Available online at www.sciencedirect.com
ScienceDirect
Europ. J. Agronomy 26 (2007) 71–81
European Journal of Agronomy
www.elsevier.com/locate/eja

Rpest—An indicator linked to a crop model to assess the dynamics of the risk of pesticide water pollution Application to banana-based cropping systems

P. Tixier[a,d,1], E. Malézieux[b,*], M. Dorel[a,2], C. Bockstaller[c,3], P. Girardin[c,3]

[a] CIRAD, UMR SYSTEM, 97130 Capesterre, Guadeloupe, French West Indies, France
[b] CIRAD, UMR SYSTEM, TA80/01, 34398 Montpellier Cedex 5, France
[c] UMR INPL-ENSAIA-INRA Agronomie et Environnement Nancy-Colmar, BP 507, 68021 Colmar Cedex, France
[d] CIRAD, UPR 26, PRAM, BP 214, 97285 Lamentin Cedex, Martinique, French West Indies, France

Received 11 June 2005; received in revised form 17 July 2006; accepted 30 August 2006

Abstract

Like many intensive monocultures, some features of banana-based cropping systems may be detrimental to the environment. Pesticide use is a major cause of surface water and groundwater pollution. The risk of water pollution due to pesticides is very high in the insular areas of the French West Indies (FWI). In order to assess these risks and help design more sustainable cropping systems, we propose using an indicator to assess the risk of pesticide pollution over time (Rpest). Rpest provides dynamic assessments through a linkage with a cropping system model that simulates environmental factors and agricultural practices. An expert validation check was conducted and demonstrated that Rpest can rank cropping systems by risk as well as experts. A sensitivity analysis highlighted that the indicator can take the properties of active ingredients and pedoclimatic data into account in assessments. Rpest helps to pinpoint high pollution risk periods. It can also be used to test alternatives and compare systems. This tool can be integrated into a model-based, global, prototyping methodology used for more sustainable cropping systems.

Keywords: Agri-environmental indicator; Banana cropping system; Pesticide water pollution; Model-indicator linkage; Dynamic evaluation

1. Introduction

Intensive agro-systems are limited by their low ecological, agronomic and socioeconomic sustainability in many tropical regions (St. Lucia: McDonald et al., 1999; Costa Rica: Castillo et al., 2000; Guadeloupe: Bonan and Prime, 2001). Soil erosion and the widespread use of chemical pesticides are the main factors that disrupt the natural environmental balance. There is considerable local, national and international demand for the development of more environment-friendly cropping systems to overcome these problems.

The banana production area in Guadeloupe is characterized by: young andic-type volcanic soils, with substantial infiltration, a saturated hydraulic conductivity of over 60 mm/h (Perret, 1993; Dorel, 2000; Poulenard et al., 2001), low runoff rates (Perret, 1993; Rishirumuhirwa, 1993; Dorel et al., 1996) and a soil organic matter content ranging from 5 to 12%. Tropical plantations that produce bananas for export on the world market are generally intensively-managed and based on monocropping systems with heavy pesticide treatment programmes. In Guadeloupe, the pesticide risk is quite high since the intensive banana plantations are close to inhabited areas and fragile natural environments (primary tropical forests, freshwater resources). Most of these plantations are on the volcanic island of Basse-Terre. The pesticide risk and environmental impact vary according to local pedoclimatic and topographical conditions (rainfall ranges from 1000 to 7000 mm year^{-1}, 0–45° slope, andisol-based toposequences), and the cropping system used. Strategies must now be developed to limit the major environmental impact on rivers, which has already been documented (Bonan and Prime, 2001).

* Corresponding author. Tel.: +33 4 67 61 55 46; fax: +33 4 67 61 55 12.
E-mail addresses: tixier@cirad.fr (P. Tixier), malezieux@cirad.fr (E. Malézieux), dorel@cirad.fr (M. Dorel), bosckstal@colmar.inra.fr (C. Bockstaller), girardin@colmar.inra.fr (P. Girardin).
[1] Tel.: +33 5 90 86 17 59; fax: +33 5 90 86 80 77.
[2] Tel.: +33 5 96 42 30 17; fax: +33 5 96 42 31 00.
[3] Tel.: +33 3 89 22 49 21; fax: +33 3 89 22 49 33.

1161-0301/$ – see front matter
doi:10.1016/j.eja.2006.08.006

New strategies for cropping systems include crop management sequences involving rotations with other crops such as sugarcane and pineapple, fallowing, tailored tillage techniques and, especially, sustainable management of cropping cycles and pest control. A trade-off between socioeconomic, ecological and agro-technical imperatives is required for the development of more sustainable agro-systems (Vereijken, 1997). Tools to evaluate different ecological risks are essential in the prototyping process for new sustainable cropping systems. Crops models are a privileged approach by scientists to meet that need. In the context of the Guadeloupe, some models are still being developed for the specific conditions found in the French West Indies (FWI) on the basis of models developed by Louchart et al. (2001) and Moussa et al. (2001) in vineyard watershed. However, these have not been developed for analysis or cropping system design but for the study of active ingredient (a.i.) transfer in some specific pedoclimatic and geological conditions. As alternative to simulation models, a growing number of authors built methods based on indicators. Different agri-environmental indicator-based assessment methods have been developed as tools to improve diagnosis, cropping system management and the design of new practices (Smith and Mc Donald, 1998; Girardin et al., 1999; Sánchez-Bayo et al., 2002; Van der Werf and Petit, 2002; Lefroy and Rydberg, 2003). These tools can be implemented by various stakeholders (farmers, scientists, agricultural and political coordinators) to assess cropping or production systems at a field or regional level (Payraudeau and Van der Werf, 2005). The simplest indicators are based on a single variable. Whereas, other more complex indicators aggregate several variables that are measured in the field (Vereijken, 1997; Smith et al., 2000), available data on farming systems (Bockstaller et al., 1997) and/or model output (Guipponi, 1998). Regarding the risk linked to pesticide use, several types of indicators were designed. Beside indicators consisting in a simple calculation, like the amount of a.i. or the number of treatments, numerous pesticides risk indicators were developed as reviewed by several authors (Levitan et al., 1995; Van Der Werf, 1996; Maud et al., 2001; Reus et al., 2002; Devillers et al., 2005). Some are expressed in form of scores resulting from the aggregation of variables linked to the fate of the a.i. and toxicologic variables; others are based on a risk ratio approach which compares a predicted concentration in the environment with help of a model and an ecotoxicological concentration.

Most of the reviewed agri-environmental indicators that are currently available are designed to improve the annual assessments of cropping systems, often for only a single cropping cycle. However, with this time scale, it is not possible to determine short-term risks or monitor risk variations over time. These indicators are thus unsuitable for evaluating perennial and semi-perennial cropping systems, such as banana cropping systems, whose features vary over successive cycles (shift from a homogeneous banana stand in the first cropping cycle to an increasingly heterogeneous stand, with plants at different phenological stages in subsequent cycles). Nevertheless, for the development of sustainable cropping systems, it is essential to be able to determine critical periods when the negative environmental impact could be high (Boiffin et al., 2001). The dynamics of the banana crop are such that the characteristics of a plot can change quickly and in various ways over time, i.e. soil cover which varies in relation with plant residues dynamic or soil compaction which changes over crop cycles. Therefore, indicators should be developed to assess short-term risks while taking into account the unique features of banana-based cropping systems.

The aim of our study was to construct a dynamic agri-environmental indicator to facilitate (i) the assessment of risks caused by pesticide leaching or runoff in these specific systems, (ii) the temporal integration of these risks in order to determine long-term changes in the systems. The proposed methodology links risk indicators with a cropping system model called SIMBA, which simulates on the long-term different characteristics of banana stands (e.g. fresh biomass, soil litter, soil compaction, leaf area index, yield) and the environment (e.g. water balance, physical characteristics of the soil) on a field level with a weekly time step. The SIMBA model has been calibrated and validated with respect to conditions in Guadeloupe (Tixier, 2004; Tixier et al., 2004a,b, 2006).

2. Material and methods

Integrated agri-environmental indicators usually consist of an aggregation of several variables. They are used to assess the impact of complex phenomena that are impossible to measure directly. These indicators are put together using the following steps (Girardin et al., 2000):

- Identification of objectives and users.
- Aggregation of information.
- Choice of thresholds
- Indicator sensitivity tests.
- Validations of the indicator.

We put together our indicator Rpest by following these four steps, taking into account the limitations of banana-based cropping systems, the dynamic aspects and long-term objectives.

2.1. Objectives and users

Our aim was to assess and compare the risks of water pollution due to pesticides in different banana-based cropping systems over time in the conditions that prevail in the FWI. The assessment was conducted at a field level because farmers generally apply their tactical and strategic options at this level. The dynamic indicator Rpest was designed to help agronomists and extension services in the development of less pollutant and more sustainable cropping systems.

The environmental categories considered were surface water and groundwater. These resources are crucial for human life and particularly sensitive to pesticide pollution. Surface water and groundwater quality is affected by the influx of a.i. carried by runoff, leaching, and drift, respectively. Soil, climate conditions and cropping practices that modify these flows have a considerable influence on the risk of environmental pollution due to pesticide a.i. and thus has to be taken into account to assess the risks accurately.

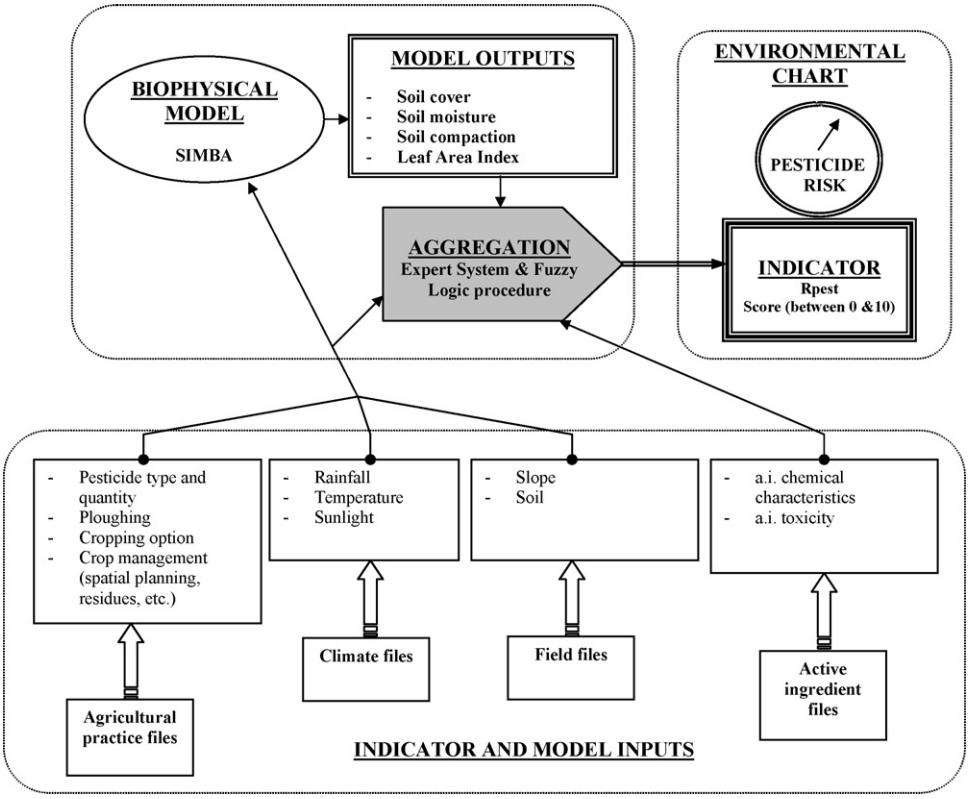

Fig. 1. General structure of the dynamic Rpest indicator. a.i. for active ingredient.

2.2. Aggregation of information

The general structure of the dynamic Rpest indicator is shown in Fig. 1. It highlights the architecture of the interactions between input data (which describe farming practices, climate, field characteristics and the a.i. used), the calculation processes and the final indicator. These input data are used directly to calculate the indicators, or used in the biophysical model to calculate variables relating to the intermediate environmental status, e.g. quantities of runoff and drained water. Rpest produces weekly risk scores at the same time step as the SIMBA model. It is compatible with on-farm measurements.

The Rpest construction process involved four steps:

- Assessment of the risk of exposure (surface and groundwater) for each a.i.
- Assessment of the toxicity of each a.i.
- Combining the exposure and toxicity to calculate a risk score for each a.i.
- Combining the risk scores for all a.i. to make a global score corresponding to the risk of the overall pesticide treatment programme.

The first two steps (assessment of exposure and toxicity risks) were conducted for groundwater and surface water. A sub-indicator of pollution risk was calculated for each category (Rsurf and Rgrnd). These two sub-indicators were then aggregated to give the global indicator (Rpest) of the overall risk of pesticide induced water pollution (Fig. 2.). The score attributed to risk varies between 0 and 10, which corresponds to no risk and maximum risk, respectively. Table 1 presents the input data and variables for the modules or sub-indicators presented.

The aggregation procedure used is similar to the methods used for agri-environmental indicators involving expert systems and fuzzy logic (Freissinet et al., 1998; Phillis and Andriantiatsaholiniainan, 2001). The concept behind the procedure has been described by Silvert (2000) and Cornelissen et al. (2001) and applied by Van der Werf and Zimmer (1998) and Pervanchon et al. (2005) in a simplified way. An expert system and fuzzy logic procedure (ESFL) can be used to aggregate different types of variables using expert scientific knowledge. It is suitable for the assessment of complex situations that cannot be handled with conventional mathematical tools (means, sums, simple weighting, and complex models). The ESFL aggregation procedure used is the one presented by Van der Werf and Zimmer (1998). This procedure can be summarized in four steps:

- Identification of representative variables.
- Definition of their favourable, unfavourable and fuzzy range.
- Definition of the weight of each variable in the expert system.
- Final calculation of the indicator score.

In the case of Rpest, the application of this procedure leads to the calculation of risk scores for each sub-indicator at each week step.

The shape of fuzzy class curves and fuzzy intervals was chosen in accordance with the knowledge: sigmoid or straight lines when the phenomena are known to follow a threshold

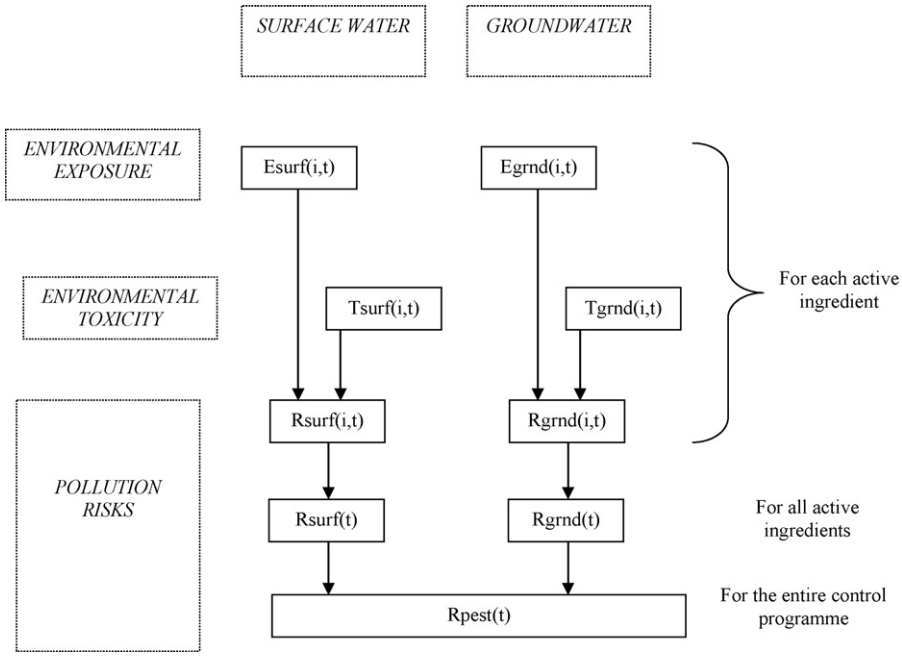

Fig. 2. Flowchart for the indicator for '*i*' active ingredients of a pest control programme at each time step '*t*' in the indicator calculation. All variables are defined in Table 1.

or a linear regression, respectively. The fuzzy class ranges for S(*i*, *t*), GUS(*i*), DRA(*t*) and RUI(*t*) are given in Table 1. The parameters of the expert system decision rules used in the EFLS procedure are presented in Table 2 and in Fig. 3 that present an example of decision rules used to calculate the Esurf(*i*, *t*) sub-indicator. The 'variable rank' and 'score weight' indicate the position of the variable in the expert system and its relative weighting in the calculation of the sub-indicator score,

Table 1
List of variables used in the Esurf(*i*, *t*), Egrnd(*i*, *t*), Tsurf(*i*, *t*), Tgrnd(*i*, *t*), Rsurf(*t*), Rgrnd(*t*) and Rpest(*t*) indicators for each a.i.

Variable (unit)	Origin	Fuzzy class range	Fuzzy class curve
Data and variables associated with the risk of surface water exposure to the a.i. '*i*' (Esurf(*i*, *t*))			
S(*i*, *t*) weekly quantity of potentially entrained a.i. '*i*' at step '*t*' (kg ha^{-1})	Calculation	0–1	Sigmoid
RUI(*t*) runoff at step '*t*' (m^3 ha^{-1} week^{-1})	SIMBA model	0–30	Straight line
Data and variables associated with the risk of groundwater exposure to the a.i. '*i*' (Egrnd(*i*, *t*))			
S(*i*, *t*) weekly quantity of potentially entrained a.i. '*i*' at step '*t*' (kg ha^{-1})	Calculation	0–1	Sigmoid
GUS(*i*) Groundwater ubiquity score	a.i. property	1.8–2.8	Sigmoid
DRA(*t*) drained water at step '*t*' (m^3 ha^{-1} week^{-1})	SIMBA model	0–100	Straight line
Data associated with the toxicity of the a.i. '*i*' in surface water (Tsurf(*i*, *t*))			
DT50(i) half-life (days)	a.i. property	1–30	Sigmoid
Aquatox(*i*) toxicity to aquatic fauna and flora (mg l^{-1})	a.i. property	0–1	Sigmoid
ADI(*i*) acceptable daily intake for human health (mg kg^{-1})	a.i. property	0–1	Sigmoid
Data associated with the toxicity of the a.i. '*i*' in groundwater (Tgrnd(*i*, *t*))			
DT50(i) half-life (days)	a.i. property	0–30	Sigmoid
ADI(*i*) acceptable daily intake for human health (mg kg^{-1})	a.i. property	0–1	Sigmoid
Variables associated with the risk of surface water pollution by the a.i. '*i*' (Rsurf(*i*, *t*))			
Esurf(*i*, *t*) risk of surface water exposure to the a.i. '*i*' at step '*t*' (score/10)	Sub-indicator	0–10	Sigmoid
Tsurf(*i*, *t*) toxicity of the a.i. '*i*' in surface water at step '*t*' (score/10)	Sub-indicator	0–10	Sigmoid
Variables associated with the risk of groundwater pollution by a.i. '*i*' (Rgrnd(*i*, *t*))			
Egrnd(*i*, *t*) risk of groundwater exposure to the a.i. '*i*' at step '*t*' (score/10)	Sub-indicator	0–10	Sigmoid
Tgrnd(*i*, *t*) toxicity of the a.i. '*i*' in groundwater at step '*t*' (score/10)	Sub-indicator	0–10	Sigmoid
Variables associated with the overall risk of pesticide water pollution (Rpest(*t*))			
Rsurf(*t*) risk of surface water pollution by a.i. '*i*' at step '*t*' (score/10)	Sub-indicator	0–10	Sigmoid
Rgrnd(*t*) risk of groundwater pollution by a.i. '*i*' at step '*t*' (score/10)	Sub-indicator	0–10	Sigmoid

a.i.: active ingredient; *t*: indicator step.

Table 2
Parameters of the expert system rules used to calculate sub-indicators

Variable	Variable rank	Score weight (range 10)
Surface water exposure to a.i. "*i*" (Esurf)		
S(*i*, *t*)	1	6
RUI(*t*)	2	4
Groundwater exposure to the a.i. "*i*" (Egrnd)		
S(*i*, *t*)	1[a]	3
GUS(*i*)	2	4
DRA(*t*)	3	3
Toxicity of the a.i. "*i*" in surface water (Tsurf)		
MIN (Aquatox(*i*); ADI(*i*))	1	6
DT50(*i*)	2	4
Toxicity of the a.i. "*i*" in groundwater (Tgrnd)		
ADI(*i*)	1	6
DT50(*i*)	2	4
Risk of surface water pollution by a.i. "*i*" (Rsurf(*i*, *t*))		
Esurf(*i*, *t*)	1[a]	5
Tsurf(*i*, *t*)	2	5
Risk of groundwater pollution by the a.i. "*i*"(Rgrnd(*i*, *t*))		
Egrnd(*i*, *t*)	1[a]	5
Tgrnd(*i*, *t*)	2	5

The variable rank is the order in which variables are used in the expert system decision rule. The score weight is the weight of the variable in the final score of the expert system decision rule. Variable descriptions and units are presented in Table 1 a.i.: active ingredient.

[a] If the variable has a favourable value, lower rank variables are not taken into account.

respectively. Fuzzy class ranges and fuzzy class curves of GUS(*i*), DT50(*i*), Aquatox(*i*) and ADI(*i*) have been adapted from the Iphy indicator (Girardin et al., 2000). Fuzzy class ranges and fuzzy class curves of DRA(*t*), RUI(*t*), and S(*i*, *t*) variables have been calibrated according to the expert knowledge. Fuzzy class ranges and fuzzy class curves of Esurf(*i*, *t*), Egrnd(*i*, *t*), Tsurf(*i*, *t*), Tgrnd(*i*, *t*), Rsurf(*t*), and Rgrnd(*t*) sub-indicators have been calibrated by accounting the whole variation range of the score (0–10).

2.3. Calculation of the Rpest indicator

2.3.1. Assessment of the risk of exposure to each active ingredient

Pesticide exposure risk assessments are based on estimated quantities of a.i. that could be caused by leaching or runoff. The a.i. stock S(*t*) varies at each time step according to a.i. inputs APP(*t*) and the potential degradation DEG(*t*) (Eq. (1))

$$S(t) = S(t-1) + \mathrm{APP}(t) - \mathrm{DEG}(t) \tag{1}$$

The potential degradation of an a.i. at time step *t* DEG(*t*) is presented in Eq. (2). It is based on the half-life of a.i. '*i*' DT50(*i*). Residual $\mathrm{deg}_{i,\mathrm{WSP}(i,t)}$ and degraded $\mathrm{DEG}_{i,\mathrm{WSP}(i,t)}$ quantities of an a.i. '*i*' are calculated in Eqs. (2′) and (2″) according to the number of weeks since the application of the a.i. '*i*' $\mathrm{WSP}_{(i,t)}$ and the quantities of a.i. '*i*' for the previous application $\mathrm{Last\_APP}_{(i,t)}$

$$\begin{cases} \text{If} & \mathrm{APP}(i,t) = 0 \\ \text{Then} & \mathrm{Last\_APP}(i,t) = \mathrm{Last\_APP}(i,t-1) \\ \text{Else} & \mathrm{Last\_APP}(i,t) = \mathrm{APP}(i,t) \end{cases} \tag{2}$$

$$\mathrm{deg}_{(i,\mathrm{WSP}(i,t)} = (\mathrm{Last\_APP}_{(i,t-1)}/((\mathrm{DT50}(i)/(\mathrm{WSP}_{(i,t)})) + 1)) \tag{2′}$$

$$\mathrm{DEG}_{(i,t)} = \mathrm{deg}_{(i,t)} - \mathrm{deg}_{(i,t-1)} \tag{2″}$$

S(*t*), APP(*t*), $\mathrm{Last\_APP}_{(i,t)}$, DEG(*t*), and $\mathrm{deg}_{(i,t)}$ are expressed in kg of a.i. per hectare.

This type of time-course pattern for soil borne a.i. concentrations has been widely described under different pedoclimatic conditions (Zheng and Cooper, 1996; Guibaud et al., 1999), and it is currently being confirmed in the andisols that are prevalent in Guadeloupe (Cattan, personal communication).

Estimating the potential a.i. stock on the basis of the half-life is simple in comparison to more complex models that take pesticide fixation on soil organic matter into account. This type of model has not yet been developed for the soils and cropping systems assessed here. Degradation is likely to have been

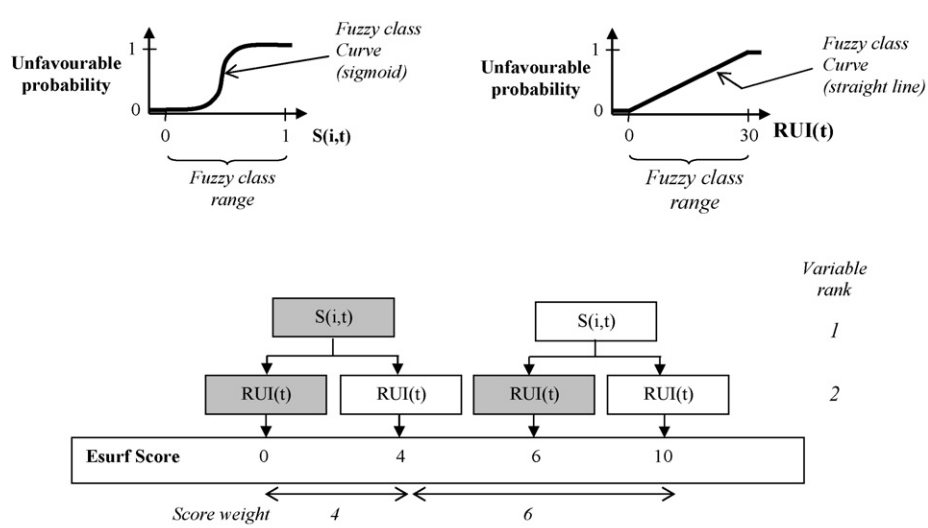

Fig. 3. Example of decision rules for the sub-indicator Surface water exposure to a.i. "*i*" (Esurf) for illustration of data given in Tables 1 and 2.

underestimated by the half-life method considering the rapid degradation of the different compounds studied (organophosphates and carbamates) in soils (Jamet and Piedallu, 1980; Simon-Sylvestre and Fournier, 1980; Zheng and Cooper, 1996; Matthiessen, 2001). However, the advantage of the proposed method is that it can pinpoint potential risk periods, even though they are likely to be overestimated. In addition, a broad range of a.i. can be compared.

The risk of surface water Esurf(i, t) and groundwater Egrnd(i, t) contamination by each a.i. 'i' is evaluated at each time step 't' by integrating:

- The potentially movable stock S(i, t) of each a.i. 'i' (for groundwater and surface water).
- The groundwater ubiquity score of each a.i. 'i' GUS(i) for groundwater (Gustafson, 1989) which is a simple method for assessing the pesticide leachability. GUS(i) of the a.i. 'i' is calculated with the half-life DT50(i) and the soil organic carbon sorption coefficient (in ml g^{-1}) Koc(i).
- The runoff RUI(t) and drained DRA(t) water volume at time step t, variables calculated by the SIMBA model. SIMBA simulates the water dynamics with soil water content, plant transpiration (in relation with leaf area index), runoff (in relation with soil cover and soil compaction), and the drained water, which is the last term of the water balance.

For each variable, a fuzzy class curve is defined in the fuzzy class range between favourable and unfavourable ranges. S(i, t) is considered to be highly unfavourable when the treatment dose is 1 kg ha^{-1}, which corresponds to the maximum quantity of a.i. applied per hectare in banana cropping systems. S(i, t) is considered to be favourable in the absence of the a.i. (0 kg ha^{-1}). A fuzzy class, defined by a sigmoid response, occurs in the interval between these two values. GUS is considered favourable when it is below 1.8 and unfavourable when above 2.8 (Van der Werf and Zimmer, 1998). RUI(t) and DRA(t) are considered to be unfavourable at 30 and 100 m^3 ha^{-1} $week^{-1}$, respectively. This occurs when there are very heavy rain storms in the study area and when conditions are conducive to runoff or drainage. They are considered to be favourable when there is no runoff or drainage (0 m^3 ha^{-1} $week^{-1}$). A fuzzy class defined by a linear response occurs in the interval between these two values.

2.3.2. Assessment of the toxicity of each active ingredient

The toxicity of each a.i. in surface water and groundwater is evaluated with the sub-indicators Tsurf(i, t) and Tgrnd(i, t), which are dependent on the intrinsic properties of the a.i. These variables are aggregated by the EFLS method according to the expert system decision rule parameters presented in Table 2. For an a.i., the variables ADI and Aquatox represent the acceptable daily intake for human health (in mg kg^{-1}) and the toxicity to aquatic fauna and flora (in mg l^{-1}), respectively. The minimum ADI and Aquatox levels are taken into consideration for surface water because it is also a source of drinking water. Only the toxicity to humans (ADI) is considered for groundwater. These variables were also selected by Roussel et al. (2000) to adapt the Ipest indicator of Van der Werf and Zimmer (1998) to a region where surface water is used for drinking. However they were aggregated with the half-life DT50(i). This variable is used to assess the persistence of the pollutant in the environment. The assumption is made that there is a correlation between the soil persistence and the persistence in water.

2.3.3. Global score calculation per active ingredient

Exposure scores for each environmental category and the toxicity of each a.i. in surface water Rsurf(i, t) and groundwater Rgrnd(i, t) are integrated by aggregating the toxicity exposure risk scores associated with each environmental category and for each a.i., using the EFLS method according to the expert system decision rule parameters presented in Tables 1 and 2.

The global score (for the set of "n" a.i.) for the risk of pesticide contamination of surface water Rsurf(t) and groundwater Rgrnd(t) is the score calculated for the a.i. that shows the highest risk (Eqs. (3) and (3′))

$$\mathrm{Rsurf}(t) = \mathrm{MAX}_{(i=1;i=n)}\mathrm{Rsurf}(i, t) \quad (3)$$

$$\mathrm{Rgrnd}(t) = \mathrm{MAX}_{(i=1;i=n)}\mathrm{Rgrnd}(i, t) \quad (3')$$

$$\mathrm{Rpest}(t) = \mathrm{MAX}(\mathrm{Rgrnd}(t); \mathrm{Rsurf}(t)) \quad (3'')$$

A global pesticide pollution risk score (Rpest) is calculated on the basis of the maximum Rsurf(t) and Rgrnd(t) values. A mean Rpest score can then be calculated to obtain a general score for the entire period for the cropping system under investigation.

2.4. Indicator evaluation procedures

2.4.1. Sensitivity test

A sensitivity analysis was carried out to test the performance of the indicators with different input variables or parameters. The analysis differed when fixed variables (slope, a.i. properties) and dynamic variables (rainfall, soil coverage) were considered. For the dynamic variables, the same cropping system was assessed under different conditions in which the variable being tested varies (e.g. rainfall in lowland and highland areas).

2.4.2. Expert validation

Indicators are used to assess complex processes that often do not have quantitative equivalents (Bockstaller and Girardin, 2003). They can be used to compare different states of one system or different systems. Dynamic indicators must be able to highlight temporal variations in real impacts and to rank cropping systems accurately, according to intrinsic pollution risks. According to Bockstaller and Girardin (2003), output of the indicator can be confronted to measured data when they are available, but also submitted to expert evaluation because of lack of measurements under banana cropping systems, we decided to ask experts to validate Rpest. Each expert ranked five cropping systems (in their pedoclimatic context). We calculated the mean expert rank and used it to rank the five tested cases again (the final expert rank ranged from 1 to 5). To test the accuracy of Rpest for ranking cropping systems according to pollution risk, we compared the final expert ranks with the Rpest ranks using a Spearman rank correlation.

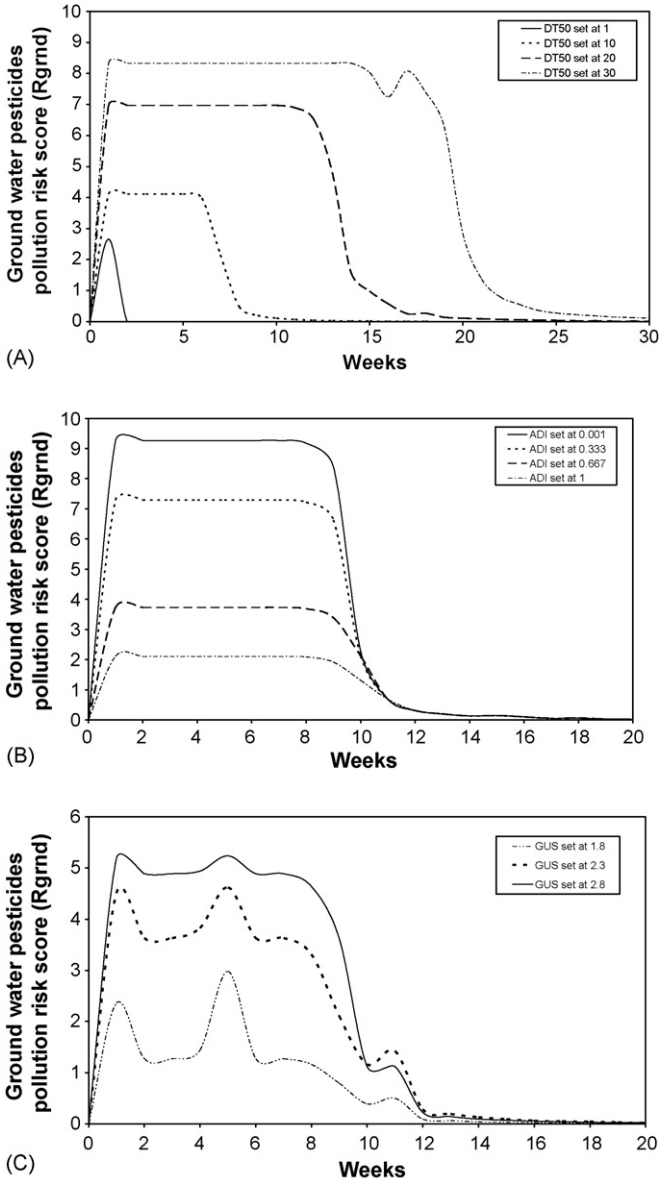

Fig. 4. Analysis of the sensitivity of the pesticide groundwater pollution risk indicator (Rgrnd) to variations of (A) DT50 (with ADI set at 0.5 and GUS set at 2); (B) ADI (with Aquatox set at 0, DT50 set at 15 and GUS set at 2); and (C) GUS (with ADI set at 0.5 and DT50 set at 15), under monoculture conditions with a pesticide treatment in week 1. For a given active ingredient, ADI is the acceptable daily intake for human health (in mg kg^{-1}), DT50 is the half-life, GUS is the pesticide leachability, and Aquatox is the toxicity to aquatic fauna and flora (in mg l^{-1}).

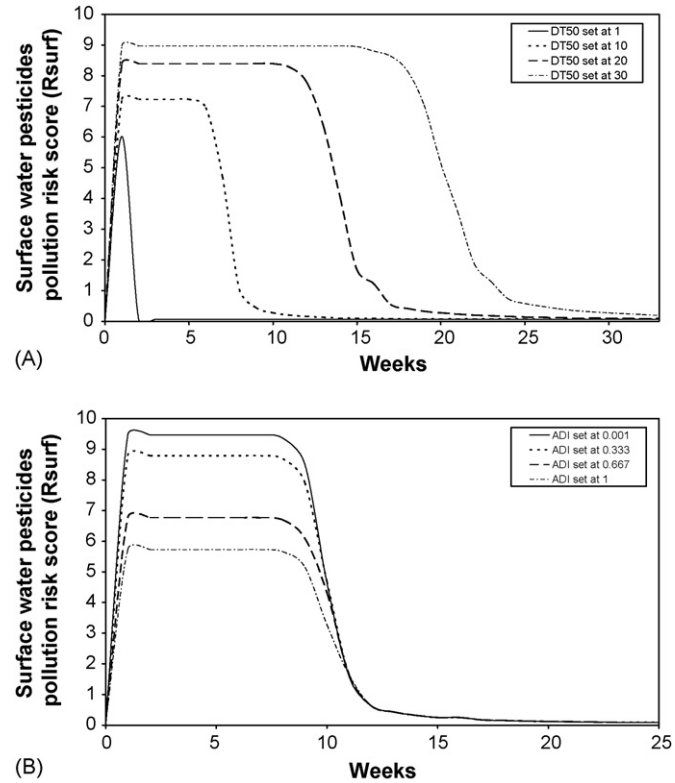

Fig. 5. Analysis of the sensitivity of the pesticide surface water pollution risk indicator (Rsurf) to variations of (A) DT50 (with ADI set at 0.5 and GUS set at 2) and (B) ADI (with Aquatox set at 0, DT50 set at 15 and GUS set at 2), under monoculture conditions with a pesticide treatment in week 1. For a given active ingredient, ADI is the acceptable daily intake for human health (in mg kg^{-1}), DT50 is the half-life, GUS is the pesticide leachability, and Aquatox is the toxicity to aquatic fauna and flora (in mg l^{-1}).

3. Results

3.1. Sensitivity test results

Fig. 4 presents the three score patterns showing the sensitivity of the indicator Rgrnd to the variation of half-life (DT50(i)), ADI(i) and GUS(i) with fixed values of non-tested variables in a banana monoculture cropping system. Fig. 5 presents the two score patterns showing the sensitivity of the indicator Rsurf to the variation of half-life (DT50(i)) and ADI(i) with fixed values of non-tested variables for the same monoculture cropping system. The results of these analyses revealed that the Rgrnd and Rsurf indicators are able to distinguish between cropping systems when a.i. with different properties are applied.

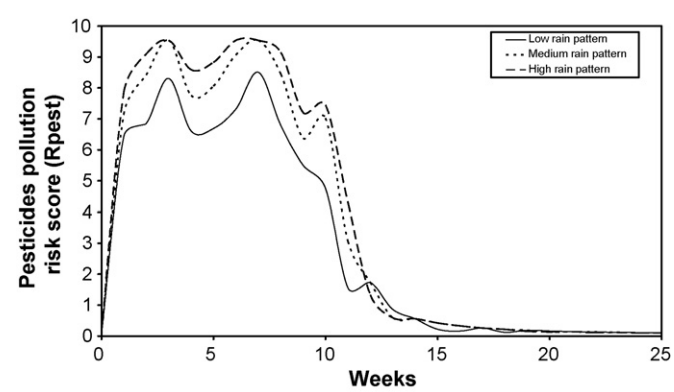

Fig. 6. Analysis of the sensitivity of global pesticide pollution risk indicators (Rpest) to rainfall variations (low, medium and high rainfall patterns with a total over the 25 weeks of 709, 1418 and 2836 mm, respectively in the same number of precipitations), under monoculture conditions with a pesticide treatment in week 1.

Fig. 6 shows variations in the Rpest indicator for the same frequently replanted banana monoculture system under three different climatic conditions: low, medium and high rainfall (same number and periods of rainfall but different total quantity of rain). Rpest accurately accounted for the amount of rainfall. The test variable (rainfall) was one of the variables, which induced temporal variations in the final indicator score. This is a key factor with respect to pesticide runoff and leaching. This sensitivity analysis revealed that Rpest can efficiently assess the pesticide pollution risk for cropping systems under different pedoclimatic conditions. The information that it provides could be useful for tailoring cropping systems to local pedoclimatic conditions.

3.2. Expert validation

Fig. 7 presents the results of the assessment of five cropping systems: Rpest ranks, the mean expert ranks (with their variation ranges), and the final expert ranks for the four experts. The latter were chosen for their expertise in environmental issues relating to banana production in Guadeloupe and pesticide contamination. A Spearman rank correlation coefficient was calculated between expert and Rpest ranks for each cropping system, i.e. 20 pairs (4 experts and 5 cropping systems). The Spearman rank correlation coefficient obtained was: $r_s = 0.9865$ ($n = 20$; degrees of freedom = 18; $t = 25.52$), so the Rpest ranking was not rejected at the 0.001 threshold. The cropping system rankings obtained with Rpest were always within the same variation range as the expert rankings. The final expert rankings obtained on the basis of the mean expert ranks was the same as that obtained with Rpest.

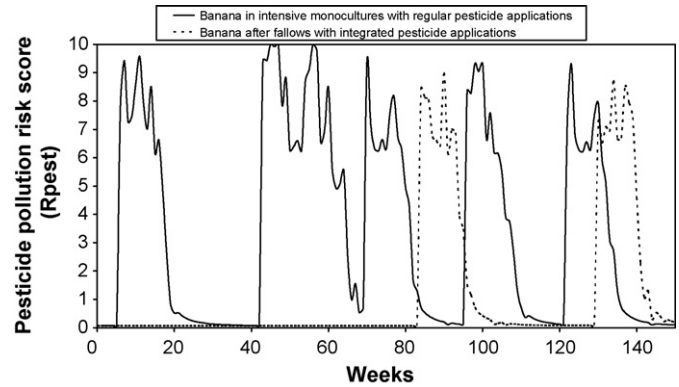

Fig. 8. Rpest scores over 150 weeks for an intensive banana monoculture and for a banana-fallow rotation cropping system; Rpest mean scores are 3.6 and 1.2, respectively.

3.3. Comparative assessment of two cropping systems using the Rpest indicator

An environmental assessment of two different cropping systems was conducted using the Rpest indicator in the same soil and climate environment (medium elevation, slope and rainfall). The first system was a frequently replanted (every 2–3 years) intensive banana monoculture system with high chemical pesticide use. The second was a rotation system where banana was planted after a fallow period using an integrated pest management strategy, whereby pesticides were only applied when nematode populations reached a level that could be detrimental to the crop. The pesticides used were nematicides (alternate

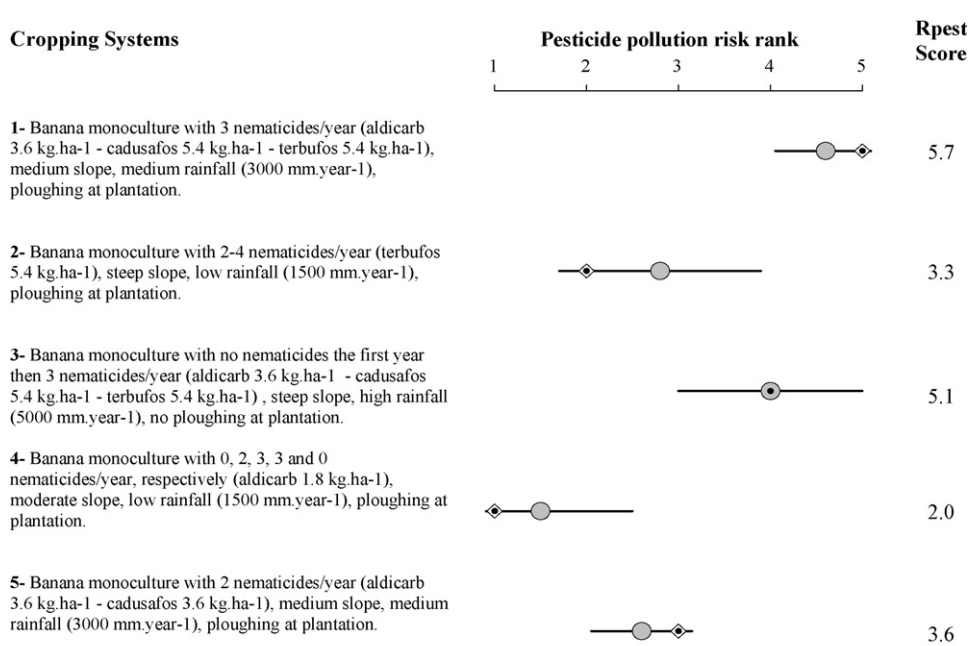

Fig. 7. Pesticide pollution risk rank for five cropping systems assessed by Rpest (◊) and by four experts; (●) final expert ranks and (-○-) mean expert rank with variation range. Pesticide quantities mentioned correspond to the a.i. input APP(i, t) the day of the application. Moderate, medium and steep slopes correspond to 3°, 15° and 30°, respectively.

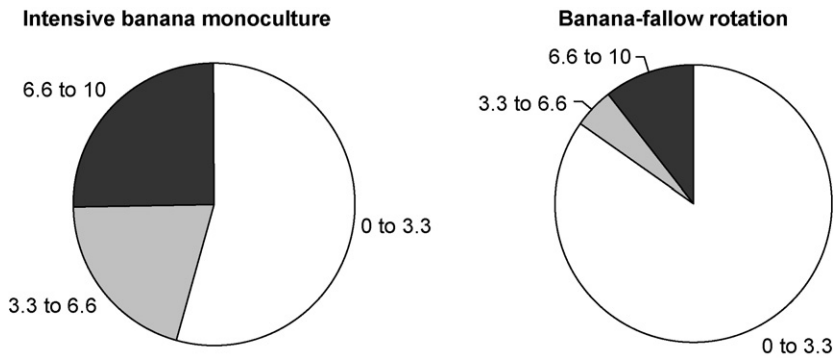

Fig. 9. Rpest percentage scores in three classes (0–3.3, 3.3–6.6 and 6.6–10) for an intensive banana monoculture and for a banana-fallow rotation.

applications of cadusafos and terbufos with APP(i, t) = 5.4 kg of a.i. per treatment).

Fig. 8 shows time-course variations in the Rpest indicator for these two systems after the banana crop was planted. This indicator highlights the risk periods. In the managed system, a period without treatment had a substantial influence on the mean indicator score over the 150-week assessment period (3.6 and 1.2 for the intensive and managed systems, respectively).

A risk profile was then drawn up for each system (Fig. 9). These profiles corresponded to the Rpest indicator score distribution (over the entire assessment period) in three score classes (0–3.3, 3.3–6.6 and 6.6–10). Contrary to the mean scores, a score distribution is an effective way of integrating data and data dynamics. Such risk profiles are useful for comparing different cropping systems. They can be considered as the environmental signature of specific cropping systems under given soil and climate conditions. Risk profiles take into account the persistence of the applied pesticides and the importance of high-risk periods. The risks can be transient or long-term, depending on the environment and type of a.i., which means the environmental impacts can differ. Thus, the risk profile can be a useful way of presenting the output for both researchers and policy makers.

4. Discussion and conclusion

In comparison to most of pesticide indicator developed until now (Levitan et al., 1995; Van Der Werf, 1996; Maud et al., 2001; Reus et al., 2002; Devillers et al., 2005), Rpest provides dynamic information on risk. Dynamic indicators are effective for evaluating time-course variations in the impact that cropping systems have on surface and ground water. Indicators are a real improvement on available tools for designing and developing more environment-friendly cropping systems. They can be used to compare the potential outcome of different strategies, such as weed control using herbicides or mechanical weeding machines, which could help stakeholders, make tactical decisions. Different types of variables can be integrated into the indicators because they are based on the modelling of biophysical cropping systems and on an “expert system” approach.

The method proposed for the environmental assessment of cropping systems is an efficient new tool to help scientists and agronomists design sustainable cropping systems. The indicators constructed provide continuous information on variations in cropping systems, thus facilitating the detection of transient risk factors and the testing of alternatives. Fig. 10 shows a potential framework for using dynamic indicators to help develop innovative cropping systems.

Combining a cropping system simulation model with environmental risk assessment tools (e.g. indicators) is an innovative methodological approach. Previous authors have proposed using indicators to assess the input variables in crop function models (Meynard et al., 2002). However, we used model outputs to

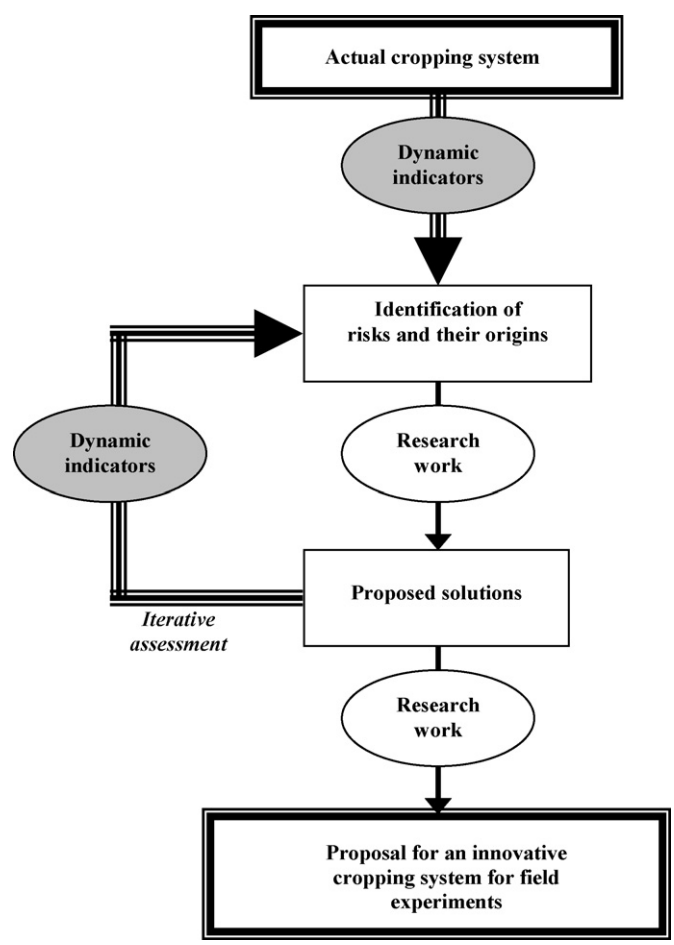

Fig. 10. Proposal for using a dynamic indicator to prototype more sustainable cropping systems.

calculate indicators that are specific to issues that cannot be simulated or are problematic (e.g. pesticides) or for which modelling would generate non-applicable tools. Some authors (Belcher et al., 2004) have already used this approach for yearly results (e.g. organic matter content in soil). However, they have not used it in a dynamic way. Modelling is, therefore, not "the only or even major tool", but rather just one strategy to facilitate the development of more sustainable cropping systems (Van Ittersum and Donatelli, 2003).

Actually Rpest is used as a research tool for the evaluation and for the conception of innovative cropping systems. The dynamical aspect of Rpest's outputs maybe useful for stakeholders and policy makers to understand the complexity of the pollution risk phenomena. It also should be taken into account in their recommendations and incentive actions. The different levels of integration of Rpest outputs (dynamic, risk profile and mean score) correspond to different needs of farmer and policy makers to choose practices with low environmental impact. Rpest will be particularly helpful when it will be used linked to the SIMBA cropping system simulation framework; providing additional information on the simulated systems (agronomic performances, economic results).

This indicator is limited by current knowledge of a.i. transport. However, the problem should soon be overcome with the development of knowledge in this field. This leads us to a major weakness of Rpest, which is related to the fact that the outputs are qualitative and not quantitative. Therefore, accurate guidelines cannot be drawn up to help stakeholders achieve goals with respect to authorised pesticide concentrations in runoff or drainage water. Rpest was designed to compare the risks of different cropping systems but not to simulate a.i. concentrations in water.

Lack of knowledge on cumulative effects of association of a.i. also explains that Rpest does not allow evaluation of mixture toxicity. This limit is found in most pesticide indicator as in the reviews quoted at the beginning of this section. Like in many pesticide indicators, the use of Aquatox and ADI to evaluate the toxicity is relatively coarse; in the future we can imagine linking our dynamical approach with models that predict the effect of a.i. on various communities or on human health. For instance, the PERPEST model (Van den Brink et al., 2002) could represents an interesting approach to predict the ecological risks of pesticides in freshwater ecosystems, based on empirical data extracted from the literature, a.i. databases.

Another methodological limit of Rpest lies in the fact that construction, calibration, and validation are in part based on scientific expertise. As datasets in modelling, there must be a separation between experts involved in the construction and those involved in the validation. If the development of the indicator includes this last step, like for Rpest, there is a possibility to test expert knowledge used to design and calibrate the indicator. The number of experts involved in the validation of Rpest is probably be too low. The consultation of experts for indicator validation has been described in a detailed way by Cloquell-Ballester et al. (2006). Another remark on the validation carried out on Rpest is that the dynamical aspect was not evaluated by experts. In case of lack of measurements, an alternative would be to compare output of Rpest with output of a model (Bockstaller and Girardin, 2003).

As a perspective, a way to improve the indicator will be the development of a spatial representation of Rpest in order to view and assess the impact of changes in cropping practices on a regional level. This would allow a mapping of the results which can help the use of the results by stakeholder which manage environmental issues at regional level.

References

Belcher, K.W., Boehm, M.M., Fulton, M.E., 2004. Agroecosystem sustainability: a system simulation model approach. Agric. Syst. 79, 225–241.

Boiffin, J., Malezieux, E., Picard, D., 2001. Cropping systems for the future. In: Nosberger, J., Geiger, H.H., Struick, P.C. (Eds.), Crop Science: Progress and Prospects. CAB International, pp. 267–279.

Bockstaller, C., Girardin, P., Van der Werf, H., 1997. Use of agro-ecological indicators for the evaluation of farming systems. Eur. J. Agron. 7, 261–270.

Bockstaller, C., Girardin, P., 2003. How to validate environmental indicators? Agric. Syst. 76, 639–653.

Bonan, H., Prime, J.L., 2001. Rapport sur la présence de pesticides dans les eaux de consommation humaine en Guadeloupe. Ministère de l'aménagement du territoire et de l'environnement, Ministère de l'emploi et de la solidarité, rapport no. 2001-070, 77 pp.

Castillo, L.E., Ruepert, C., Solis, E., 2000. Pesticide residues in the aquatic environment of banana plantation areas in the north Atlantic zone of Costa Rica. Environ. Toxicol. Chem. 8, 1942–1950.

Cloquell-Ballester, V.A., Cloquell-Ballester, V.A., Monterde-Diaz, R., Santamarina-Siurana, M.C., 2006. Indicators validation for the improvement of environmental and social impact quantitative assessment. Environ. Impact Assess. Rev. 26, 79–105.

Cornelissen, A.M.G., Van den Berg, J., Koops, W.J., Grossman, M., Udo, H.M.J., 2001. Assessment of the contribution of sustainability indicators to sustainable development: a novel approach using fuzzy set theory. Agric. Ecosyst. Environ. 86, 173–185.

Devillers, J., Farret, R., Girardin, P., Rivière, J.-L., Soulas, G., 2005. Indicateurs pour évaluer les risques liés à l'utilisation des pesticides: Londres. Lavoisier, Paris, New-York, p. 278.

Dorel, M., Lafforgue, A., Bretaud, P., Le Breton, M., 1996. Etude de la contamination des eaux de ruissellement par les pesticides utilisés en bananeraie. Rapport d'exécution du Projet CORDET 93 D A 14, CIRAD-FLHOR, Guadeloupe, 27 pp.

Dorel, M., 2000. Effet des pratiques culturales sur les propriétés physiques des sols volcaniques de Guadeloupe et influence sur l'enracinement du bananier. Thèse de Docteur en Sciences Agronomiques et Ing2nierie Biologique. Université catholique de Louvain, Belgique, 129 pp.

Freissinet, C., Cunge, J., Erlich, M., Vauclin, M., 1998. CNFGG Rapport quadriénnal. 95–98, 261–268.

Girardin, P., Bockstaller, C., Van der Werf, H., 1999. Indicators: tools to evaluate the environmental impacts of farming systems. J. Sustain. Agric. 13, 5–21.

Girardin, P., Bockstaller, C., Van der Werf, H., 2000. Assessment of potential impacts of agricultural practices on the environment: the AGRO*ECO method. Environ. Impact Assess. Rev. 20, 227–239.

Guibaud, G., Baudu, M., Ayele, J., 1999. Etude du transfert par ruissellement et par drainage de pesticides utilisés sur un verger de pommier. J. Europ. Hydrol. 29, 171–187.

Guipponi, C., 1998. Environmental evaluation of alternative cropping systems with impact indices of pollution. Eur. J. Agron. 8, 71–82.

Gustafson, D.I., 1989. Environ. Toxicol. Chem. 8, 339–357.

Jamet, P., Piedallu, M.A., 1980. Comportement des nématicides organophosphorés et des carbamates dans le sol et la plante étude bibliographique. Phipatrie Phitopharmacie 29, 175–199.

Lefroy, E., Rydberg, T., 2003. Energy evaluation of three cropping systems in southwestern Australia. Ecol. Model. 161, 195–211.

Levitan, L., Merwin, I., Kovach, J., 1995. Assessing the relative environmental impacts of agricultural pesticides: the quest for a holistic method. Agricult. Ecosyst. Environ. 55, 153–168.

Louchart, X., Voltz, M., Andrieux, P., Moussa, R., 2001. Herbicide transport to surface waters at field and watershed scales in a mediterranean vineyard area. J. Environ. Qual. 30, 982–991.

Matthiessen, J., 2001. Accelerated degradation of nematicides used on citrus in South Africa. CSIRO Report 3, September 2001, 2 p.

Maud, J., Edwardsjones, G., Quin, F., 2001. Comparative evaluation of pesticide risk indices for policy development and assessment in the United Kingdom. Agric. Ecosyst. Environ. 86, 59–73.

McDonald, L., Jebellie, S.J., Madramootoo, C.A., Dodds, G.T., 1999. Pesticide mobility on a hillside soil in St. Lucia. Agric. Ecosyst. Environ. 72, 181–188.

Meynard, J.M., Cerf, M., Guichard, L., Jeuffroy, M.H., Makowski, D., 2002. Which decision support tools for the environmental management of nitrogen? Agronomie 22, 817–829.

Moussa, R., Voltz, M., Andrieux, P., 2001. Effects of the spatial organization of agricultural management on the hydrological behaviour of a farmed catchment during flood events. Hydrol. Process. 16, 393–412.

Payraudeau, S., Van der Werf, H.M.G., 2005. Environmental impact assessment for a farming region: a review of methods. Agric. Ecosyst. Environ. 107, 1–19.

Perret, S., 1993. Facteurs d'évolution des horizons culturaux, implications agronomiques et écologiques. Thèse de Doctorat en Sciences Agronomiques. ENSAM, Montpellier, France, 279 pp.

Pervanchon, F., Bockstaller, C., Amiaud, B., Peigne, J., Bernard, P.-Y., Vertes, F., Fiorelli, J.-L., Plantureux, S., 2005. A novel indicator of environmental risks due to nitrogen management on grasslands. Agric. Ecosyst. Environ. 105, 1–16.

Poulenard, J., Podwojewski, P., Janeau, J.-L., Collinet, J., 2001. Runoff and soil erosion under rainfall simulation of Andisols from the Ecuadorian Paramo: effect of tillage and burning. Catena 45, 185–207.

Phillis, Y.A., Andriantiatsaholiniainan, L.A., 2001. Sustainability: an ill-defined concept and its assessment using fuzzy logic. Ecol. Econom. 37, 435–456.

Reus, J., Leendertse, P., Bockstaller, C., Fomsgaard, I., Gutsche, V., Lewis, K., Nilsson, C., Pussemier, L., Trevisan, m., Van der Werf, H., Alfarroba, F., Blümel, S., Isart, J., McGrath, D., Seppälä, T., 2002. Comparison and evaluation of eight pesticide environmental risk indicators developed in Europe and recommendations for future use. Agric. Ecosyst. Environ. 90, 177–187.

Rishirumuhirwa, T., 1993. Potentiel du bananier dans la gestion et la conservation des sols ferrallitiques du Burundi. Cah. Orstom, Sér. Pédol. XXVIII (2), 367–383.

Roussel, O., Cavelier, A., Van Der Werf, H.M.G., 2000. Adaptation and use of a fuzzy expert system to assess the environmental effect of pesticides applied to field crops. Agric. Ecosyst. Environ. 80, 143–158.

Sánchez-Bayo, F., Baskaran, S., Kennedy, I.R., 2002. Ecological relative risk (EcoRR): another approach for risk assessment of pesticides in agriculture. Agric. Ecosyst. Environ. 91, 37–57.

Silvert, W., 2000. Fuzzy indices of environmental conditions. Ecol. Model. 130, 111–119.

Simon-Sylvestre, G., Fournier, J.C., 1980. Les nématicides et la microflore des sols. Phytotiatrie Phytopharm. 29, 161–172.

Smith, C., Mc Donald, G., 1998. Assessing the sustainability of agriculture at the planning stage. J. Environ. Manage. 52, 15–37.

Smith, O.H., Petersen, G.W., Needelman, B.A., 2000. Environmental indicators of agroecosystems. Adv. Agron. 69, 75–97.

Tixier, P., 2004. Conception assistée par modèle de systèmes de culture durable. Application aux systèmes bananiers de Guadeloupe. Thèse de Doctorat en Sciences Agronomiques. ENSAM, Montpellier, France, 223 pp.

Tixier, P., Malézieux, E., Dorel, M., 2004a. SIMBA-POP: a cohort population model for long-term simulation of banana crop harvest. Ecol. Model. 180, 407–417.

Tixier, P., Malézieux, E., Dorel, M., Wery, J., 2004b. SIMBA: a comprehensive model for agro-ecological assessment and prototyping of banana-based cropping systems. An application to the banana cropping systems in French West Indies. In: Proceedings of the Fourth International Crop Science Congress, Brisbane.

Tixier, P., Malézieux, E., Risède, J.-M., Dorel, M., 2006. Modelling populations of banana phytoparasitic nematodes: a contribution to the design of sustainable cropping systems. Ecol. Model.

Van den Brink, P.J., Roelsma, J., Van Nes, E.H., Scheffer, M., Brock, T.C.M., 2002. Perpest model, a case-based reasoning approach to predict ecological risks of pesticides. Environ. Toxicol. Chem. 21, 2500–2506.

Van Der Werf, H.M.G., 1996. Assessing the impact of pesticides on the environment. Agric. Ecosyst. Environ. 60, 81–96.

Van der Werf, H.M.G., Zimmer, C., 1998. An indicator of pesticide environmental impact based on a fuzzy expert system. Chemosphere 36, 2225–2249.

Van der Werf, H.M.G., Petit, J., 2002. Evaluation of the environmental impact of agriculture at the farm level: a comparison and analysis of 12 indicator-based methods. Agric. Ecosyst. Environ. 93, 131–145.

Van Ittersum, M.K., Donatelli, M., 2003. Modelling cropping systems—highlights of the symposium and preface to the special issues. Eur. J. Agron. 18, 187–197.

Vereijken, P., 1997. A methodical way of prototyping integrated and ecological arable farming systems (I/EAFS) in interaction with pilot farms. Eur. J. Agron. 7, 235–250.

Zheng, S.Q., Cooper, F.F., 1996. Adsorption, desorption, and degradation of three pesticides in different soils. Arch. Environ. Contam. Toxicol. 30, 15–20.