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# Helping farmers to reduce herbicide environmental impacts

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ABSTRACT

While pesticides help to effectively control crop pests, their collateral effects often harm the environment. On the French island of Reunion in the Indian Ocean, over 75% of the pesticides used are herbicides and they are regularly detected in water. Agri-environmental models and pesticide risk indicators can be used to predict and to help pesticide users to reduce environmental impacts. However, while the complexity of models often limits their use to the field of research, pesticide risk indicators, which are easier to implement, do not explicitly identify the technical levers that farmers can act upon to limit such transfers on their scale of action (the field). The aim of this article is to contribute to developing a decision support tool to guide farmers in implementing relevant practices regarding the reduction of pesticide transfers. In this article, we propose a methodology based on classification and regression trees. We applied our methodology to a pesticide risk indicator (I-PHY indicator) for identifying the importance of the variables, their interactions and relative weight in contributing to the score of the indicator. We applied our methodology to the assessment of transfer risks linked to the use of 20 herbicides applied to all soils in Reunion and according to different climate, plot management and product application scenarios (4096 scenarios tested). We constructed regression trees which identified, for each herbicide on each soil type, the contribution made by each input variable to the construction of the indicator score. The tree is represented graphically, and this aids exploration and understanding. The 20 herbicides were divided into 3 groups that differed through the main contributing variable to the indicator score. These variables were all technical levers available to farmers to limit transfer risks. These trees then become decision support tools specific to each pesticide user, enabling them to take appropriate decisions with a view to reducing pesticide environmental impacts.



## 1. Introduction

While pesticides help in effectively controlling the main crop pests (including weeds), their collateral effects are often harmful to human health (Pedlowski et al., 2012) and more generally to biodiversity (Pedlowski et al., 2012; Reichenberger et al., 2007). According to the FAO (Food and Agriculture Organization of the United Nations), based on statistics from 58 countries, almost 43% of the pesticide volumes applied worldwide in 2010 were herbicides (FAOSTAT, 2013). On the French island of Reunion in the western Indian Ocean (located at 21°06 S, 55°36 E), the predominance of herbicides is even more marked. In 2011, 75% of the pesticide volumes sold were herbicides (Maillary, 2012). The sustainable development objectives of the island are spearheaded by the *Parc National de la Réunion* (70% of the island's area belongs to the UNESCO World Heritage List) and encompass the reduction of surface water and groundwater contamination. Indeed, in 2010, out of 21 active ingredients found in the waters of Reunion, 17 were herbicides or their degradation products (Badat, 2011). Such contamination can be linked to poor agricultural practices (wrong choice of herbicide, equipment or application conditions, etc.) but also to local pedoclimatic and topographical conditions (Oliver and Kookana, 2006; Davis et al., 2011; Mottes et al., 2013), which can vary substantially in the Tropics. For example, in Reunion, rainfall varies from 600 to 7000 mm year$^{-1}$ and slopes from 0 to 45%. In the circumstances, replacing one herbicide by another and/or appropriate application conditions would help to limit environmental impacts (Reichenberger et al., 2007). Decision–support tools are needed to help farmers identify relevant technical levers to deal with this issue of reducing water contamination by herbicides.

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The degree of herbicide transport in the environment depends on several factors, such as the application rate, herbicide persistence and mobility, rainfall, topography, and climate (Lin et al., 1999). Pesticides in soil are subject to sorption as well as several biological and chemical degradation mechanisms. These involve chemical, microbial, and photodecomposition, which lead to a decrease in pesticide concentrations in the soil. Pesticides may be transported to different parts of the environment by volatilization, runoff erosion, and leaching. Transport by runoff and leaching may cause the contamination of surface water and groundwater. Many models can be used to simulate these different pollution processes (Mottes et al., 2013) but their complexity often limits their use to the field of research and to specific assessment situations (Voltz et al., 2005). Many pesticide environmental risk indicators based on operational models that are easier to implement have been developed for predicting or assessing the environmental risks linked to pesticide use (Bockstaller et al., 2009; Payraudeau and Gregoire, 2012). These pesticide risk indicators can be used to assess these risks, which are often difficult to perceive as a whole (Payraudeau and Gregoire, 2012; Reus et al., 2002). However, as these indicators are less accurate than models, Voltz et al. (2005) recommended using them as a decision–support tool to prioritize risk situations rather than as a tool to predict pesticide flows.

These pesticide risk indicators combine a more or less large number of variables and consider agricultural practices and application conditions to varying degrees (Devilliers et al., 2005). All indicators produce a score to reflect environmental risk or performance; this outcome is generally the only result. Indeed, indicators do not explicitly provide information on the levers for action to be acted upon in order to improve practices. The large number of variables used and their interactions, but also the aggregation methods and the often incomplete sensitivity analyses of these indicators (Devillers et al., 2005), make the search for levers a complex business. This finding contributes to the "black box" image that such tools are often criticized for; this is also why these indicators are rarely decision–support tools for farmers (Reus et al., 2002).

In this article, we propose some solutions for analysing these levers which, to our knowledge, have yet to be explored. We applied our methodology, based on classification and regression trees, to the I-PHY indicator of the assessment method INDIGO (Bockstaller et al., 2009). We tested this indicator and our method to assess the environmental risks associated with the application of 20 herbicide active ingredients used in Reunion. We then discuss our results and our method to identify and prioritize importance variables for this indicator in order to make it a decision–support tool for farmers.

## 2. Materials and methods

### 2.1. I-PHY indicator

The pesticide risk indicator I-PHY was developed in parallel to other environmental indicators for the assessment method INDIGO (Bockstaller et al., 2009). The score of the indicator was published by Van der Werf and Zimmer (1998) and enhanced, adapted and tested for arable farming (Bockstaller et al., 2008). Since then, I-PHY has been adapted to other farming systems such as wine growing, fruit production, field vegetable production, palm trees, etc. In the last 5 years, the I-PHY indicator has been used in more than 100 cases in France by advisers mainly working on the assessment of risks at field/farm level or working on the development of innovative cropping systems (Bockstaller et al., 2008).

Calculation of the indicator is based on four components respectively assessing the risk linked to the amount of active ingredient (a.i.) applied and the risk for groundwater, surface water and air. In a second step, an overall indicator is calculated. Three types of input variables are used (Table 1):

1. Pesticide properties related to environmental fate or to the ecotoxicology effect,
2. Site-specific conditions (e.g. runoff sensitivity),
3. Characteristics of pesticide application (e.g. rate of application).

A fuzzy expert system is used to aggregate all these heterogeneous variables into indicator modules and to subsequently aggregate these modules into a synthetic indicator. By using fuzzy subsets the effect of a knife-edge limit of a given class can be avoided. Output values for each module, as well as for the overall indicator, are expressed on a qualitative scale used in the INDIGO method: between 0 (maximum risk) and 10 (no risk) with a reference value of 7 (maximum acceptable risk).

Fig. 1 shows an example for groundwater risk where the main weight is given to a pesticide property variable (ground water ubiquity score – GUS) (Gustafson, 1989), with less weight given to position (crop interception here) and soil sensitivity to leaching. Aggregation rules are defined according to knowledge about the processes for each module. It should be noted that for surface water (Fig. 2), the sensitivity of the field to runoff and drift plays a major role in comparison with the pesticide property (half-life of a.i. (DT50) variable). This aggregation method enables to cope with cases of compensation between input variables as well as cases of non-compensation (Sadok et al., 2008). For the groundwater surface water and air component of I-PHY, aggregation rules integrate knowledge on the processes. Compensation between variables may occur only when a variable belonging to the 'favourable' class limits pesticide transfer. For instance, this is the case of 'position' variable that indicates that pesticide may be in a position out of reach for leaching or runoff by interception by crop cover or incorporation into soil (see Figs. 1 and 2). For the environment component of I-PHY (Fig. 3), we assumed that low spraying rate compensates a high transfer risk. This is based on some literature data (e.g. Battaglin et al., 2000; De Lafontaine et al., 2014) and pesticide registration data (Tomlin, 2006). Conversely, we do not accept a high level of compensation between the three risk components, groundwater surface water and air. We considered that when one is unfavourable and the rate is high, the situation is unacceptable for stakeholders. This is given by a low score of 2 out 10 for the environment component of I-PHY (Fig. 3), showing a high risk. Finally, in all components of I-PHY, the toxicity or ecotoxicity variable can increase but not decrease the risk. In conclusion, in no case can total compensation occur between input variables.

In order to carry out our study, we constructed some use scenarios for 20 active ingredients for the whole arable area of Reunion. These scenarios were constructed from the known values related to the pesticide properties and the characteristics of the soil (Table 1, variables 1–12) and from values related to the use of the pesticide, considered by the scenarios (Table 1, variables 13–27).

### 2.2. Choice of active ingredients studied and their characteristics

We studied 20 herbicide active ingredients (Table 2). Sixteen active ingredients were herbicides marketed in Reunion between 2009 and 2011, three of which (glyphosate, 2,4-D and S-metolachlor) alone amounted to 80% of herbicide sales (Maillary, 2012). Three other active ingredients (isoxaflutole, thiencarbazone and nicosulfuron), earmarked to eventually replace some active ingredients, were also studied. Lastly, atrazine