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Predictive quality of 26 pesticide risk indicators and one flow model: A multisite assessment for water contamination

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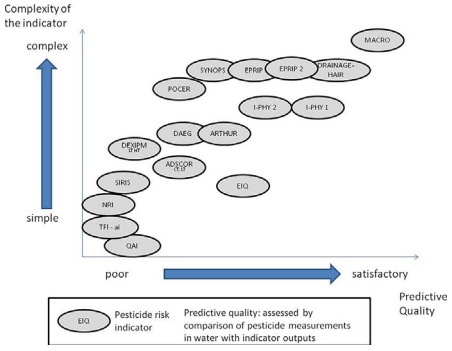
HIGHLIGHTS

- Information on predictive quality of pesticide risk indicators is scarce
- Outputs of 26 indicators and 1 model were compared to pesticide measurements in water
- 3 comparison tests were performed for a dataset of 1040 measurements from 3 sites
- Predictive quality was low to medium for the indicators and acceptable for the model
- The model and indicators with medium predictive quality can be recommended for use

GRAPHICAL ABSTRACT



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ABSTRACT

Stakeholders need operational tools to assess crop protection strategies in regard to environmental impact. The need to assess and report on the impacts of pesticide use on the environment has led to the development of numerous indicators. However, only a few studies have addressed the predictive quality of these indicators. This is mainly due to the limited number of datasets adapted to the comparison of indicator outputs with pesticide measurement. To our knowledge, evaluation of the predictive quality of pesticide indicators in comparison to the quality of water as presented in this article is unprecedented in terms of the number of tested indicators (26 indicators and the MACRO model) and in terms of the size of datasets used (data collected for 4 transfer pathways, 20 active ingredients (a.i.) for a total of 1040 comparison points). Results obtained on a.i. measurements were compared to the indicator outputs, measured by: (i) correlation tests to identify linear relationship, (ii) probability tests comparing measurements with indicator outputs, both classified in 5 classes, and assessing the probability i.e. the percentage of correct estimation and overestimation (iii) by ROC tests estimating the predictive ability against a given threshold. Results showed that the correlation between indicator outputs and the observed transfers are low ($r < 0.58$). Overall, more complex indicators taking into account the soil, the climatic and the

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environmental aspects yielded comparatively better results. The numerical simulation model MACRO showed much better results than those for indicators. These results will be used to help stakeholders to appropriately select their indicators, and will provide them with advice for possible use and limits in the interpretation of indicator outputs.

1. Introduction

Ever since the end of the Second World War, widespread use of pesticides is one factor that has led to an incredible rise and securing of agricultural yields. Nevertheless, side effects on the environment (Richardson 1998) and in particular on water quality (Flury et al., 1995; Real et al., 2005; Grung et al., 2015; Lopez et al., 2015) have been observed. Consequently, regulations have been strongly reinforced, first by the European Water Framework Directive 2000/60/CE followed by various action plans which have come into existence, such as the Pesticide Package 2009/128/CE. In all cases, stakeholders involved in actions to reduce the use and impact of pesticides need operational tools to assess crop protection strategies in regard to environmental impact. The aim of such assessment may be to monitor and to report on the current status of water bodies quality, to produce references for the good management of crop protection and to work on innovative systems (Bockstaller et al., 2015).

The need of assessment tools for the pesticide issues has led to the development of numerous indicators. The simplest ones rely on and take into account the amount of quantities supplied, the Quantity of Active Ingredients (QAI) or the Treatment Frequency Index (TFI) calculating the ratio of applied pesticide to the registered rate. Although those indicators have been developed to describe the evolution of pesticide use intensity, they are often used as main indicators to address the environmental effects due to pesticide spraying in environmental assessment method (Eckert et al., 2000; Vilain et al., 2008). Pesticide risk indicators (Levitan, 2000) addressing complementary variables such as active ingredient properties, crop management data and pedoclimatic variables are more elaborate and were reviewed by several authors (Maud et al., 2001; Reus et al., 2002; Feola et al., 2011; Keichinger et al., 2013). However, these reviews have remained mainly descriptive, without providing thorough assessment of the strengths and weaknesses of the indicators. An important point in such assessment is to deal with the predictive quality of the indicators as recommended by (Bockstaller et al., 2008). Such studies have been conducted to assess the predictive quality of dynamic transfer models but on a relatively small number of active ingredients (Vanclooster et al., 2000). Stenrod et al. (2008) compared 2 indicators (EIQ and NRI) and 1 model (SWAT) to the measurement of pesticide concentration at the outlet of two watersheds. However, only one active ingredient (MCPA) was monitored. In the absence of measured data, outputs of indicators were compared between them (Maud et al., 2001; Reus et al., 2002; Feola et al., 2011), as recommended by Bockstaller and Girardin (2003). The paucity of references is therefore explained by the lack of measure datasets adapted to pesticide measurement in water with the comparison of indicator outputs.

Here we present a study aiming to assess the predictive quality of a set of pesticide risk indicators partly taken from the reviews of Devillers et al. (2005) and Keichinger et al. (2013), both based on international literature. We tried to cover the whole gradient of complexity of existing indicators. To extend this gradient, we added to our study one of the most frequently implemented models, the physically based one dimensional simulation model of vertical water and pesticide flow MACRO (Larsbo et al., 2005). The data set used for the comparison was to our knowledge unprecedented in terms of size and diversity (number of active ingredients (a.i.), pedoclimatic contexts and transfer pathways).

2. Materials and methods

2.1. Measurement of water contamination

Data from 3 different sampling sites were available, namely: La Jaillière, where pesticide transfers by drainage and runoff (mainly by saturation) are monitored since 1994; Le Magneraud where measurements of pesticide transfers by percolation have been performed since 2001; and Geispitzen, where transfers by hortonien runoff were monitored between 2000 and 2012 (Fig. 1). La Jaillière and Le Magneraud sites are managed by the cereals growers' technical institute, Arvalis - Institut du Végétal, while the Geispitzen site was managed in collaboration between Arvalis - Institut du Végétal and a regional association, the Association pour la Relance Agronomique en Alsace (ARAA).

As shown on Fig. 1 and described below, these sites cover different soil and climatic contexts of France and different transfer pathways of pesticide to water bodies (surface water and groundwater). The outcomes are considered over a period of no more than one year after the date of application. For each application of a.i., the monitoring was stopped when the a.i. was not detected for 4 consecutive weeks. The data set is collected on a weekly basis for the Jaillière and the Magneraud sites, and according to the runoff events on the Geispitzen site. During the monitoring period, pesticide measurements were performed by an external certified laboratory that provided detection thresholds evolving from 0.05 μg/L to 0.01 μg/L or 0.02 μg/L depending on the active ingredient (except for the glyphosate and its degradation product AMPA which both have a threshold of 0.1 μg/L). The calculation of the following variables further referred to as "measured variables" was carried out from the pesticide measurements during the monitoring period for each a.i. on each plot:

i) frequency of exceedance of the threshold of the water quality standard of drinking water: 0.1 μg/L (fd1)

$$fd1 = n1_{ijk}/n_{ijk} \quad \text{(Eq.1)}$$

with $n1_{ijk}$: number of measurements with concentration > 0.1 μg/L for active ingredient i on plot j at sampling time k; n_{ijk}: total number of measurements for active ingredient i on plot j and sampling time k

ii) maximum concentration of active ingredient measured in μg/L (cmax)

$$cmax = MAX(c_{ijk}) \quad \text{(Eq.2)}$$

with c_{ijk}: concentration of active ingredient i on plot j and sampling time k

iii) maximum flux measured in mg/ha (fmax)

$$fmax = MAX(f_{ijk}) \quad \text{(Eq.3)}$$

with f_{ijk}: flux of active ingredient i on plot j and sampling time k; $f_{ijk} = c_{ijk} \cdot w_{jk}$ with w_{jk}: water flux (drainage or runoff) from plot j during sampling time k.