Effect type	EC50 (µg/L)		NOEC (µg/L)	
	EC50	NOEC		Log Mean	Log sd	Log Mean	Log sd
Clopyralid	7	8	Growth, Population, Reproduction, Development, Mortality	11.45	1.99	7.73	3.67
Fluroxypyr-meptyl	16	11	Population, Mortality	7.08	2.06	6.03	2.01
MCPA	45	20	Population, Mortality, Growth, Morphology, Development, Reproduction	9.56	3.11	7.07	2.10
Prothioconazole	11	10	Population, Mortality, Growth	7.41	1.78	6.17	2.00
Trifloxystrobin	19	17	Growth, Development, Mortality, Population, Morphology	4.48	1.72	3.18	1.77

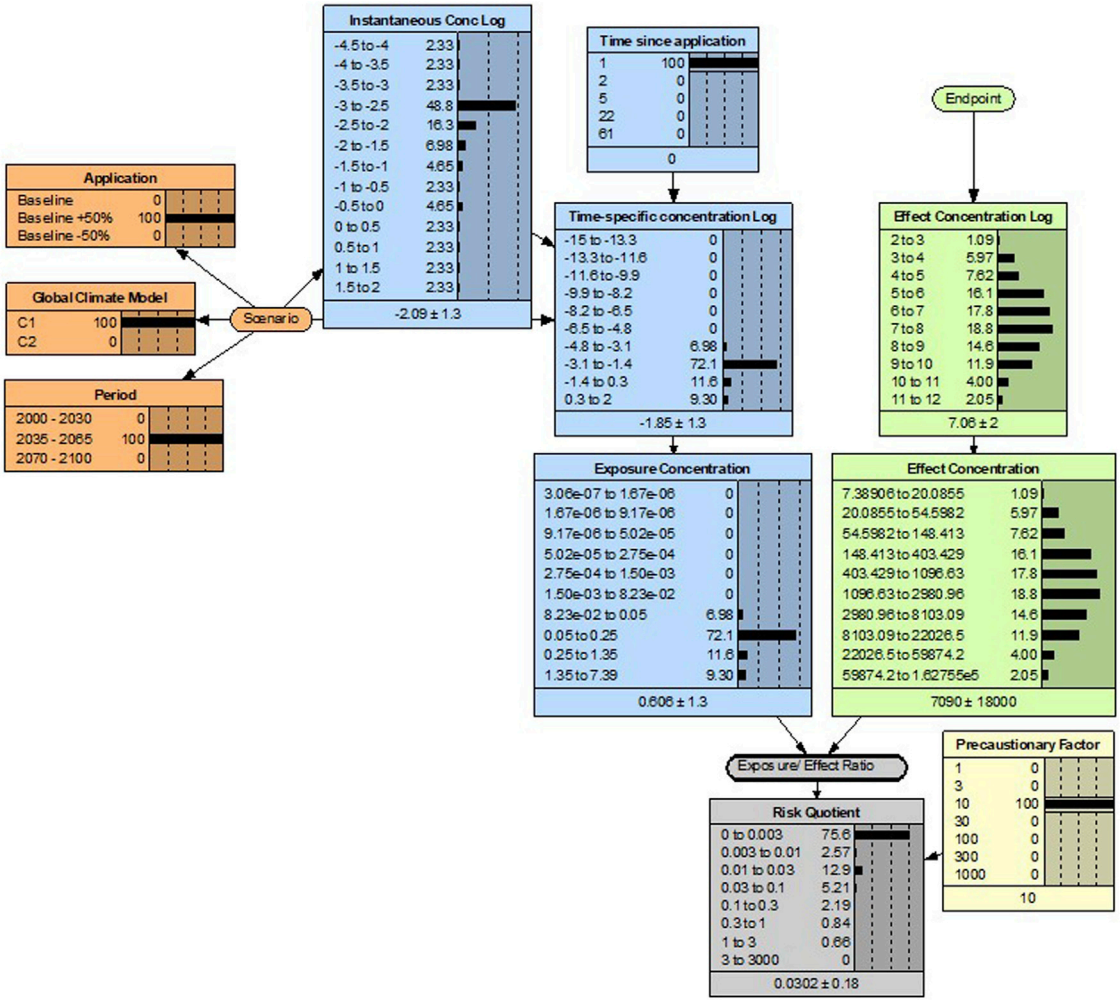

FIGURE 3
Example of the Bayesian network parameterized for fluroxypyr-meptyl, with a baseline+50% application, global climate model C1, time period of 2035–2056, for a time since application of 1 day and a EC50 based effect distribution.

TABLE 5 Results from Mann-Kendall trend analysis of the predicted pesticide exposure concentrations for the following WISPE model settings: climate models C1 and C2; baseline application in May (herbicides) and October (fungicides). The predicted exposure concentration series represent both acute and chronic conditions (day 1 and 21 since application, respectively). For each series, the overall trend for the whole period of years 2000–2100 was analyzed. The test statistic τ denotes increasing (τ > 0) or decreasing (τ < 0) trend.

Scenario	Climate model	Days since application	Pesticide	Pesticide type	Time of application	Kendall's τ coefficient	*p* value
1	C1	1	Clopyralid	Herbicide	May	−0.005	0.951
1	C1	1	Fluroxopyr-meptyl	Herbicide	May	0.038	0.634
1	C1	1	MCPA	Herbicide	May	0.034	0.655
1	C1	1	Prothiocanazole	Fungicide	October	0.138	0.084
1	C1	1	Trifloxystrobin	Fungicide	October	0.182	0.024
1	C1	21	Clopyralid	Herbicide	May	0.006	0.935
1	C1	21	Fluroxopyr-meptyl	Herbicide	May	−0.020	0.773
1	C1	21	MCPA	Herbicide	May	0.048	0.490
1	C1	21	Prothiocanazole	Fungicide	October	0.039	0.618
1	C1	21	Trifloxystrobin	Fungicide	October	0.082	0.312
10	C2	1	Clopyralid	Herbicide	May	0.111	0.142
10	C2	1	Fluroxopyr-meptyl	Herbicide	May	0.159	0.044
10	C2	1	MCPA	Herbicide	May	0.133	0.078
10	C2	1	Prothiocanazole	Fungicide	October	0.002	0.983
10	C2	1	Trifloxystrobin	Fungicide	October	−0.054	0.506
10	C2	21	Clopyralid	Herbicide	May	0.034	0.620
10	C2	21	Fluroxopyr-meptyl	Herbicide	May	0.078	0.269
10	C2	21	MCPA	Herbicide	May	0.054	0.432
10	C2	21	Prothiocanazole	Fungicide	October	−0.125	0.111
10	C2	21	Trifloxystrobin	Fungicide	October	−0.14	0.080

mortality, reproduction and growth. The distribution was fitted using the R package MASS (Venables and Ripley, 2002). The data preparation was carried out with the R package tidyverse (Wickham et al., 2019) (see Supplementary Information SIII).

2.2.4 Risk characterization

This module consists of three nodes: exposure/effect ratio, a precautionary factor and the risk quotient (RQ). In traditional risk assessment, an RQ higher than 1 indicates a reason for concern (Bruijn et al., 2002).The assumptions for the node input are described in Table 1. The BN was run for the different scenarios and with either an EC50 (and day 1 since application), representing an acute exposure scenario, or a NOEC distribution (and day 1–61 since application), representing a chronic exposure scenario. As explained in Mentzel et al. (2021), the precautionary factor was introduced as a scaling factor to have a similar role as the assessment factors, which are frequently used in risk assessment to obtain a higher safe concentration threshold (see TGD (SCHEER, 2017)). Thus, a higher assessment factor or a higher precautionary factor will increase the probability of the RQ exceeding 1. In traditional risk assessment, the decision on an appropriate assessment factor is based on evaluation of the available toxicity test data used to derive the effect distribution to account for uncertainties in the used data set and for extrapolation. In the approach presented by Mentzel et al. (2021), an appropriate precautionary factor was found by calibrating the RQ distribution predicted by the BN to the single-value RQ of a corresponding traditional risk calculation. In the case study by Mentzel et al. (2021) it was found that for a fully probabilistic approach with exposure data derived from monitoring with infrequent sampling though reflecting chronic exposure to the ecosystem, and collected effect e.g. toxicity test (NOECs), the most appropriate precautionary factor was 30–300. In the current study, some of the uncertainties associated with the exposure concentrations were overcome by using predicted exposure concentrations that enabled the use of peak concentrations in addition to the declining concentrations over time (see Figure 2). In our view, this justified the usage of a lower precautionary factor of 1–10. To account for additional interspecies variation in sensitivity that

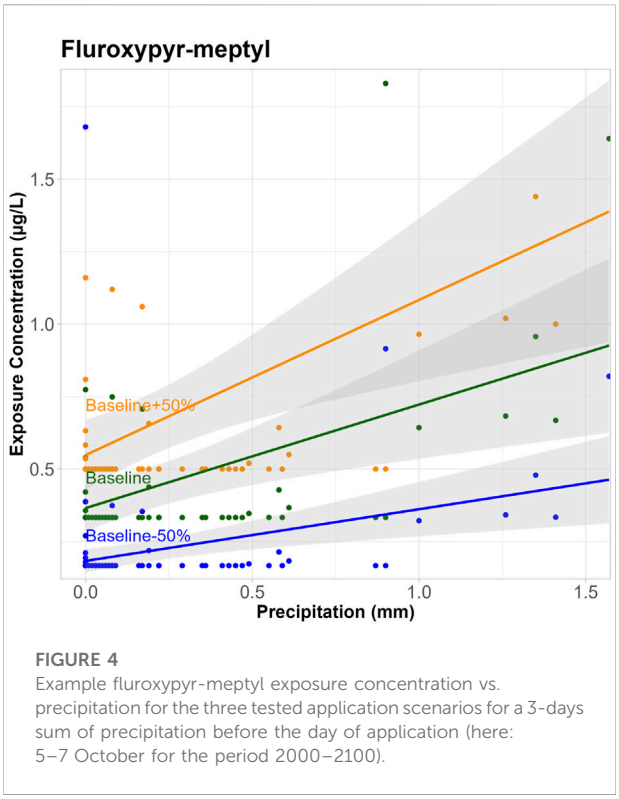

FIGURE 4
Example fluroxypyr-meptyl exposure concentration vs. precipitation for the three tested application scenarios for a 3-days sum of precipitation before the day of application (here: 5–7 October for the period 2000–2100).

was not represented by the relatively small data set on effects, a more conservative precautionary factor of 10 was applied for all RQ distributions displayed in this study (see Figure 3).

A Mann-Kendall trend analysis a statistical method that is rank-based and non-parametric, and widely used in hydrometeorological time series trend detection (Wang et al., 2020). The trend analysis was carried out for the predicted exposure concentration (WISPE platform output) for baseline application, C1 and C2, Day 1 and 21 since application and for all of the selected pesticides (see Table 5). A positive trend indicates an increase of the predicted exposure concentration. The trend was concluded to be negative whenever the test statistic Kendall's $\tau < 0$ and the $p < 0.1$. The trend was concluded to be positive when $\tau > 0$ and $p < 0.1$.

3 Results

3.1 Predicted pesticide exposure

Some of the trends in the projected climate variables such as mean temperature, precipitation, radiation, evapotranspiration and wind (see Supplementary Table S2) were also reflected in the trends of the predicted exposure. The Mann-Kendall trend analysis showed mostly no significant trends over the whole range of years (2000–2100), for the different pesticides and seasons. However, C1 had a positive trend in mean temperature, precipitation and evapotranspiration in October, this trend is also reflected in a positive trend of the exposure concentration of fungicides prothiocanazole and trifloxystrobin that are applied in October (for C1) (Table 5).

A closer look at the relationship between the instantaneous exposure concentration and precipitation, one of the determining climate conditions for the transport and fate of pesticides, revealed that higher amount of precipitation was associated with increased exposure concentration (Figure 4). In addition, there was a positive interaction between pesticide application and precipitation, as the effect of precipitation was higher (steeper slope) when the pesticide application was higher. This relationship was not further investigated here, but the pesticide concentrations predicted by the WISPE platform predictions showed similar temporal trends as the those described for the climate variables (see Supplementary Table S2).

3.2 Predicted risk quotient distribution for various scenarios

The output for each of the settings (evidence) used in this study has been reported in the Supplementary Information SIV. It contains a detailed collection of the probabilities for each of the RQ node intervals depending on the selected evidence. In the following, the predicted RQ node distributions for the different scenarios (see Table 3 for reference) are visualized as stacked bar plots for easy comparison (Figure 5). The RQ was calculated with an effect distribution based on either NOEC values (RQNOEC) or EC50 values (RQEC50). This analysis enabled the identification of periods with higher risk of environmental effects of individual pesticides or groups of pesticides.

3.2.1 Risk quotient distribution across the time since application

For a baseline application scenario, at day 1 the probability of RQNOEC to be higher than 1 was 1% for MCPA (Figure 5C), 0.98% for fluroxypyr-meptyl (Figure 5B), and 0% for Clopyralid (Figure 5A), prothioconazole (Figure 5C), and trifloxystrobin (Figure 5E). Overall, the time-specific RQNOEC declines with time since application (Figure 5). So, at Day 2 probability of RQNOEC to be higher than 1 decreased to 0.79% for MCPA and 0.65% for fluroxypyr-meptyl. At Day 5 the RQNOEC to be higher than 1 decreased further to 0.69% for MCPA and 0% for fluroxypyr-meptyl. Considering a lower RQ threshold (corresponding to a higher precautionary factor), the probability of RQ > 0.1 at Day 1 was highest for MCPA, followed by fluroxypyr-meptyl, trifloxystrobin, clopyralid and prothioconazole.

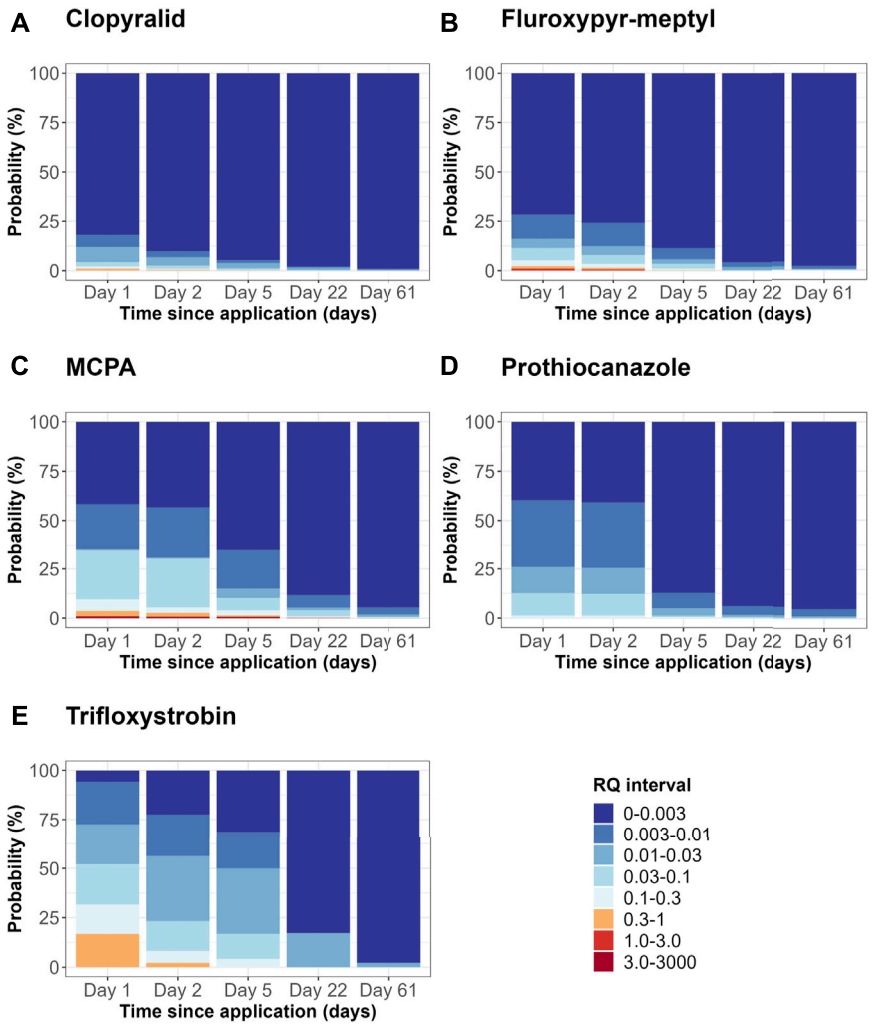

FIGURE 5
Example of predicted risk quotient distribution for clopyralid **(A)**, fluroxypyr-meptyl **(B)**, MCPA **(C)**, prothioconazole **(D)** and trifloxystrobin **(E)** over time for 1, 2, 5, 22, and 61 days after application, for the baseline application scenario, climate model C1 and the time interval of 2070–2100 for NOEC-based effect distribution.

3.2.2 Plausible scenarios: Combination of climate change and pesticide application

A change in pesticide application patterns such as an increase in the rates or number of applications per season can be considered as an adaptation to consequences of climate change (e.g. increased pest pressure). Therefore, the scenario combining future climate projections (period 2035–2065) with increased pesticide application was considered as a plausible scenario. On the other hand, the combination of future climate projections with reduced pesticide application represent a scenario more in line with EU's pesticide policy. Hence, we compare the RQEC50 of the current time period (2000–2030) and baseline application with the predicted RQEC50 for a future time period (2035–2065) as well as baseline-50% and baseline+50% application scenarios. In general, the probability of RQEC50 exceeding 1, which commonly used as a threshold for concern, was low and not much influenced by the different time periods or application scenarios.

Focusing on lower RQ thresholds, examples are shown for the fungicide trifloxystrobin (Figure 6A) and the herbicide fluroxypyr-meptyl (Figure 6B). Trifloxystrobin had more than 10% probability of RQEC50 exceeding 0.03 for the current practice. In future, applying less fungicide resulted in a shift towards lower RQ intervals and an overall decrease in risk. From the BN prediction, it was observed that applying 50% less resulted in a shift towards lower RQ intervals, with a probability to be above 0.3 decreasing from 12.5% to 3.5%. Comparing baseline

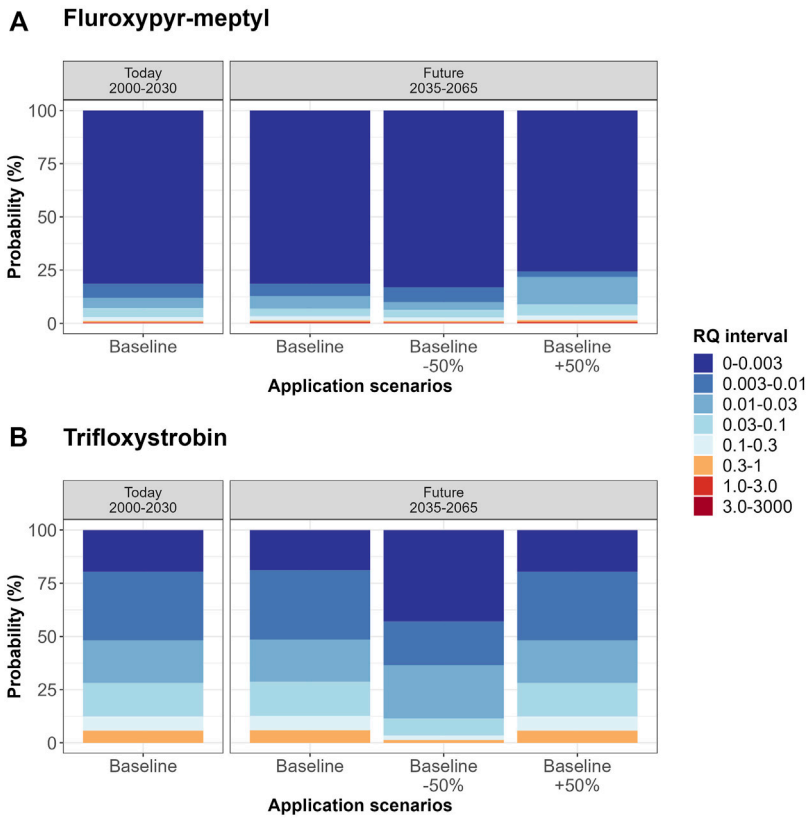

FIGURE 6
Predicted risk quotient distribution for a selected herbicide and fungicide, for a time since application of 1 day, for the climate model C1 and for EC50-based effects distribution. The scenarios 1,4,5,6 (Table 3) are displayed for the herbicide fluroxypyr-meptyl **(A)** and the fungicide trifloxystrobin **(B)**.

and baseline+50% the RQEC50 distributions were similar, with a probability of being above 0.03 of about 12.5%. This was also the case for some of the other pesticides (e.g. clopyralid or MCPA) (see Supplementary Figure S2). Fluroxypyr-meptyl, on the other hand, showed a change to higher RQEC50 intervals for the baseline+50% application. For this herbicide the probability for RQEC50 to be above 0.03 increased from 7.2% (for baseline) to 8.9% (for baseline+50%) and decreases to 6.4% (for baseline-50%).

4 Discussion

As monitoring of environmental pesticide concentration is costly and time-consuming, future climate conditions need to be incorporated for better risk assessment. The complexity of processes in pesticide risk assessment can to some degree be overcome by taking advantage of the BNs' ability to use data from various different sources, which is one of their benefits (Chen and Pollino, 2012; Gibert et al., 2018; Mentzel et al., 2021; Troldborg et al., 2021). Moreover, they can be constructed as causal models that help comprehend hazard pathways and vulnerability relations better and with that assist in risk prioritization (Sperotto et al., 2017). For example, a BN developed for predicting spatial distributions of pesticide exposure in a drinking water catchment was informed by multiple information sources including GIS as well as expert knowledge (Troldborg et al., 2021). A study by Gaasland-Tatro (2016) showed how CC factors and other stressors can be integrated in BNs by using a relative risk model that evaluates ecological parameters over landscape scale regions. Along these lines, Landis et al. (2013) pointed out that today's environmental risk assessment should also consider interactions among contaminant and noncontaminant stressors, together with new regimes of precipitation and temperature at specific geographical sites (Landis et al., 2013).

The BN model presented here demonstrates how a traditional risk characterization score such as the RQ can be made more informative by being presented as a probability distribution. While the traditional risk assessment has focused on whether a single-value RQ score exceeds 1, the BN approach allows for a systematic analysis also of lower risk situations, such as the probability of RQ exceeding 0.3 or 0.1. This way, the model can be used to explore plausible environmental scenarios and

identify early-warning trends in RQ towards levels of concern. Moreover, in our approach, the precautionary factor is used in a more transparent way and better separated from the pesticide effect characterization than the corresponding assessment factor is in traditional risk assessment (Mentzel et al., 2021). The assignment of a precautionary or assessment factor involves a subjective evaluation of data quality and other uncertainties by the risk assessor and should therefore be better separated from the calculation of chemical concentrations, in our opinion. The traditional assessment factor is applied to calculate an assumed safe concentration threshold (predicted no-effect concentration), which is in turn used as the denominator in the calculation of the traditional RQ. In our model, in contrast, the exposure/effect ratio distribution is calculated and displayed before the precautionary factor is included as a final step to obtain the RQ distribution.

The BN model predicted a slight increase in the probability of RQ exceeding 1 for future time periods, for most of the pesticides investigated. In other words, the model predicts higher risk for aquatic organisms under the A1B climate scenario for the intermediate (2035–2065) and last time periods (2070–2100) investigated. This is expected and consistent with previous suggestions regarding pesticide fate and transport being influenced by precipitation in northern Europe. In other words, increased precipitation in future can imply increase risk of pesticides to freshwater ecosystems in agricultural areas. We aim to investigate the role of precipitation and other climate variables on predicted pesticide exposure in the WISPE platform more systematically in later studies, to obtain functional relationships between climate variables and pesticide exposure under different climate scenarios. A quantification of such functional relationships will allow for more efficient exploration of pesticide risk under different climate and agricultural scenarios.

Considering the prediction for future periods, the climate projection used in this study was obtained from an existing project and based on a relatively old climate scenario (A1B). Moreover, the climate models used in this study were not properly bias-corrected for the study area. Thus, improved precision and realism of the BN model predictions could be achieved by using more updated climate projections from more relevant climate scenarios (e.g. RCP4.5 and 8.5) and based on a larger number of climate models. Further model development with a newer and refined version of the WISPE, could reduce some of the uncertainty related to predictions.

The applicability domain of the BN model presented here is constrained by the current applications and calibration of the WISPE model platform. Until now, the WISPE platform was validated by Bolli et al. (2013) and offers the possibility to predict environmental concentrations for specific and representative study fields in Norway. The platform takes into account chemical properties and environmental factors when predicting the exposure of pesticides in the selected water body (Bolli et al., 2013). A predicted exposure time series with multiple peak concentrations could not easily have been incorporated in the exposure module of the BN, which currently assumes a log-linear decrease in pesticide concentration over time. Further development of this module would be needed to account for a more complex temporal exposure pattern.

In addition, extending the current BN with more developed pesticide application, scenarios, including selected crop and pesticide types, and the use of other representative study areas would be beneficial for the integration of variability in model predictions. This BN model could also be further developed to predicting the cumulative risk of intentional pesticide mixtures. Further research efforts could also explore more advanced options for risk characterization as alternatives to the currently used RQ approach, for example making better use of causal dose-response relationships from mesocosm studies in cases where such information can be obtained. Therefore, we are considering an approach that incorporate not only an exposure prediction model under alternative future conditions but also an effect prediction model for selected groups of aquatic species.

The use of BN models in ecotoxicology is still rare compared to other types of environmental assessment (Kaikkonen et al., 2021) even though their use has increased in chemical risk assessment in recent years (Moe et al., 2021a). One of the inherent shortcomings of BNs is the loss of precision due to discretization of continuous variables (Marcot, 2017; Nojavan et al., 2017); this phenomenon was also observed in the predicted exposure concentrations for some of the pesticides in this study, e.g. MCPA. Although the instantaneous pesticide concentration distribution differed between the baseline and baseline+50% scenarios, these differences were not reflected in the exposure concentration node, where the probability distribution appeared very similar. This resulted in similar RQ distribution for the two application scenarios, given the current discretization (Marcot, 2017; Nojavan et al., 2017). The number of node states is often kept low in BN models, because a higher number of states implies that more information is needed for parameterization of the conditional probability tables. In our BN model, however, most of the CPTs were derived from equations and can therefore easily be adapted to a higher number of intervals. It is therefore straight-forward to increase the resolution of this BN model. More generally, this technical problem can potentially be amended by through dynamic discretization which can enable higher resolution and reduce the information loss of the BN predictions (Carriger et al., 2016; Fenton and Neil, 2018).

5 Conclusion and future outlook

With this study, we have demonstrated how inputs and outputs from a pesticide exposure prediction model can be incorporated into a Bayesian network to deriving a risk quotient distribution for various scenarios. The constructed network integrates and propagates uncertainty of all

components in a transparent way when performing the probabilistic risk characterization. In general, compared to the current period (2000–2030), the Bayesian network model predicted a slight increase in the probability of risk quotient exceeding 1 for the intermediate (2035–2065) and latest time period (2070–2100) due to changes in future climate conditions, for most of the pesticides investigated in this study.

For further development of this approach we aim to integrate more updated and properly bias-corrected climate projections from a larger ensemble of climate models in the BN, as well as more realistic and better-informed pesticide application scenarios. Nevertheless, the presented approach shows promise in its ability to characterize the environmental risk of pesticides under future scenarios by integrating different types of information from agricultural practice, climate models, pesticide exposure models and toxicity testing.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

Conceptualization, SM, SJM; Data curation—WISPE platform, RH and SM; Data curation—BN model, SM; Formal analysis, SM; Funding acquisition, SJM, MG, MS, and KET; Investigation, SM, SJM, and RH; Methodology, SM and SJM; Project administration, SJM; Software, SM; Visualization, SM; Writing—original draft, SM; Writing—review and editing, SJM, RH, MG, MS, KET, and SM.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.957926/full#supplementary-material

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Paper II Supplement material

Supplement Information

Content

I. Study area

Figure S. 1 Map of Norway detailing the Syverud location (red dot).

II. Pesticide properties

Table S. 1 Summary of pesticide properties considered in the WISPE platform (Lewis et al., 2016)

	Mol. Weight	Solubility, mg/L	Plant Uptake Factor	Koc	DT50soil, lab, days	Vapour pressure, mPa	Freundlich exp. 1/n	EXAMS Aerobic metabolism, days (DT50water)	Q10, 20 °C	EXAMS Anaerobic met. days (DT50 sediment)	Direct Photolysis, days
Clopyralid	192	7850	0.5	5	23.2	1.36E-09	na *	148	2.58	1000	271
Fluroxypyr-meptyl	367.24	0.136	0	19550	1	0.01	na *	34.7	2.58	1000	63
Mcpa	200.62	29390	0.5	74	24	0.4	0.68	13.5	2.58	1000	0.05
Prothioconazole	344.26	22.5	0.5	2556	0.44	7.40E-06	0.88	0.0	2.58	1000	2.1
Trifloxystrobin	408.37	0.61	0	2287	0.34	3.40E-03	0.96	1.1	2.58	1000	2.7

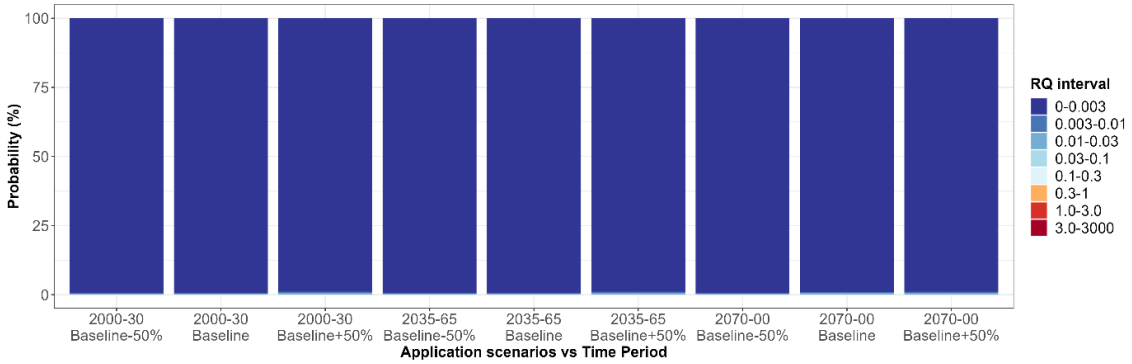
III. Comparison Climate variables Climate model 1 & 2: Mann-Kendall -trend analysis

Table S. 2 Mann-Kendall trend analysis for Climate variables of Climate model 1 (C1) and Climate model 2 (C2) for mean day since application (mean over 3 previous days) and 21 days (mean of 10 previous days) climate conditions for application in May and October.

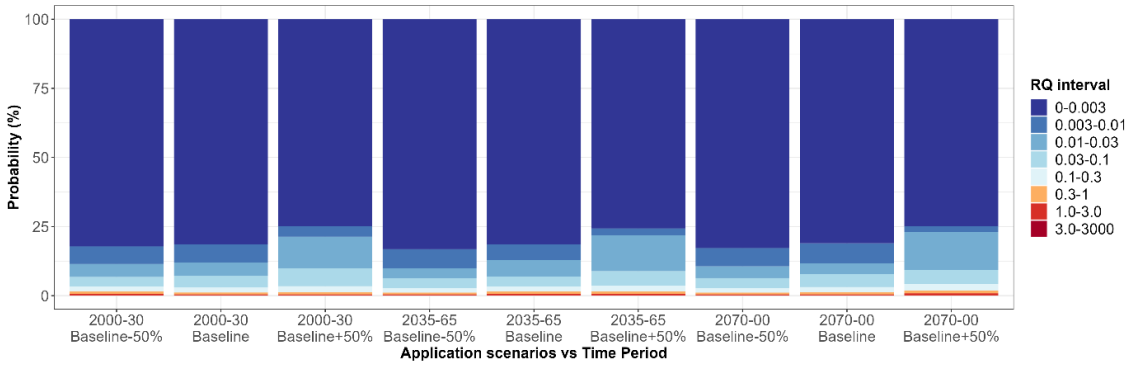
		May			October		
Days since application	output	MK.tau	MK.p	conclusion	MK.tau	MK.p	conclusion
1	MeanTemp1	0.167	0.252	zero	**0.273**	**0.059**	pos
1	MeanPrecip1	-0.011	0.962	zero	**0.361**	**0.012**	pos
1	MeanEpot1	**0.244**	**0.093**	pos	**0.25**	**0.084**	pos
1	MeanWind1	0.196	0.191	zero	0.131	0.374	zero
1	MeanRadiat1	-0.067	0.657	zero	0	1	zero
1	MeanTemp2	0.16	0.272	zero	0.053	0.726	zero
1	MeanPrecip2	0.135	0.369	zero	**-0.32**	**0.029**	neg
1	MeanEpot2	0.05	0.744	zero	-0.127	0.387	zero
1	MeanWind2	-0.168	0.264	zero	0.172	0.242	zero
1	MeanRadiat2	**-0.36**	**0.012**	neg	-0.067	0.657	zero
21	MeanTemp1	**0.249**	**0**	pos	**0.301**	**0**	pos
21	MeanPrecip1	-0.029	0.676	zero	0.015	0.83	zero
21	MeanEpot1	**0.279**	**0**	pos	**0.318**	**0**	pos
21	MeanWind1	0.018	0.79	zero	-0.037	0.588	zero
21	MeanRadiat1	-0.063	0.358	zero	**-0.123**	**0.072**	neg
21	MeanTemp2	**0.267**	**0**	pos	**0.451**	**0**	pos
21	MeanPrecip2	**-0.124**	**0.069**	neg	0.088	0.201	zero
21	MeanEpot2	**0.196**	**0.004**	pos	**0.412**	**0**	pos
21	MeanWind2	0.072	0.29	zero	0.07	0.308	zero
21	MeanRadiat2	-0.005	0.942	zero	**-0.195**	**0.004**	neg

IV. Visualized Result output for all selected pesticides for direct and indirect climate effect- Risk quotient distribution for climate model 1 and application scenarios

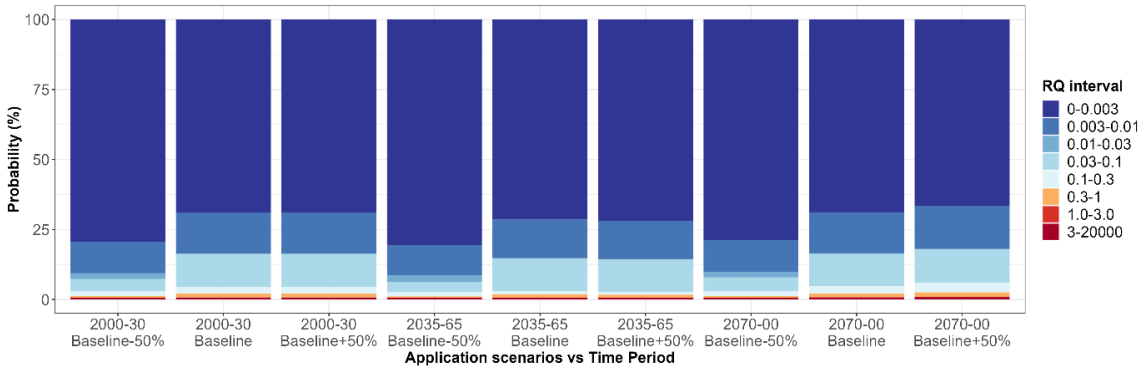
a)



b)



c)



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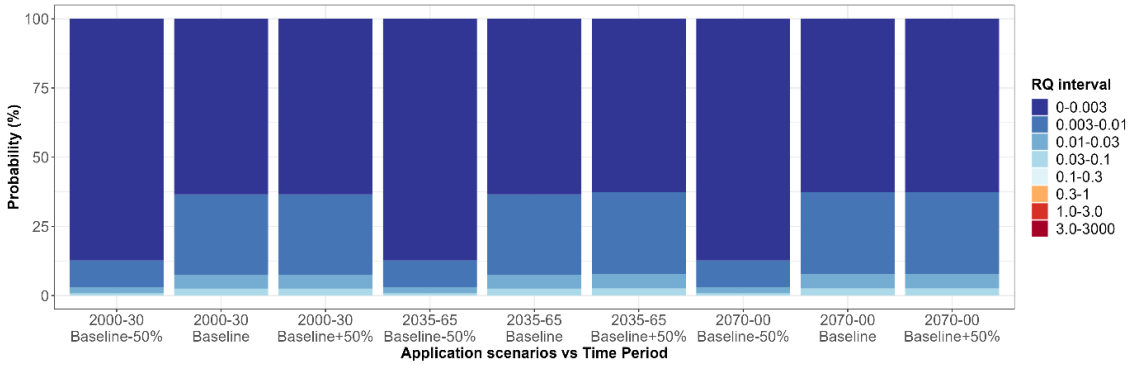

e)

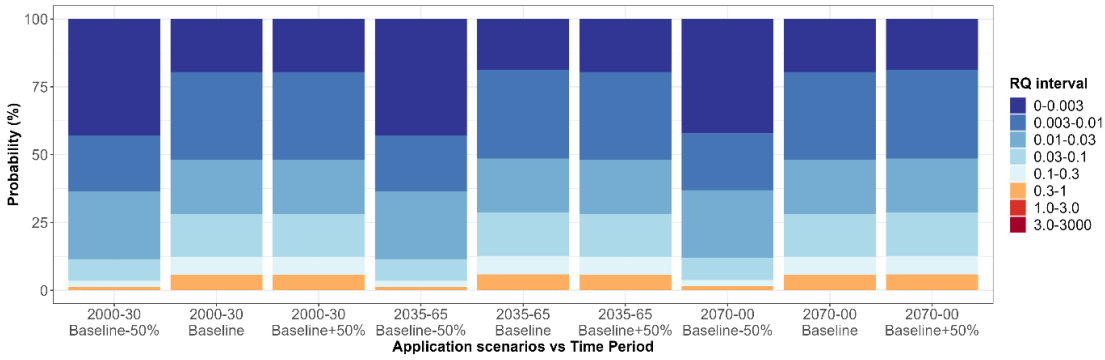

Figure S. 2 Risk estimation of a selected herbicides, clopyralid (a), fluroxypyr-meptyl (b), MCPA (c) and fungicides, prothiocanazole (d) and trifloxystrobin €, for a time since application of 1 day, for the climate model C1 and for EC50 based effects distribution, for all time period and application scenarios.

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III

Using a Bayesian network model to predict effects of pesticides on aquatic community endpoints in a rice field – A southern European case study [preprint]

Sophie Mentzel, Claudia Martínez-Megías, Merete Grung, Andreu Rico, Knut Erik Tollefsen, Paul J. Van den Brink, and S. Jannicke Moe

Abstract

In recent years, Bayesian network (BN) models have become more popular as a tool to support probabilistic environmental risk assessments (ERA). They can better account for and communicate uncertainty compared to the deterministic approaches currently used in traditional ERA. In this study, we used the BN as a meta-model to predict the potential effect of various pesticides on different biological levels in the aquatic ecosystem. The meta-model links the inputs and outputs of a process-based exposure model (RICEWQ), that is run with various scenarios combination built on meteorological, hydrological, and agricultural scenarios, and a probabilistic case-based effect model (PERPEST), which bases its prediction on a database of microcosm and mesocosm experiments. The research focused on pesticide exposure in rice fields surrounding a Spanish Natural Park, considering three selected pesticides for this case study: acetamiprid (insecticide), MCPA (herbicide), and azoxystrobin (fungicide). For each of the pesticide types, the developed BN model enabled the prediction of their effects on biological endpoints, endpoint groups, and community in an aquatic ecosystem. Also, it enables comparison between the different pesticide types, their effects on endpoint groups and community. While directly linking future scenarios of climate and agricultural practice to the exposure concentration and indirectly linking them to the effect on biological endpoints as well as community. In summary, azoxystrobin and MCPA seem to have a higher predicted risk for the community with at least one of the biological endpoint being effected compared to acetamiprid. Generally, the developed approach facilitates the communication of uncertainties associated with the predicted effect on different biological levels of the aquatic ecosystem. This transparency in all model components can aid risk management and decision making.

1 Introduction

In the future, changes in agricultural practices, as for instance, the use of new or more plant protection products (Delcour et al., 2015) can cause a change of risk to biodiversity in aquatic ecosystem. Some agricultural methods lead to an intensive use of pesticides. This is of special concern in the Albufera Natural Park (Valencia, Spain) a lake enclosed by rice fields, known for its diversity in bird and fish species (Soria, 2006). In this area, the rice production and other anthropogenic stressors already had a negative impact on lake's water quality and ecosystem health throughout the last century (Calvo et al., 2021; Vera-Herrera et al., 2021). Realistic assessment of risk posed by these expected stressors is therefore crucial for the future ecological sustainability of the Albufera National Park.

1.1 Importance of effect assessment using predictive models

Today's ERA is mostly based on deterministic approaches, usually relying on single value risk estimation, such as risk quotients, to provide predictions based on individual effects data (for larger organisms) or sub-populations (for smaller organisms run in lab tests with subsets of a population). Thus far, good and reliable assessment of pesticide risk requires realistic exposure and effect data, as well as understanding of ecosystem processes (Schmolke et al., 2010).

ERA often uses monitoring studies for exposure assessment, though these can be time-consuming and expensive, and their results are quite site specific and have a wide range of uncertainties (Lammoglia et al., 2018). Ergo, for pesticide ERA, using pesticide fate simulation models (Pereira et al., 2017) is a needed tool for the prediction of exposure concentration and for the characterization of spatial and temporal long-term patterns. Moreover, as future land-use and climate changes (CC) are expected to alter the distribution and fate of pesticides in the aquatic environments. In the Mediteranean, it is expected that droughts occur more frequently, and water is less available, thereby resulting in lower dilution. On the other hand, severe precipitation events are expected to occur more often which may result in higher pesticide runoff. For this southern region, an expected increase in temperatures, may facilitate microbial degradation of pesticides but also higher uptake by organisms (Arenas-Sánchez et al., 2016; Balbus et al., 2013; García de Jalón et al., 2014; Noyes et al., 2009). In recent years, the CC's influence on pesticide fate and transport has been the subject of increased concern (Bloomfield et al., 2006; Delpla et al., 2009; Lamon et al., 2009; Noyes et al., 2009). Exposure prediction models can aid exposure assessment in cases where monitoring data is scarce, or for example assist the analysis of future land-use and CC impact in prospective exposure assessment. As these process-based exposure models are able to integrate a wide diversity of scenario combinations such as agricultural practices, soil properties, crop types and meteorological conditions, consequently being a relative rapid and cost efficient tool assessing the exposure of pesticides to the environment (Lammoglia et al., 2018).

For effect assessment based on toxicity test, indirect effects are frequently not considered, nor is the complexity of the population and population dynamics accounted for neither is the complex interactions occurring between populations in a community structure. Whilst some exceptions may be mesocosm studies, that are often based on single-chemical and single-species, certain environmental media (soil, water, or sediment) and under laboratory conditions (Di Guardo & Hermens, 2013). The traditional assessment, species response and interaction have to be extrapolated and accounted for by applying assessment factors to the most sensitive toxicity test or hazard concentration from a species sensitivity distribution (Schmolke et al., 2010; Topping et al., 2020). The current effect assessment lacks insights into the concentration-response relationship between different trophic levels of the ecosystem (Van den Brink et al., 2006). Furthermore, ERA needs to better consider the interaction of contaminant and noncontaminant stressor (Landis et al., 2013), such as changes in climate conditions (temperature & precipitation) as well as changes in land use practices as they can lead to shifts in ecosystems, their hydrological processes. In turn, this may lead to changing responses to contaminants by affected species (Landis et al., 2013). Multiple stressors have been found to affect freshwater ecosystem functioning and structure long-term, and can influence the resilience and recovery of the ecosystem (Polazzo et al., 2022). Instead of basing the effect assessment only on single-species toxicity tests, multi-species models can be used to predict and analyse possible indirect effects within community. Food chain models

can include food-web models, that only consider trophic relationships, or community models, that also consider some inter-species interaction (Larras et al., 2022).

Some multi-species models are based on case-based reasoning (CBR). These CBR based models are based on "*a paradigm of artificial intelligence and cognitive science that models the reasoning process as primarily memory based. Case-based reasoners solve new problems by retrieving stored 'cases' describing similar prior problem-solving episodes and adapting their solutions to fit new needs*" (Leake, 2001). They can consider various factors such as endpoints, experimental ecosystems and test design in their prediction. One such model is the PERPEST model used in this study (Van den Brink et al., 2002), which predicts direct effects on communities. At the same time, it accounts for some indirect effects and interaction among species groups informed by observations from mesocosm studies (Davis et al., 2013) while considering the mode of action in its prediction (Larras et al., 2022; Van den Brink et al., 2006; Van den Brink et al., 2002).

1.2 Probabilistic environmental risk assessment method needed to handle sources of variability and uncertainty

Often, European prospective ERA is based on toxicity exposure ratios or other single values where potential risk is often calculate by comparing predicted exposure (concentration) to no-effect concentration (Di Guardo & Hermens, 2013; Schmolke et al., 2010). In ERA, this deterministic approach describes risk either as a "margin of safety" using uncertainty factors, or the exceedance and frequency of exceedance of safe thresholds. Both derive qualitative output that lack indication of the level of certainty related to the input and output parameters (EUFRAM, 2006). In reality, however, pesticide exposure and effect have spatial and temporal variability determined by environmental and biological characteristics, and pesticide application patterns (FOCUS, 2007). Improving prospective ERA by considering and integrating future scenarios in the prediction of risk to the aquatic environment would improve prevention of further and future damage (Topping et al., 2020). Some of the limitations of traditional ERA can be overcome with probabilistic approaches that characterize both toxicity and exposure, typically using distributions or assigning probabilities. Consequently, they are able to account for variability and uncertainty better (Carriger & Newman, 2012; EUFRAM, 2006; Solomon et al., 2000; Verdonck, 2003). The use of probabilistic approaches has also been recommended by the European Union (Jager et al., 2001). Commonly used probabilistic methods are joint probability curves, quantitative overlap, or risk quotient distribution (Campbell et al., 2000; Mentzel et al., 2021; Verdonck, 2003). These commonly used probabilistic approaches outputs can be hard to understand and communicate to decision-makers (Dreier et al., 2020; Giddings et al., 2000).

Bayesian networks can overcome some of these limitations and better communicate and quantify uncertainties to decision-makers and other stakeholders (Carriger et al., 2016; Carriger & Newman, 2012). While being used in situations where data is limited or processes lack characterization, BNs are able to incorporate these various sources of information e.g., expert elicitation, model outputs or literature (Carriger et al., 2016; Carriger & Newman, 2012; Gibert et al., 2018; Hamilton & Pollino, 2012). Besides, BNs have the ability to act as a meta-model (e.g. Mentzel et al. (2022)), allowing for the incorporation of inputs and outputs from various different models (in a single model). Summarized, they are probabilistic graphical models that contain nodes (variables) linked through arcs representing conditional probability tables (CPT) (Aguilera et al., 2011; Kaikkonen et al., 2021). The nodes have assigned states (intervals) that can be quantified by probabilities and probability distributions.

Based on new evidence, these Direct Acyclic Graphs (DAG) use Bayes' rule to update the probability distributions throughout the network (Carriger et al., 2016; Kanes et al., 2017). The overall objective is to predict the risk of pesticides to biological communities represented by multiple biological species groups. To achieve this, the probability of effect on biological endpoints was predicted for the different pesticides. Secondly, the developed BNs predicted the cumulative probability of the effects of a pesticide on different endpoint groups (e.g., invertebrates) as well as the whole community. Thirdly, the effects of different pesticide types on various endpoint groups are compared at the community level. Lastly, this BN model aims to predict the probability of effects under scenarios of pesticide application or climate change.

2 Material and methods

2.1 Description of the case study region

The study area is a coastal wetland around five kilometres south of Valencia on the Mediterranean Spanish coast, with an area of about 210 km^2 (Figure 1). The Natural Park has ecological relevance as it is a nesting and transfer point for approximately 250 species of migrating birds and mentioned in as a special protection area by Birds Directive (Directive 2009/147/EC), listed as European habitat in Natura 2000, and Ramsar Convention of wetlands (Calvo et al., 2021; GV, 2020; Vera-Herrera et al., 2021). Within its bound, 34% of Spanish rice is produced (Canet et al., 2003) as 73% of the wetland is dedicated to rice cultivation (Vera-Herrera et al., 2021). Also, the lake's water level is regulated by a network of irrigation channels and seasonal rainfall (mainly spring and autumn). Agricultural and other anthropogenic activities had negative impact on the shallow (1-1.2 m mean depth) and oligohaline (1-2% salinity) lake located in the centre of the wetland (Calvo et al., 2021; Vera-Herrera et al., 2021).

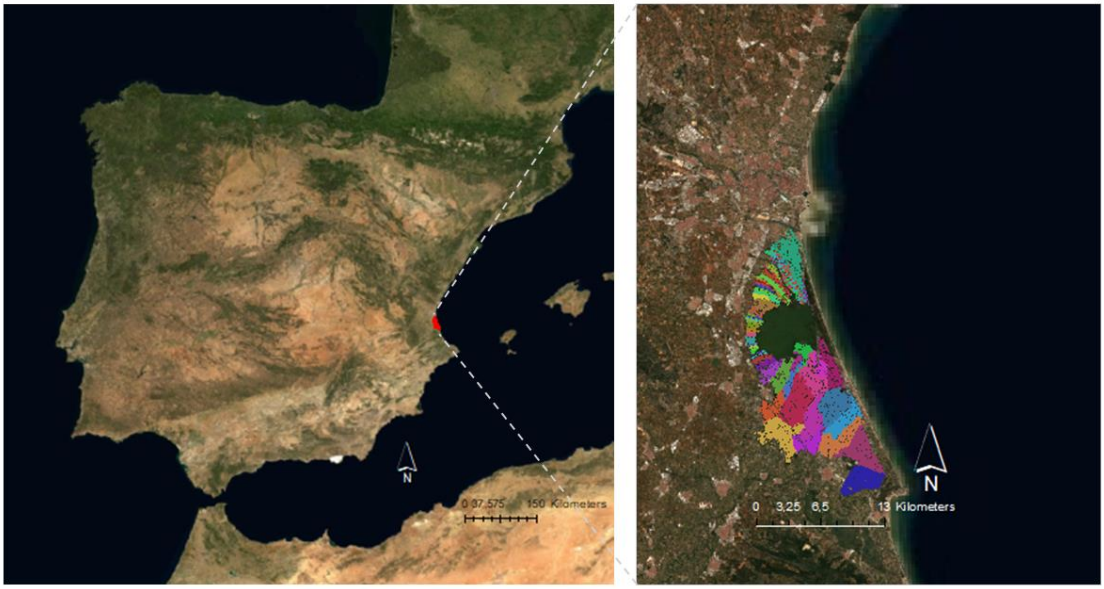

Figure 1 Location of Albufera Natural Park near Valencia (red) and location of rice field clusters (coloured areas) (adapted from IGN (2022), Retrieved from www.ign.es, Accessed on 28 April 2022)

2.2 Bayesian network conceptual model and assumptions

The general approach is to integrate predicted outputs from both exposure and effect prediction models into a Bayesian network serving as a meta-model. In this study, the RICE Water Quality model – RICEWQ was used to simulate the pesticide exposure in the water in rice paddies (Karpouzas & Capri, 2006; Miao et al., 2004) and the Predicts the Ecological Risks of PESTicides (PERPEST) model was used to simulate the pesticide effect to various biological endpoint (Van den Brink et al., 2002). We developed a BN meta-model structure incorporating temporal variability in the effect estimation of pesticide for various endpoints in the aquatic ecosystem. Thus, the simulated peak concentrations (RICEWQ output) are converted to a probability distributions. The gradients predicted for each biological endpoint (PERPEST outputs) are manually added as prior probabilities in the CPTs of the related biological endpoint nodes in the BN.

The BN model is composed of three modules: the scenarios and exposure module (blue), effect on biological endpoint module (green) and effect on community (grey) module (Figure S. 3). The first module, scenario and exposure, is composed of the scenario combination (red) that define the exposure concentration distributions fitted to the RICEWQ model output. The second module is derived by the PERPEST model output that provides the effect concentration states and the prior probabilities of the biological endpoint nodes. Finally, in the third module, cumulative risk to community, each of the biological endpoint nodes are transferred to Boolean nodes (true/false) before being aggregated to their respective endpoint group nodes (light grey) (e.g. effect on Vertebrates) and further aggregated to the community level (Figure 2). Thus the node "Macrophytes bool" is meant to quantify the probability of a pesticide effect to macrophytes (true/false); the node "Effect on plants" will quantify the cumulative probability of effects to any of the plant endpoints; and the node "Effect on Community" will quantify the cumulative probability of effects to any of the endpoint groups.

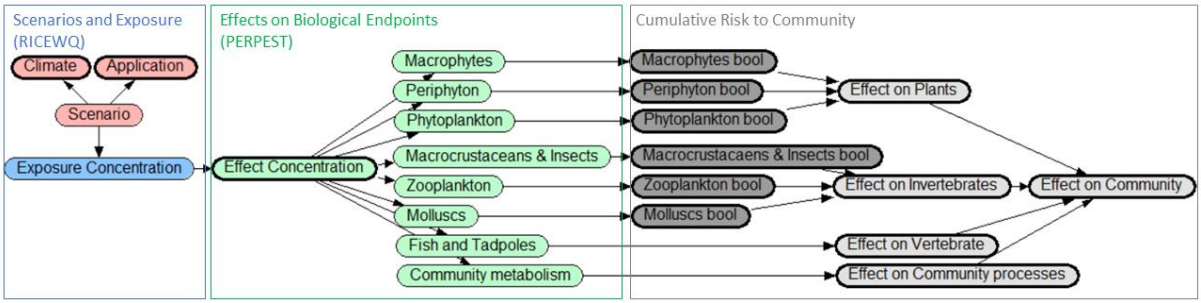

Figure 2 Conceptual model for the effect estimation of a pesticide (acetamiprid) on an aquatic community. Pesticide exposure derives input from the RICEWQ model and is determined by the associated future and application scenarios. The PERPEST model input derives the effect on biological endpoints and endpoint groups and in turn the effect on the community.

In this study, the BN was constructed with the Netica software (Norsys Software Corp., www.norsys.com). For each of the selected pesticides, the BN illustrates the predicted exposure concentration and effect on the various biological endpoint and endpoint groups and summarizing effect on community. The parameterized model can be run by selecting a set of scenarios e.g. climate time and application scenario as evidence. The probability distributions will then be updated throughout the BN to predict the probability of effect classes on the output nodes. Model assumptions and a more detailed node description are detailed in Table 1.

Table 1 Bayesian network node description containing the node name, type, number of states and information source.

Module	Node name	Node type	No. of states	Node input source
Scenario and Exposure	Climate time	Categories	3	Scenarios (2008, 2050, 2100)
	Application scenario	Categories	2	Scenarios (baseline, baseline+50%)
	Scenario combination	Categories	6	Combination of the scenarios
	Exposure concentration	Intervals	8	Scenario-dependent distribution: Normal Distribution (mean, sd)
Effects on biological endpoints	Effect concentration	Intervals	6-10	= exposure concentration with discretization adapted to intervals used by PERPEST
	Biological endpoint node	Ranked categories	3	Pesticide effect (no, slight, clear) on biological endpoints as predicted by PERPEST
Cumulative risk to community	Effect on endpoints	Boolean	2	FALSE = no effect TRUE = slight effect + clear effect
	Effect on endpoint group	Boolean	2	Effect on functional groups = $1-(1-node_a)*(1-node_b)*\ldots.(1-node_n)$
	Effect on Community	Boolean	2	Effect on Community = $1-(1-node_a)*(1-node_b)*\ldots.(1-node_n)$

2.3 Exposure prediction with RICEWQ - prediction and settings

As previously mentioned, the RICEWQ model was developed to simulate pesticide exposure in water of rice paddies. It is a process-based model that at field level simulates pesticide runoff specific for use in rice paddies (Williams et al., 1999). Thus far, it is considered to be the most suitable and reliable for higher-tier pesticide fate and exposure prediction (Daam et al., 2013; Karpouzas & Capri, 2006; MED-Rice, 2003). Besides, it has been widely applied in the US (Karpouzas & Capri, 2006; Miao et al., 2004) to track the fate of both parent and metabolite chemicals (Christen et al., 2006). Various processes are reflected in RICEWQ modelling, such as biological, hydrological and physico-chemical processes (Wang et al., 2019).

This exposure prediction model requires the following inputs: daily weather information, paddy soil properties, pesticide chemical properties, pesticide management information, and water management practices (Wang et al., 2019). The reader is referred to (Williams et al., 1999) for a more detailed information of the model function, assumptions and description.

In this study, the latest version, RICEWQ 1.92 (Waterborne Environmental Inc, 2022), was run for various scenarios incorporating different rice crop types, management practices,

meteorological and hydrological conditions, and for selected pesticides used for the rice crops in the region. Moreover, we selected three active substances that are regularly applied around Albufera lake by farmers. The derived pesticide application scenario is based on the recommended manufacturer dosages from which we derived two scenarios: one maximum recommended dosage (referred to as Baseline application throughout this study) and one that is 150% of that baseline dosage (Baseline+50%). Initially, we had aimed to have at least three different emission scenarios' climate projections to include more variability. We used them as input for the RICEWQ model runs, based on what had been previously used in a study by Pool et al. (2021). However, available prediction data was limited for the specific meteorological station 8416 near the National park. Therefore, only one climate prediction data set was collected from AEMET (2021) at "Climate projections for the XXI Century – Daily data", derived with the model "GCM MPI-ESM-LR" and an emission scenario "representative concentration pathways (RCP) 8.5". Based on this data set, three "climate-time" scenarios for the years 2008, 2050 and 2100 were used to run the exposure prediction model.

The exposure prediction model was run for 552 rice crop clusters. The maximum exposure concentration from each cluster was used to fit to the exposure distribution. A detailed description of the assumptions made to derive these clusters, as well as the automatization of the RICEWQ with a handy interface, are available in Martínez-Megías et al. (2022). In total, six different scenarios were developed each of which is the combination of year and application scenario, and pesticide. They were run with autoRICEWQ (open source under GPL-3.0 License, programmed in Python 3), which can be accessed at Fuentes-Edfuf and Martínez-Megías (2022).

The prior probability of exposure concentration node is assumed to be a normal distribution with varying mean and standard deviation depending on the scenario combination (Table 2). This paper focuses on the predicted effect in 2050, which was considered sufficient for the concept development. The predictions for the other years will be presented in supplementary, as valid predictions of the effect of climate models on the various biological endpoints, would require more climate model scenarios to account for uncertainty and variability in future appropriately.

Table 2 The exposure peak concentration means and standard deviations used as input on the Bayesian network for the selected pesticides and scenarios, also detailing the year and application scenario. (three significant digits were chosen)

Scenario	**Pesticide type**	**Pesticide**	**Year**	**Application**	**Mean (µg/L)**	**Sd (µg/L)**
1	Insecticide	Acetamiprid	2008	Baseline	0.35	0.27
2				Baseline+50%	0.47	0.36
3			2050	Baseline	0.86	0.45
4				Baseline+50%	**1.14**	0.60
5			2100	Baseline	0.58	0.20
6				Baseline+50%	0.77	0.26
1	Fungicide	Azoxystrobin	2008	Baseline	80.5	10.0
2				Baseline+50%	**121**	15.0
3			2050	Baseline	71.9	9.80

4				Baseline+50%	108	14.7
5			2100	Baseline	69.6	8.74
6				Baseline+50%	105	13.1
1	Herbicide	MCPA	2008	Baseline	37.7	5.59
2				Baseline+50%	**56.5**	8.40
3			2050	Baseline	33.1	5.20
4				Baseline+50%	49.6	7.81
5			2100	Baseline	24.3	4.79
6				Baseline+50%	36.5	7.16

2.4 Effect prediction with PERPEST – model assumptions and prediction

The PERPEST model was developed to simulate pesticide effects on various biological endpoints (Van den Brink et al., 2002) and can be used for risk assessment of single and mixed applications of pesticides (Rämö et al., 2018). It is considered more comprehensive compared to the traditional ERA that uses risk or hazard quotient approaches (Polidoro & Morra, 2016; Rämö et al., 2018). This effect prediction model applies case-based reasoning approach (CBR) to draw empirical ecotoxicological data from micro- and mesocosm experiments (Davis et al., 2013; Rämö et al., 2018). It can predict direct and indirect effects of contaminants while incorporating hydrological properties and acute and chronic exposure in the prediction (Van den Brink et al., 2002). The PERPEST model compares environmental exposure concentrations to previous observations in mesocosm and microcosm toxicity tests to estimate the probability of the pesticide having a toxic effect on various pesticide type dependent biological endpoints and endpoint groups.

The PERPEST model predicts a probability gradient for three (default) effect classes on biological endpoints depending on the modelled pesticide type. Following Van den Brink et al. (2002) these three classes are:

- "No effect" - No consistent adverse effects are observed as a result of the treatment. Observed differences between treated test systems and controls do not show a clear causality;
- "Slight effect" - Confined responses of sensitive endpoints (e.g. partial reduction in abundance). Effects observed on individual sampling dates only and/or of a very short duration directly after treatment; and
- "Clear effect" – severe reductions of sensitive taxa over a sequence of sampling dates are demonstrated, but the duration of the study is too short to demonstrate complete recovery within eight weeks after the last treatment (Davis et al., 2013).

The reader is referred to Van den Brink et al. (2002) for more detailed information of the model function, assumptions and description.

In this study, we used the PERPEST model to predict the effect of a fungicide, herbicide and insecticide on the biological endpoint associated with being affected by the different types of pesticides. The selected pesticides for this study were not currently available in the PERPEST case base, therefore their physico-chemical properties were collected from literature and databases such as PPDB (Lewis et al., 2016), PubChem (Kim et al., 2020) and CompTox (Williams et al., 2017). The median hazard concentration (HC50) was calculated for each of the pesticides using MOSAIC (Charles et al., 2017) with EC50 toxicity data collected from ECOTOXicology Knowledgebase (Olker et al., 2022). The used input information that is compared to the toxicity dataset by the PERPEST model is shown in Table 3.

Table 3 Chemical, biological and physical properties of the selected pesticides included in the PERPEST model

CAS	Chemical name	Type of substance	Mode of action	Molecule group	DT50 (days)	Henry's law (Pa m^3 mol^{-1})	HC50 (µg/L)	Koc (L/kg)
135410-20-7	Acetamiprid	Insecticide	Other insecticide	Neonicotinoid	2950 *	5.3E-08	93	199.5
131860-33-8	Azoxystrobin	Fungicide	Other fungicide	Strobilurin- quinone outside inhibitor	6.1	7.4E-09	503	3320
94-74-6	MCPA	Herbicide	Other herbicide	Aryloxyalkanoic acid	19.5	0.000055	5300	56

* above max range - the value was higher than maximum amount of days that could be entered, in this case the max of 1000 days was used.

The PERPEST model predicts the probability of no effect, slight effect and clear effect along a gradient of pesticide exposure concentrations for a set of biological endpoints (e.g. insects or phytoplankton). The selection of endpoints depended on the pesticide types (for a more complete description of endpoints, see Supplement Information I Figure S. 1).

The latest version of the PERPEST software (Van den Brink et al. [2002]; version 4.0.0) was used to predict the probability of effects for the three selected pesticides (www.perpest.wur.nl) in this study. In principle, the model was used with default settings, additionally weighted with “toxic unit (TU)” and “DT50”, and exposure being set to “not used”.

An example of the PERPEST gradient output is added in the supplement information (Supplement Information I Figure S. 2), a detailed overview of the output tables used as conditional probability tables of the biological endpoint nodes can be found in the supplement information II. This example displays the gradient for the predicted effect of acetamiprid (insecticide) on the algae and macrophytes groups.

3 Results

A parameterised example of the BN is shown in Figure 3 for the insecticide acetamiprid. It displays the event of scenario 4, so for the climate in 2050 with a Baseline+50% application scenraio, resulting in the displayed exposure distribution (exposure concentration node). For this event the predicted effect on the biological endpoint varied. There was no effect on fish and other macroinvertebrates. Also, there was mostly no effect on rotifers, community metabolism, algae and macrophytes, with a probability of 80-90%. The highest probability of a clear effect was predicted for macrocrustacea, with about 24%. The effect on the endpoint groups also varied, with no biological endpoint predicted to be affected in the vertebrates, and most likely none being affected in the endpoint group of plants (ca. 97%). The summarizing node "community" had a predicted effect on at least one of the biological endpoints, with about 77%.

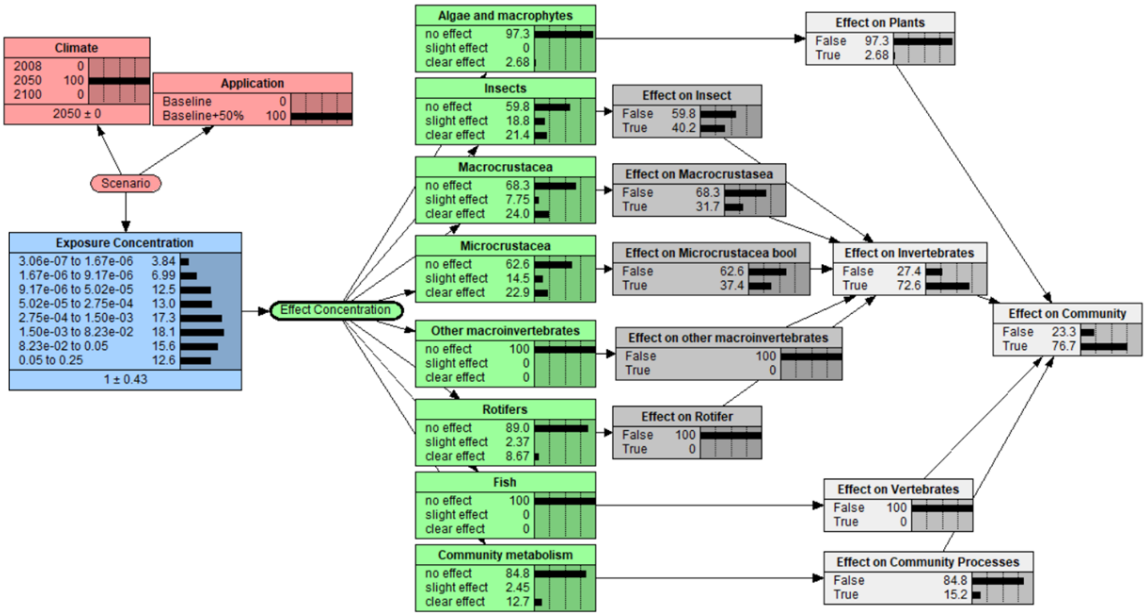

Figure 3 Example of the parameterised Bayesian network for the insecticide acetamiprid. It displays the predicted effect on the biological endpoints and endpoint groups for climate conditions of 2050 and a baseline+50% application scenario.

In the subsequent, the probabilities of the output nodes predicted by the BN are displayed in a bar chart to enable easier comparison between the different scenarios, biological endpoint and pesticides types.

3.1 Predicted effect on biological endpoints

Focusing on the biological endpoints, the BN predicted the effect of the insecticide acetamiprid for eight biological endpoints. Insects, macro- and microcrustaceans had a probability of up to 30% to be in the state of slight to clear effect. Community metabolism, algae and rotifers were mostly unaffected. fish and macroinvertebrates were most likely to not be affected by the insecticide (Supplement Information I Figure S. 5).

For this fungicide azoxystrobin, eleven biological endpoints were considered by the PERPEST model. Macroinvertebrates, microcrustacean and other zooplankton taxa were the biological endpoints predicted to be clearly affected ,with a likelihood of 50%, followed by other zooplankton, phytoplankton, community metabolism, and macrocrustacea. Fish and macrophytes were similarly affected, with a 15 to 20% probability of being in the “no effect” state. Finally, decomposition and periphytic were predicted not to be affected (approx. 100%) (Supplement Information I Figure S. 7).

The PERPEST model considered eight biological endpoints for this herbicide MCPA. Here zooplankton even had a probability of more than 50% to be in the clear effect state and phytoplankton, and periphytic had a probability of 25%. Macrophytes and community metabolism were also primarily unaffected. Fish and molluscs were predicted not to be affected by about 100% (Supplement Information I Figure S. 9).

There were few biological endpoints all pesticides had in common, one of them was macrocrustacea (see Figure S.5, Figure S.7, Figure S.9). For all pesticides the distribution of probabilities over the three states were similar. The fungicide and insecticide were predicted to have a probability of 25% to be in the clear effect state in 2050. Compared to the other pesticides, the insecticide had lowest predicted probability of being in a clear effect state at about 20%. The pesticides showed the highest probability of the macrocrustacea not being affected.

3.2 Aggregation of the predicted effect from biological endpoints to endpoint groups

The BN model output could be defined as the effect on a specific biological endpoint (Figure 4). In the following, an example of acetamiprid dispalys the aggregation from the PERPEST defined states to the effect on the biological endpoint. It was expected that insects were affected with a probability of approx. 22 %, slightly affected with 18 %, and not be affected with 60 % by acetamiprid (Figure 4a).

To summarize this example, the likelihood of there being an effect on insects was true with approx. 30% and false with approx. 70% (Figure 4b).

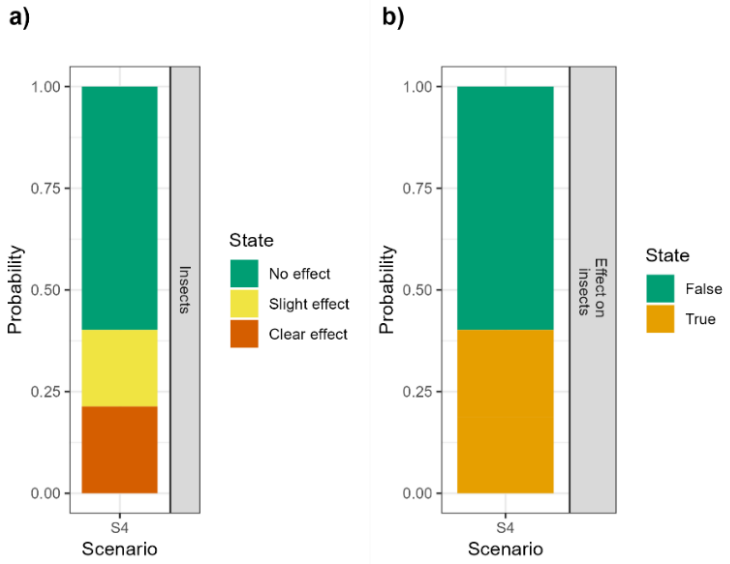

Figure 4 Example BN output predicted effect on insects by acetamiprid for a specific scenario (a) and summarising Boolean node output displaying whether or not an effect of the pesticide can be assumed (b), for climate condition in 2050 and a Baseline+50% application.

An assumption can be made for the effect on biological endpoints and the endpoint groups (Figure 5). When comparing some of the biological endpoints for the insecticide acetamiprid, it can be observed that macroinvertebrate was predicted not to be affected by acetamiprid with a likelihood of almost 100 %. Unlike the insects, macro-and microcrustaceans had a higher probability of being affected, with a 25-30% likelihood. The effect on the endpoint group could also be aggregated with the BN. In this insecticide example the biological endpoints displayed were all considered for the endpoint group of invertebrates. It can be concluded that the predicted probability of an effect on any of these biological endpoints of

the invertebrates endpoint group was false with approx. 25 % and true with approx. 75%. In other words, it is more probable for at least one of the biological endpoints to be affected.

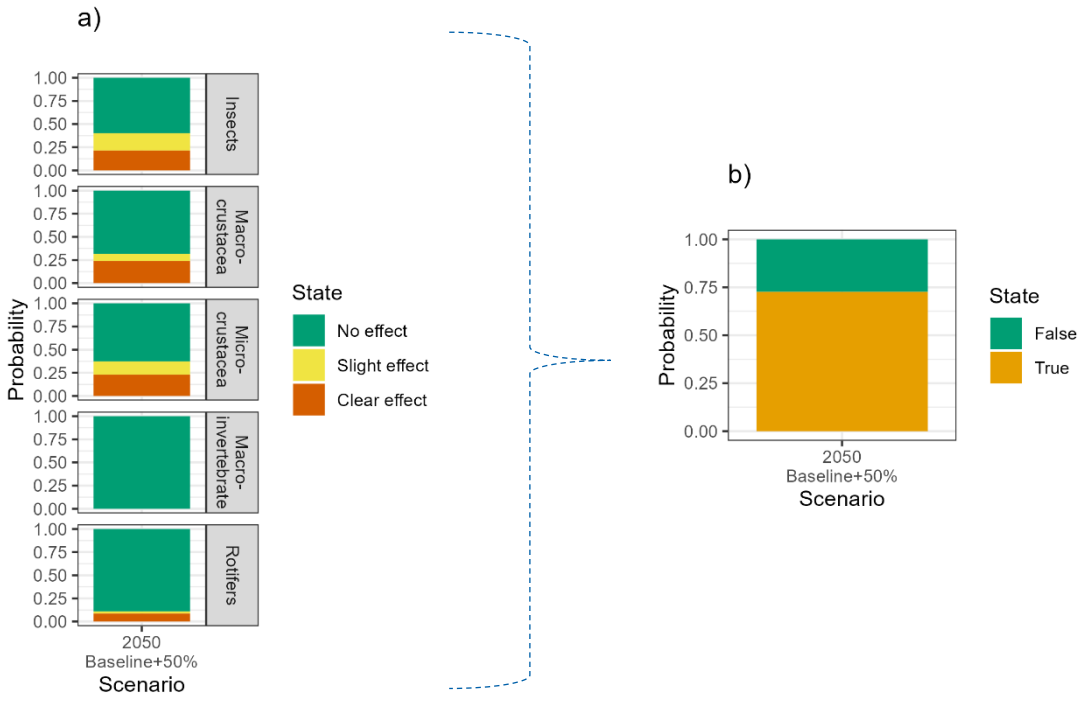

Figure 5 Example for the predicted effect of insecticide on the biological endpoints (a), which are considered in the endpoint functional group "Invertebrates" (b), for climate conditions in 2050 and Baseline+50% application.

3.3. Comparison of the predicted effect of pesticides on the endpoint groups and community

Another output of the BN was the effect on the endpoint groups and community, which describes the combined probability of any biological endpoints being affected.

The fungicide azoxystrobin had a probability of 50% for any of its biological endpoints in the plant endpoint group to be affected (for the baseline application scenario). The endpoint group of ecosystem system processes had a probability of less than 50% for any of its biological endpoints to be affected. On the other hand, the vertebrates were not affected (Supplement Information I Figure S. 8 – upper panel).

For the herbicide MCPA, the probability of any of the plant's biological endpoints being affected was about 50%. With a probability of 15-20% of any of the biological endpoints of the ecosystem processes being affected by the herbicide. Again, no biological endpoint was affected for the vertebrate endpoint group. (Supplement Information I Figure S. 10 – lower panel).

With a probability of 50-75% it was predicted that any of the biological endpoints of the invertebrates were affected by the insecticide acetamiprid. In contrast, the endpoint groups of plants and ecosystem processes were predicted to have mostly none of the biological endpoints affected. For this pesticide type, the vertebrates were expected to not be affected (Supplement Information I Figure S. 6 – lower panel).

The summarizing effect on community node shows that all three pesticides influenced at least one of the biological endpoints (Figure 6). The fungicide (Azoxystrobin) affected any of the biological endpoints of the community with a predicted probability of almost 100%, while the herbicide (MCPA) had almost 90 % probability of affecting one of the endpoints. The insecticide (Acetamiprid) had the lowest predicted risk to the community, with a probability of almost 75% of any of the biological endpoints being affected.

In the following example, the results display the effect on any of the biological endpoints of the invertebrate, plant endpoint groups and community for either baseline and baseline+50% application scenario under the same future climate conditions (2050) (Figure 6). Focusing on the endpoint groups, the invertebrates had the highest probability of being affected by azoxystrobin and the lowest by acetamiprid. It was observed that the probability of an effect on any of the biological endpoints of the plant community (endpoint group) was highest for MCPA with approx. 60 % (for the baseline application), and lowest for acetamiprid with approx. 2%. Azoxystrobin has the highest probability (98%) of any of the biological endpoints in the community being affected, and acetamiprid had the lowest probability with 75%. From these BN predictions, it can also be observed that the increase in effect of any of the biological endpoint is highest for azoxystrobin whenever a higher application scenario is used, whereas the lowest increase in probability was observed for acetamiprid.

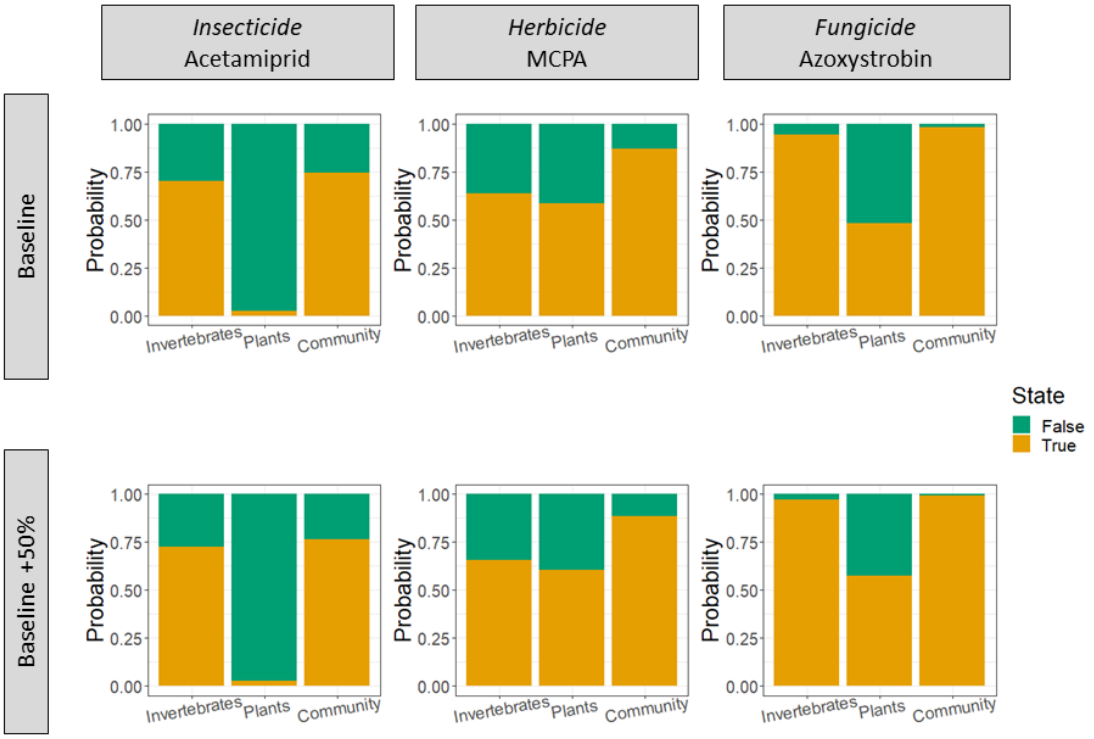

Figure 6 Example of effect on invertebrates, plant endpoint group and community displaying the probability in a bar chart for the selected pesticides, for a baseline and Baseline+50% application under climate conditions in 2050.

4 Discussion

In general, the BN predicted at least one of the biological endpoints was affected by the pesticides under any of the scenario combinations. Azoxystrobin was most likely to affect at least one of the biological endpoints, followed by MCPA which also had a high likelihood. Whereas acetamiprid, compared to the other two pesticides, had the lowest effect. Furthermore, a trend from the predictions could be observed for the higher application of pesticides that resulted in a shift towards a higher probability for any of the biological endpoint and endpoint groups being affected for all pesticides. On the other hand, the climate condition at the time had no trend on the effect on biological endpoints that can be observed for all pesticide types.

We aimed to carry out an effect assessment of three selected pesticides using a probabilistic approach, as these have been recommended to better account for uncertainty in pesticide exposure (Carriger & Newman, 2012) and effect (Dreier et al., 2020). Therefore, we linked the inputs and outputs of two prediction models into a Bayesian network (BN). We had succeeded in developing a BN model that can predict the effect on multiple biological endpoints and the cumulative effect on endpoint groups and communities. These BN predictions enabled comparison between different pesticide types, community levels, as well as pesticide application and climate change scenarios.

Some initial precision of the prediction model outputs might be lost due to a common BN shortcoming when discretisation of continuous variables is applied (Marcot, 2017; Nojavan et al., 2017). A higher resolution of BN predictions can be achieved by applying dynamic discretisation (Carriger et al., 2016; Fenton & Neil, 2018). The credibility of developed BN is mainly influenced by the assumptions and input data derived from predictions from the process-based exposure model and case-based effect model. The RICEWQ model used to predict the exposure concentrations in the rice paddy is readily available for simulation and can be used for higher tier exposure assessment (MED-Rice, 2003). A detailed description of uncertainties related to this model can be found in Miao et al. (2004). We chose this model as it enabled simulation of agricultural conditions for rice production, such as the controlled release of water, overflow, and flooding, unlike other pesticide fate and transport models. Moreover, it was considered as the first option when carrying out an exposure prediction for rice cultures (MED-Rice, 2003). However, some assumptions and input data that led to uncertainty in our modelling efforts. We could have derived more realistic model outputs by updating or adding scenarios to our model efforts. The use of multiple climate models with different greenhouse gas emission scenarios allows integration of more variability (Fernández et al., 2017). The model could be improvement by using more and different climate models, as some papers by Steffens et al. (2014) and Moe et al. (2022) recommended. These mentioned that using an ensemble of various lobal and regional climate models together with various greenhouse gas emission scenarios would potentially enable more robust estimations of pesticide losses in future. In addition, we assumed more realistic application scenarios could be developed and used to run the autoRICWQ model. Future work for the prediction of the exposure concentration could also be extended to the discharge channel, by using the RIVWQ model, which would enable the consideration and integration of dilution better.

There is also some uncertainty associated with the PERPEST model, connected to the ecotoxicology database. The database on which the case-based effect model bases its predictions on has limited data availability for fish and tadpoles. Furthermore, its incorporated data is primarily based on datasets from temperate climate such as Europe and North-America (Davis et al., 2013; Van den Brink et al., 2002), and therefore is limited in its predictions for the Mediterranean climate zone.

Henceforth, this limitation could be overcome by updating the database with more and regional relevant bioassays. Some other uncertainties of the PERPEST model can be associated with the input information such as pesticide properties for the model run. Consequently, we tried to minimize this, by using the same information source for the selected pesticides whenever possible. For example, we collected toxicity data from ECOTOXicology Knowledgebase (Olker et al., 2022) and thereafter using the same method to prepare the data used on MOSAIC (Charles et al., 2017) to predict the HC_{50}. In essence, the effect prediction model has simple data requirements making it easy to use (Davis et al., 2013). In addition, some uncertainty is also linked to how the PERPEST model output is integrated in the BN, as it is a gradient, and its concentration range thus far cannot be adjusted to fit better with the exposure distribution. Some other restraints are pointed out by Davis et al. (2013) detailing that PERPEST output might be challenging to use and understand by stakeholders and used in risk management due to the lack of an "established threshold risk value". To overcome this limitation of the PERPEST model Davis et al. (2013) suggested to set acceptable probabilities. In this study, we tried a different approach to enable easier communication of BN outputs integrated with a summarizing node for the effect on endpoint group and community. These nodes show the probability of any of the biological endpoints to be affected to be true or false. This far there is no direct link from the scenarios to the effect module of the network. This relationship needs to be further explored, as the combined effect of climate conditions and chemical exposure are expected to change the effect on the different biological endpoints.

Additional research and model development may result in a better integration and use of the prediction model outputs. An updated PERPEST model database would greatly decrease uncertainties. Regarding the RICEWQ model calibration, larger number of models runs with more applications and climate scenarios, and crop types would be beneficial to increase reflection of variability. In addition, the BN model could also be run for other pesticides commonly used for rice production in the area. Thenceforward this could also allow the prediction of cumulative risks of intentional mixtures. Most of these improvements will likely require some changes to the model structure. Nevertheless, this model enables accounting for uncertainty of all compartments of the BN model, which allows for transparency when communicating the effect of pesticides to various biological endpoints, endpoint groups and the community in the aquatic environment.

5 Conclusion and future outlook

This study shows how to use a Bayesian network model to integrate the outcomes of two different predictive models - the pesticide exposure model RICEWQ and the biological effect model PERPEST, and thereby predicts the risk of a pesticide on biological endpoints and endpoint groups in the aquatic ecosystem of a rice paddy. The BN, we have developed can carry out probabilistic calculation of risk for various event such as pesticide application scenarios. This approach builds upon our probabilistic model versions of the traditionally used Risk Quotient calculation, displaying uncertainty transparently of all its model components. The current study further expands this approach by including the risk calculation for individual biological endpoints as well cumulative risk for the endpoint groups and the community.

For example, the fungicide azoxystrobin was predicted to have the highest probability (about 98%) of affecting any of the biological endpoints in the community. Followed by the herbicide MCPA, which had a probability of 85% of affecting any of the biological endpoints in the community. MCPA, compared to azoxystrobin, the invertebrate's endpoint group had a lower probability of any endpoints being affected, and the plant endpoint group a higher probability. The insecticide acetamiprid had the lowest probability of affecting any of the biological endpoint groups in the community. In comparison to the two other pesticides, its plant community (endpoint group) has higher probability of none of the biological endpoints to be affected.

Future research efforts can incorporate more scenarios such as additional crop types, application patterns and an ensemble of climate models to derive a more realistic idea of pesticide effects on the aquatic ecosystem. In addition, we aim to carry out an effect assessment of the intentional mixtures applied in the Albufera Natural Park to move away from a single compound assessment.

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Software availability
RICEQW - Please contact info@waterborne-env.com to register to receive a download of this model.

autoRICEWQ code - https://zenodo.org/record/5940235#.YhXv8uiZMZA

A free version of NeticaTM is available online at: http://www.norsys.com/downloads.html, along with a glossary of Bayesian network terms and tutorials.

List of figures in Supplement

Supplement information overview
Overview PERPEST model inputs

Overview autoRICEWQ inputs

Overview of BN output

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Paper III Supplement Material

Supplement Information I

Content

I. Endpoint groups per pesticide type

The following lists the biological endpoint groups that are considered by the PERPEST model.

Fungicide:

- Invertebrates: Microcrustacea, Macrocrustacea, Insecta, Other zooplankton taxa, Other macro-invertebrate taxa
- Plant: Periphytic algae, Phytoplankton, Macrophytes
- Vertebrates: Fish and tadpoles
- ecosystem process: DO-pH metabolism, Decomposition

Insecticide:

- vertebrates: Fish
- invertebrates: Insects, Macrocrustacea, Microcrustacea, Other macro-invertebrates, Rotifers
- plants: Algae and macrophytes
- ecosystem process: Community metabolism

Herbicide:

- ecosystem process: Community metabolism
- invertebrates: Zooplankton, Macrocrustaceans & Insects, Molluscs
- vertebrates: Fish and Tadpoles
- plants: Macrophytes, Periphyton, Phytoplankton

II. PERPEST model description and output

2.1 Description of assumption and processes on the PERPEST model

In contrast to most effect models, PERPEST is based on empirical data from micro- and mesocosms extracted from literature. It searches for situations in the database which resemble the case in question, based on relevant (toxicity) characteristics of the compound. This allows the model to predict effects of pesticides for which no evaluation on a semi-field scale have been published. PERPEST results in a prediction showing the probability of three effect classes (no, slight or clear effects) for the various grouped endpoints. For each taxon group, the predicted probability of effect classes along the pesticide concentration gradient is used to derive the conditional probability table for this taxon node in the BN.

2.2 Example gradient output for an insecticide

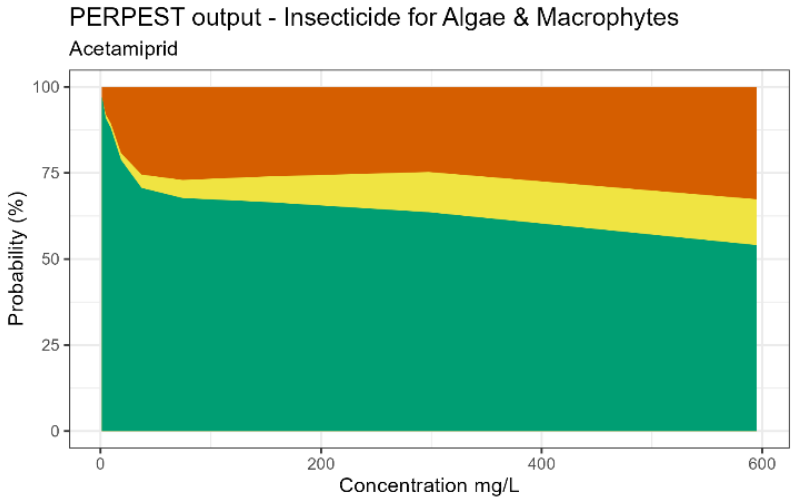

Figure S. 1 Example of the predicted effect on the taxonomic group Algae and Macrophytes that where derived for the herbicide.

III. Bayesian network output for the biological endpoints and endpoint groups

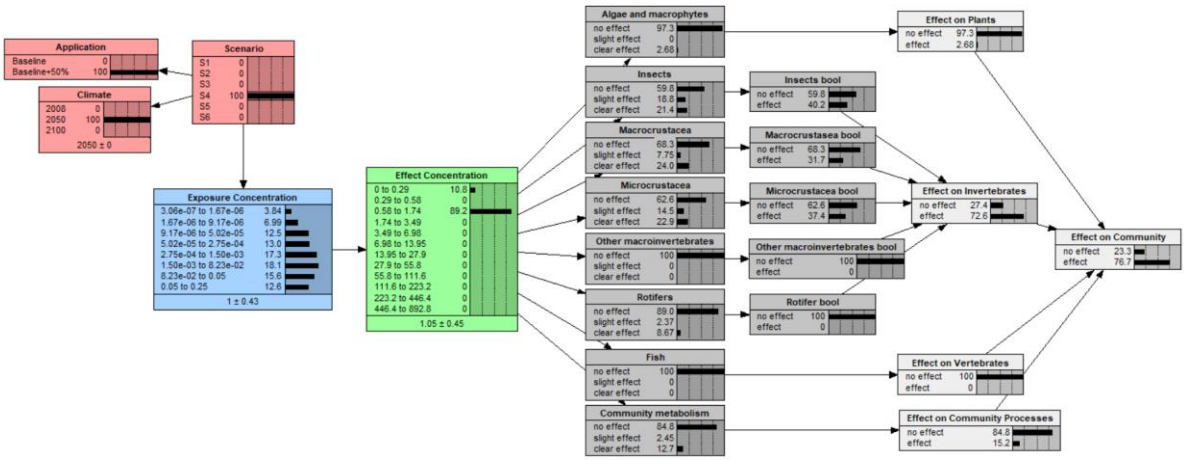

Figure S. 2 Bayesian network model for the insecticide

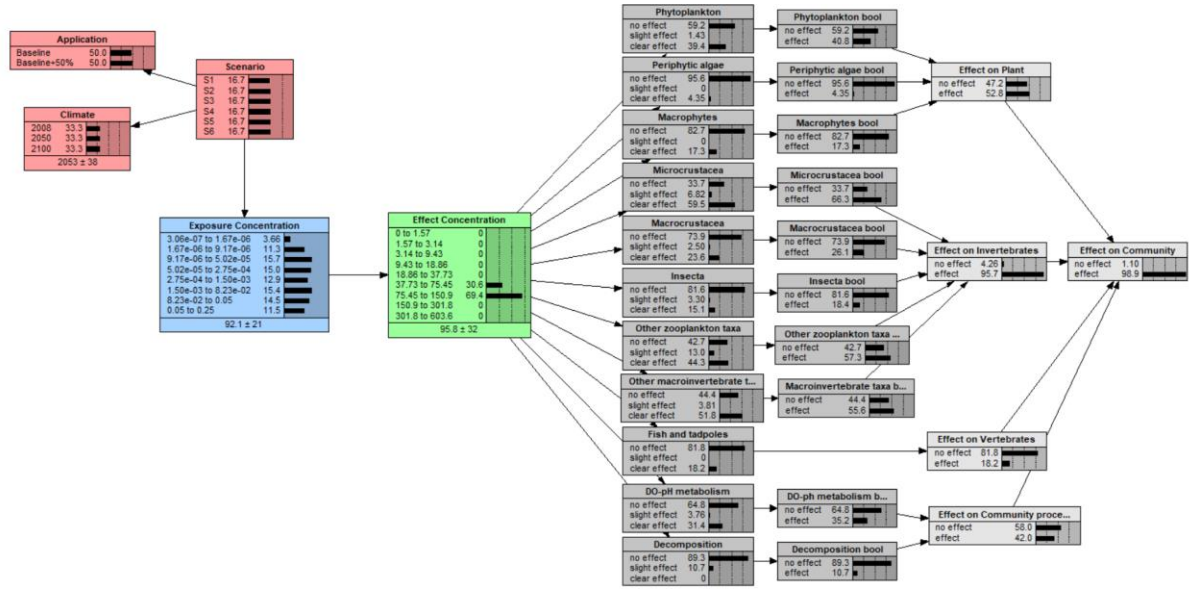

Figure S. 3 Bayesian network for the fungicide

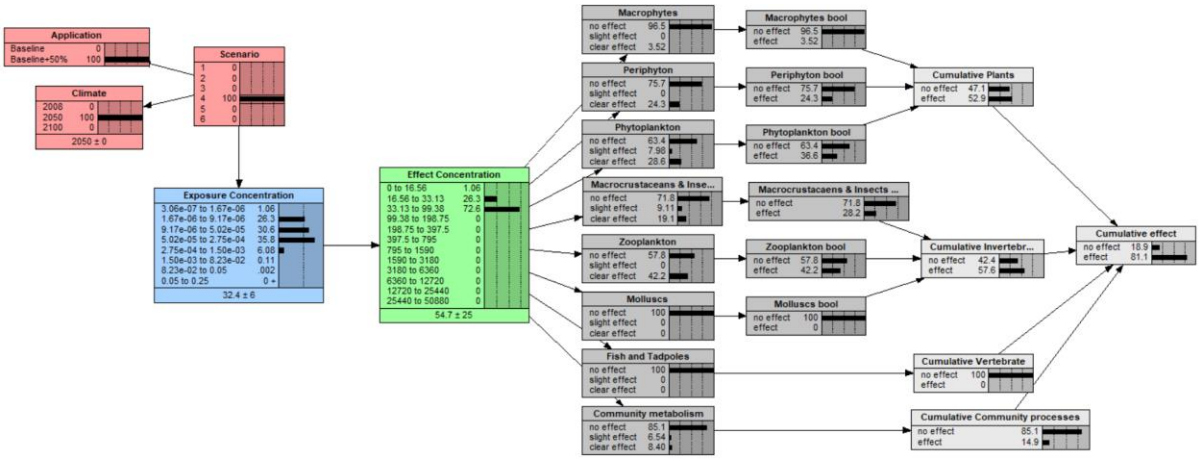

Figure S. 4 Bayesian network for the herbicide

It can be observed that for the insecticide. The probability of the biological endpoints to had slight and clear effect state was higher in 2050 and 2100. The opposite could be observed for the fungicide azoxystrobin, here the probability of the biological endpoint to be in the slight and clear effect state decrease in 2050 and 2100. The herbicide MCPA, also showed a decrease of probability of the biological endpoints to be in slight and clear effect state for 2100 and predicted a similar probability of the previous climate-time scenarios. For the fungicide, the probabilities for any of the biological endpoints in the endpoint groups didn't seem to change much over the years, with one exception, ecosystem processes had a higher probability of none of the biological endpoints to be affect in 2100. As for the herbicide, in general azoxystrobin had lower effect on the endpoint groups in 2100 than previous time-periods. The overall trend for the insecticide was that the likelihood of any of the biological endpoints not being affected was highest in 2008 and lowest in 2050. The Probability were slightly higher for the biological endpoints to be affected by MCPA in 2050 and 2100. Whereas, a decreased was observed for azoxystrobin for the climate conditions in 2050 and 2100. For acetamiprid an increase was observed in probability for a biological endpoint to be affected for the climate conditions in 2050 for acetamiprid followed by a decrease in 2100.

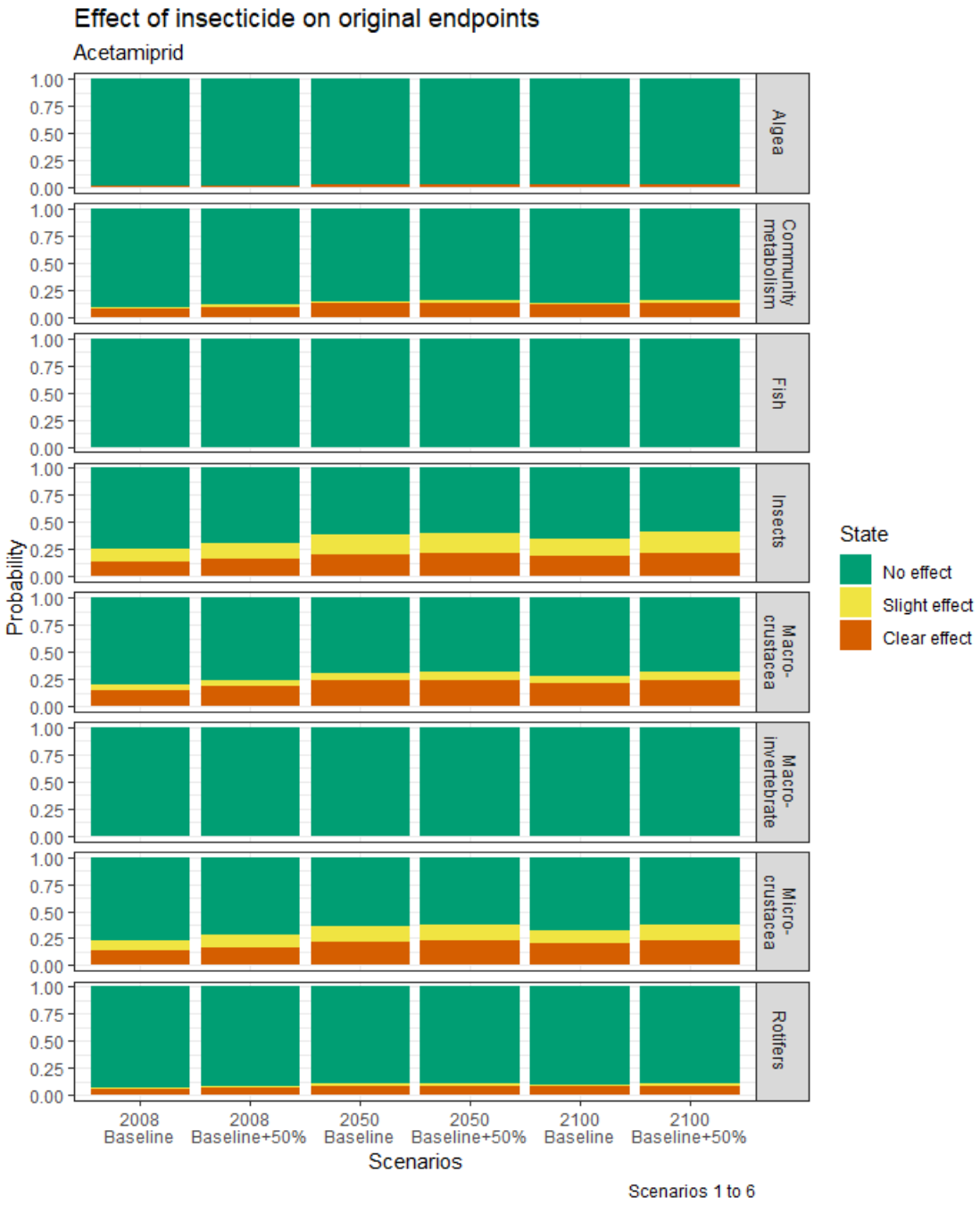

Figure S. 5 Overview of effects on the biological endpoints by the selected insecticide (acetamiprid) for all selected scenarios.

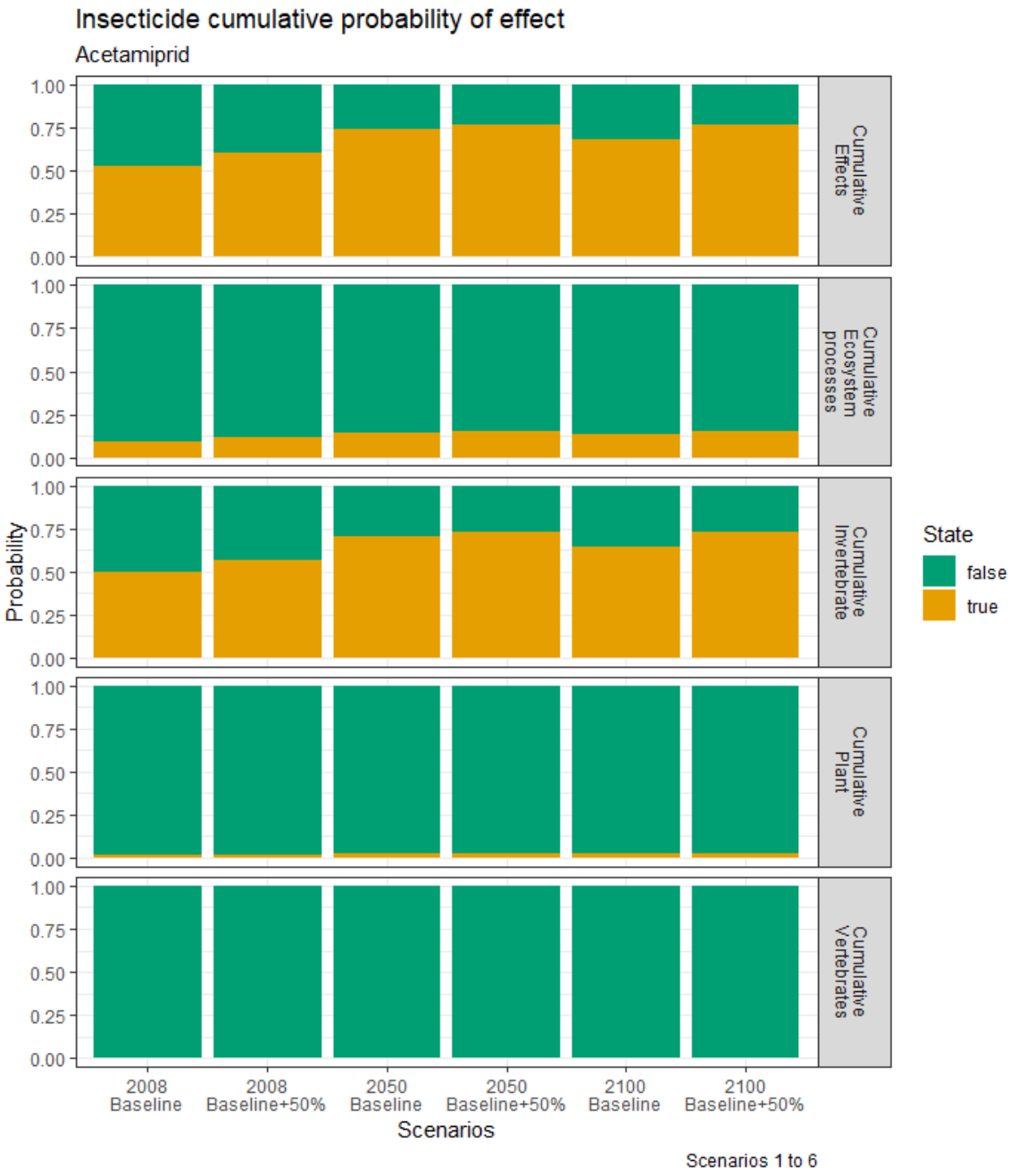

Figure S. 6 Overview of effects on the endpoint groups community level by the selected insecticide (acetamiprid) for all selected scenarios.

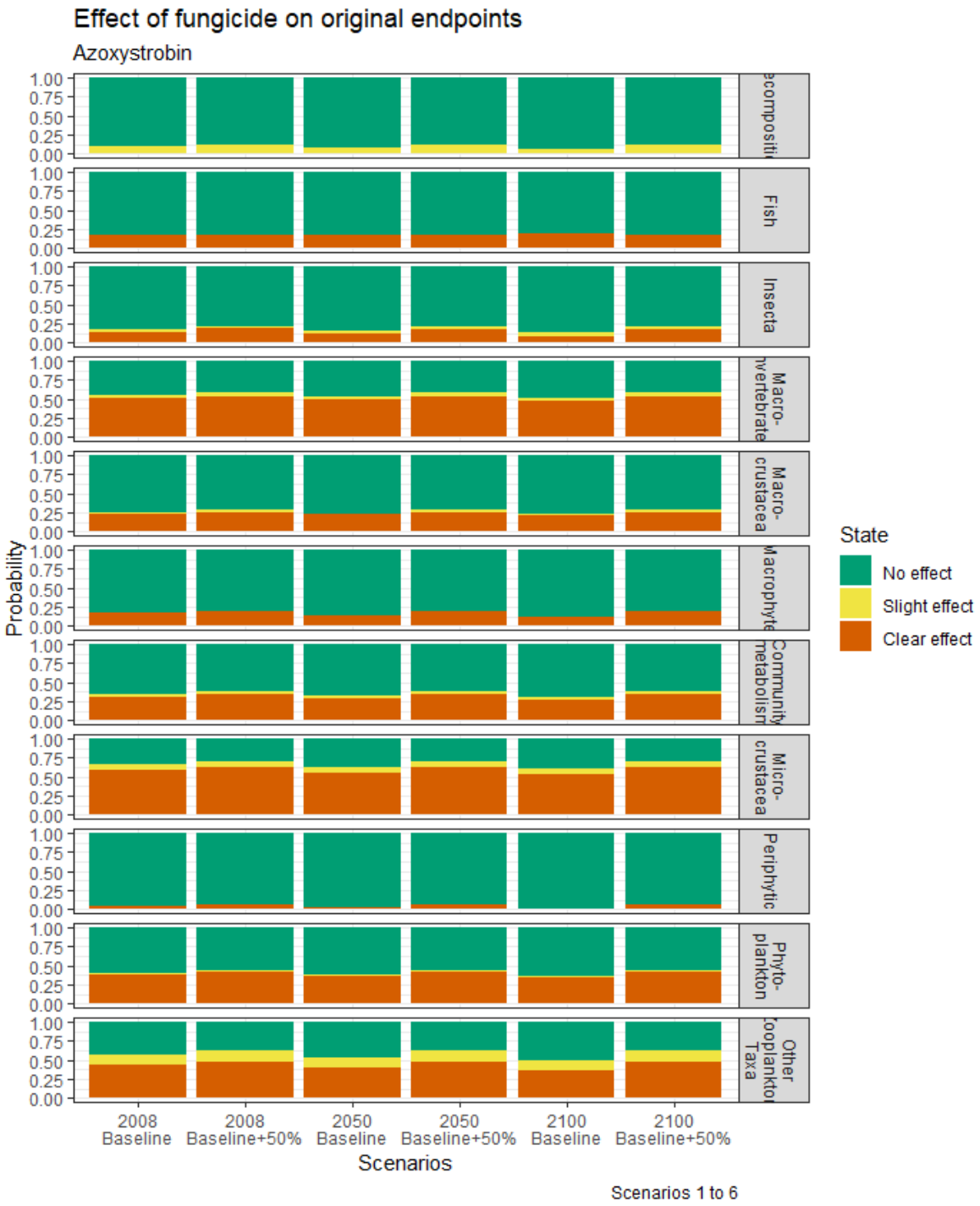

Figure S. 7 Overview of effects on the biological endpoint by the selected fungicide (azoxystrobin) for all selected scenarios.

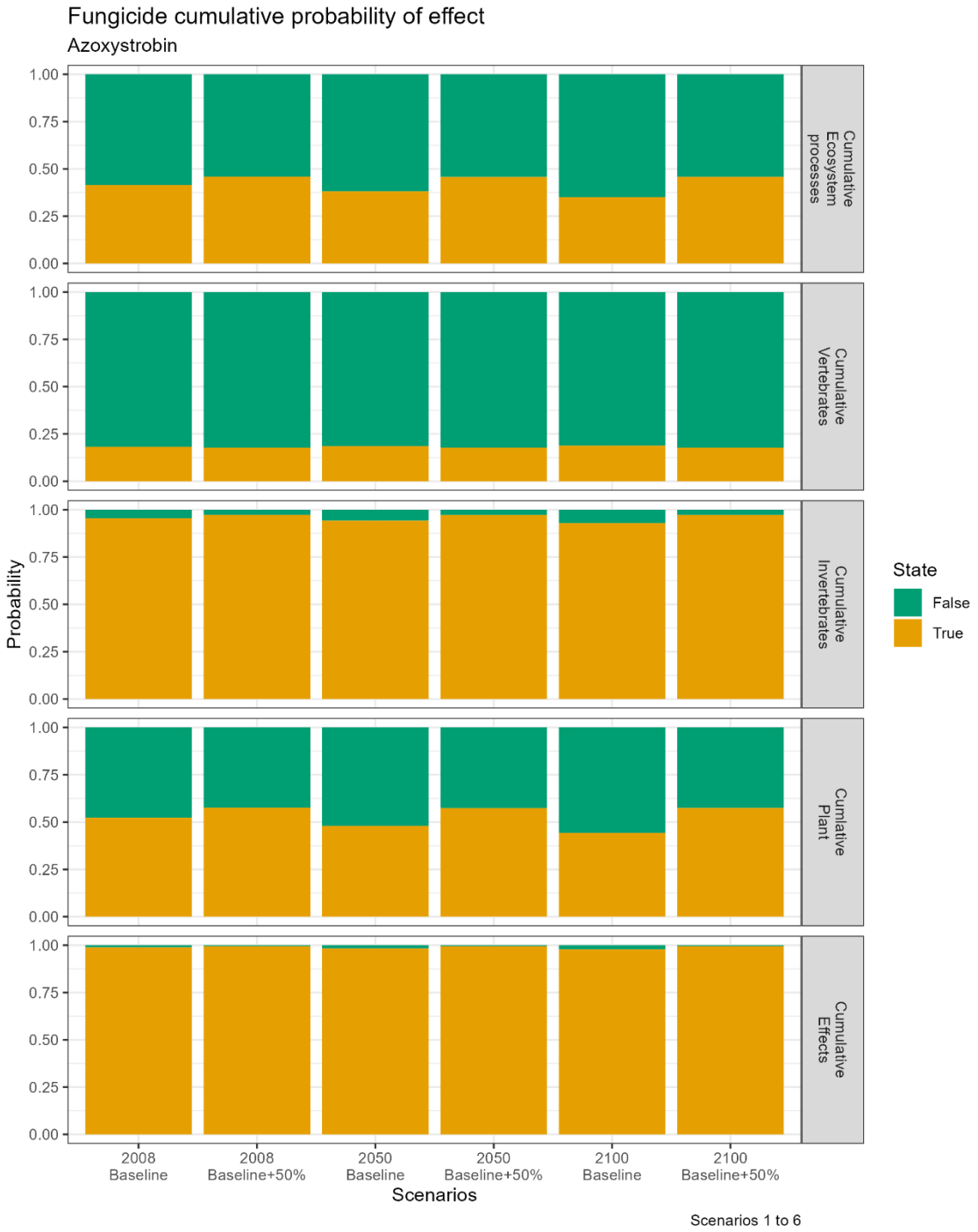

Figure S. 8 Overview of effects on the endpoint groups community level by the selected fungicide (azoxystrobin) for all selected scenarios.

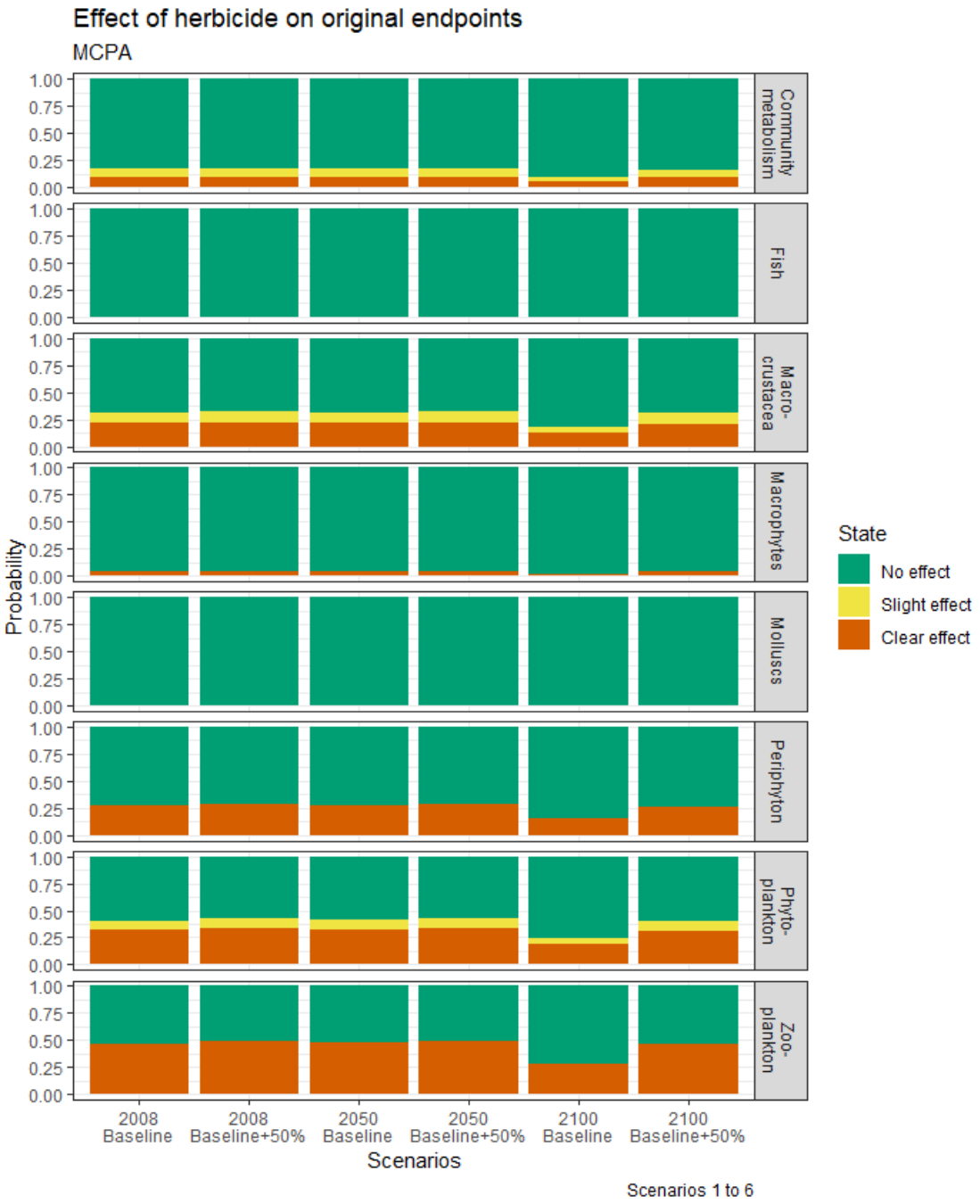

Figure S. 9 Overview of effects on the biological endpoint by the selected herbicide (MCPA) for all selected scenarios.

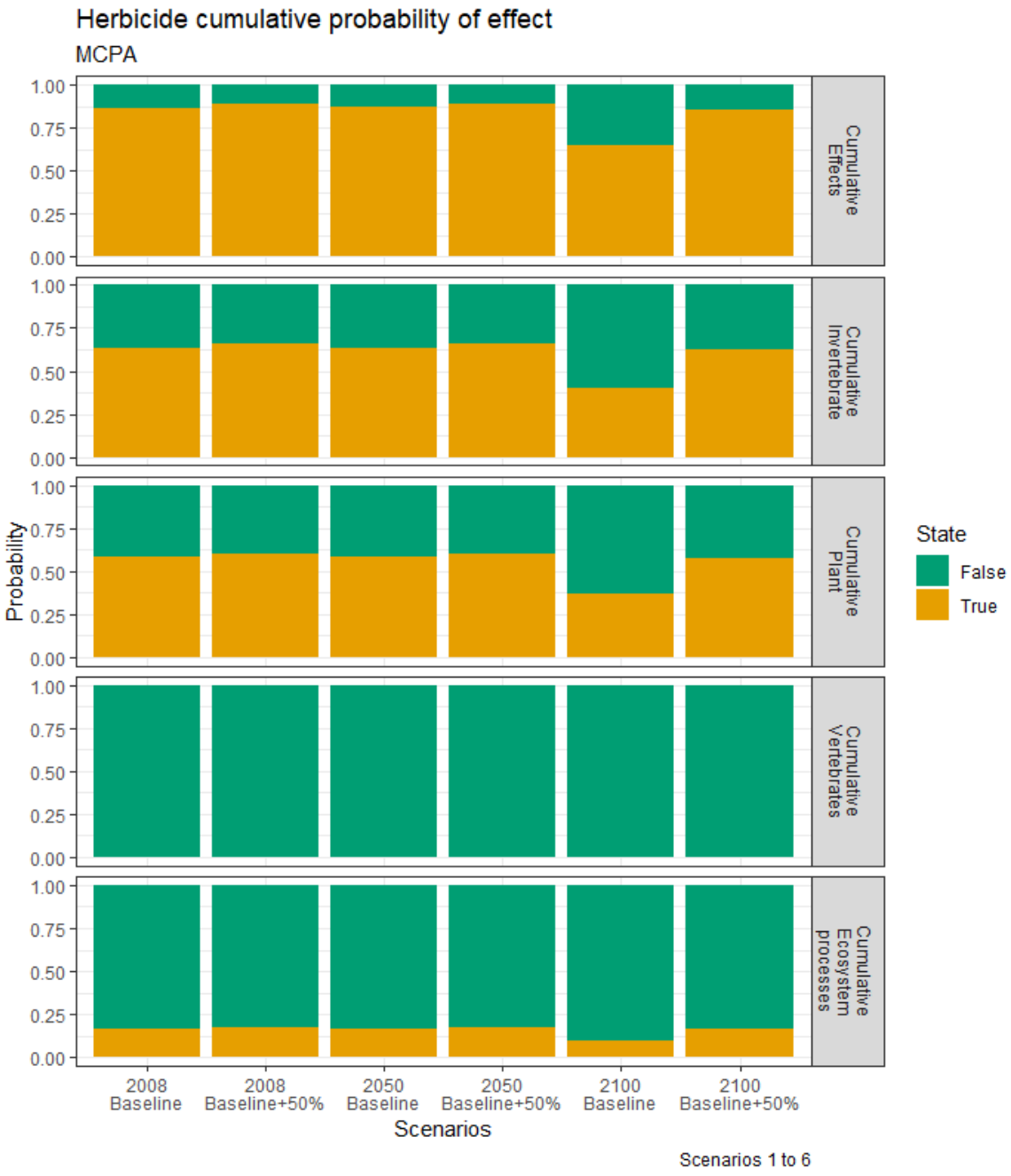

Figure S. 10 Overview of effects on the endpoint groups and community level by the selected herbicide (MCPA) for all selected scenarios.