Sensitivity analysis of a phosphorus index for Québec

L. Beaulieu[1], J. Gallichand[1]*, M. Duchemin[2] and L.E. Parent[1]

[1]Département des Sols et de Génie Agroalimentaire, FSAA, Université Laval, Québec, Québec G1K 7P4, Canada; and [2]Institut de Recherche et de Développement en Agroenvironnement Inc., Sainte-Foy, Québec G1P 3W8, Canada. *E-mail: jacques. gallichand@sga.ulaval.ca

Beaulieu, L., Gallichand, J., Duchemin, M. and Parent, L.E. 2006. **Sensitivity analysis of a phosphorus index for Québec.** Canadian Biosystems Engineering/Le génie des biosystèmes au Canada **48**: 1.13 - 1.24. The presence of phosphorus (P) in surface water is a major cause for water quality degradation in agricultural areas. Available tools for estimating the relative P contribution from fields include P-index (PI) models. We performed sensitivity analyses on a PI model, adapted for the province of Québec, to identify the site characteristics and input variables impacting most on the calculated PI value. The probability density functions of the 17 input variables and ten site characteristics were determined on a 10 301 km^2 study area south of Québec City. Monte Carlo simulations were performed with the @RISK software and stepwise regressions were used to determine which variables and characteristics the PI was sensitive to. The PI was mainly affected by the weights, determined by experts, related to each site characteristic. When ignoring these weights, 58.7% of the PI variation was caused by the organic P budget and 11.7% by the subsurface drain spacing. Results for the input variables showed that the crop type impacted the most PI by explaining 46.4% of the PI variation, followed by subsurface drain spacing (12.0%), and amount of organic P applied to the field (10.9%). This information can be used by field staff to obtain accurate PI values without wasting human and financial resources on input variables that contribute little to the final P index value. **Keywords:** phosphorus index, sensitivity analysis, surface water quality, Monte Carlo simulations.

La présence de phosphore (P) dans les eaux de surface est l'une des principales causes de la dégradation de la qualité de l'eau en milieu agricole. Les outils disponibles pour estimer la contribution relative du P à partir des champs incluent les modèles d'indice de risque de perte du P (IRP). Nous avons effectué des analyses de sensibilité sur un modèle IRP adapté pour le Québec, afin d'identifier les caractéristiques de site et les variables d'entrée qui influencent le plus la valeur de l'IRP. Les fonctions de distribution des 17 variables d'entrée et des dix caractéristiques de site ont été déterminées sur une zone d'étude de 10 301 km^2 au sud de la ville de Québec. Des simulations de Monte Carlo ont été effectuées avec le logiciel @RISK, ainsi que des régressions multiples pas à pas, pour déterminer à quelles caractéristiques de site et variables d'entrée l'IRP était le plus sensible. L'IRP était principalement affecté par les poids de chaque caractéristique de site, poids qui ont été déterminés par un panel d'experts. En ignorant les poids, 58.7% de la variation de l'IRP était causé par le bilan en P organique et 11.7% par l'espacement entre les drains souterrains. Pour les variables d'entrée, c'est le type de culture qui affectait le plus l'IRP, soit 46.4% de la variation suivi de l'espacement entre les drains (12%) et de la quantité de P organique appliquée (10,9%). Ces informations peuvent être utilisées par des groupes conseils pour obtenir des valeurs précises de l'IRP sans utiliser inutilement des ressources humaines ou financières sur des variables qui ne contribuent que peu à la valeur finale de l'IRP. **Mots-clés:** indice, risque, phosphore, analyse de sensibilité, qualité de l'eau, simulations de Monte Carlo.

INTRODUCTION

In Québec, intensive livestock production has resulted in excess phosphorus (P) in agricultural soils (Giroux and Tran 1996) and in concentrations of P in surface water above the standard of 0.03 mg/L for aquatic life (MENV 2001). Phosphorus concentrations from 0.1 to 0.2 mg/L have been observed in the streams of several agricultural watersheds (Gangbazo 1997; Painchaud 1996). Phosphorus from agricultural activities has also been related to the presence of cyanobacteria in 13 lakes in Alberta (Kotak et al. 2000) and in the Missisquoi Bay on the USA-Québec border (Blais 2002). Reduction of P losses from agricultural land is therefore needed if improvement of surface water quality is to be reached (Dorioz and Trevisan 2000; Eghball and Gilley 2001). Several solutions have been considered to reduce P losses to surface water such as, among others, controlling animal feed (Knowlton et al. 2004) and creating buffer zones along watercourses (White 1993). Sharpley et al. (2001) suggested that the reduction of P export could be done by 1) adjusting P applications to crop requirements, 2) defining a soil P test value not to be exceeded, and 3) evaluating potential risks of P losses in order to better distribute the P applications within or among fields. This last suggestion implies the use of mathematical models integrating crop needs and environmental risks (Sims 1998). The fact that most existing hydrological water quality models, such as SWAT and HSPF (Borah and Bera 2004), are complex and require too much data to be used by field staff (Sharpley et al. 2001), has prompted the development of phosphorus index (P-Index) models. P-Index models do not provide details regarding the amount, forms, and transport mechanisms of P to surface water, but supply the user with an indication of the relative P losses to surface water from cultivated fields.

The initial P-Index concept and model was developed by Lemunyon and Gilbert (1993). It provides a qualitative estimation of agricultural sites vulnerability to P losses by incorporating the effect of eight site characteristics related to either the source (availability) or the transport of P. These eight site characteristics are: soil erosion, irrigation erosion, runoff class, soil P test, P fertilizer application and method, and organic P application and method. The method of Lemunyon and Gilbert (1993) can be summarized by Eqs. 1-3.

$$PI = \sum_{i=1}^{n} \left(PLRV \cdot WF \right)_i \qquad (1)$$

$$PLRV_i = fc_1\left(VC_i\right) \qquad (2)$$

$$VC_i = fc_2\left(V_i\right) \qquad (3)$$

where:

PI	=	P-Index for the site,
$PLRV$	=	P loss rating value (0 to 8),
WF	=	weighting factor,
VC	=	vulnerability category ("none" to "very high"),
V	=	value of a site characteristic,
fc_1	=	vulnerability function which assigns a numerical value to each vulnerability category (e.g. "medium" corresponds to 2),
fc_2	=	categorical function that relates the value of a site characteristic to its vulnerability category (e.g. 15 t/ha corresponds to a "medium" erosion vulnerability),
i	=	index for the number of site characteristics, and
n	=	total number of site characteristics, i.e. eight in this case.

The method of Lemunyon and Gilbert (1993) is described as an 8 x 5 matrix, i.e. 8 site characteristics and 5 vulnerability categories. Because all weighted values ($PLRV_i \times WF_i$) are summed, that method is called additive. Other possibilities of calculating the P-Index include the multiplicative approach by which source and transport site characteristics are summed independently and multiplied by each other (Gburek et al. 2000; Giasson et al. 2003).

To accommodate disparities between regions in the USA, Canada, and Europe, the model of Lemunyon and Gilbert (1993) has been modified by deleting or adding site characteristics. Modifications include characteristics such as vertical P migration in the soil profile (Giasson et al. 2003; Bechman et al. 2003), distance between fields and watercourses (Gburek et al. 2000), presence of filter strips (Jokela 1999), degree of P saturation (P/Al) (Khiari et al. 2000; Sims et al. 2002), and presence of a freeze/thaw cycle (Uhlen 1989). The necessity for adjustment of P-Index methods to local conditions has prompted the Québec provincial government to develop its own P-index (Beaudet et al. 1998) which has a structure similar to that of Lemunyon and Gilbert (1993), but with some characteristics either removed (e.g. irrigation), added (e.g. subsurface drain spacing), or modified (e.g. fertilization).

Because P-Index models still need the measurement or estimation of many input variables to calculate the site characteristic values, there is a need to identify which input variables have more impact on the PI value. Sensitivity analyses have long been recognized as a key tool for quantifying the importance of the input variables of environmental models (McCuen 1973). However, maybe because of the wide variety of P-Index models available, no sensitivity analysis appears to have been done for any of them. Sensitivity analyses are either deterministic or stochastic (Zhang and Haan 1996; Biesemans et al. 2000). Stochastic sensitivity analyses, mostly implemented by Monte Carlo (MC) simulations, allow the use of complete probability distribution of input variables, to specify correlation between input variables and provide probability distribution of the output variable (Dubus and Brown 2002). Stochastic sensitivity analyses are preferred for quantifying uncertainty of environmental models (Hession et al. 1996a; Tarantola et al. 2002), and have been used for P transport in Finland with ICE-CREAM (Tattari et al. 2001), and for contaminant transport by RZWQM (Ma et al. 2000). Software has been developed to help data manipulation, probability distribution identification, control of convergence, and regression analyses (Tattari et al. 2001; Dubus and Brown 2002, Hession et al. 1996a). Because of the large numbers of input variables involved in the calculation of a P-Index model, input data cannot be sampled all at the same scale. Biesemans et al. (2000) described the results of a sensitivity analysis on RUSLE where the probability density functions (pdf) of the spatial factors were derived from a sampling density ranging from about 150 to 800 measurements per hectare, depending on the factor considered. Since spatial data come from different sources (different acquisition techniques) sensitivity analyses assume that the errors associated with different geographical variables are independent and, therefore, do not introduce a bias in the outcome of the analysis (Crosetto and Tarantola 2001). For this reason, the pdf of the input variables were defined based on available data, even though it was sampled at different scales and its amount varied greatly from one variable to another.

The influence of an input variable on the P-Index depends upon four factors: (1) the categorical function, fc_1 in Eq. 2, (2) the vulnerability function, fc_2 in Eq. 3, (3) the weighting factor, WF in Eq. 1, and (4) the nature of the site characteristic itself. Functions fc_1 and fc_2 have not been given much attention; fc_1 usually progresses geometrically with the vulnerability category, whereas fc_2 is mostly based on an arbitrary division of the range that can be assumed by the site characteristic. Weighting factors are determined based on professional judgment and, therefore, arbitrary and subject to questioning. On the other hand, site characteristic values are clearly defined and their probability distribution can be determined. Therefore, the objective of this study was to perform two stochastic sensitivity analyses of the P-Index model of Beaudet et al. (1998) for an agricultural region near Québec City. First, the non-modified method will be used to determine which site characteristics affect the P-Index when the proposed weighting factors are used. Second, considering the arbitrary nature of the weighting factors, another analysis will be performed with unitary weighting factors to isolate the effect of the site characteristics and input variables on the variation of the P-Index.

MATERIALS and METHODS

Study area

The study area corresponds to the agricultural portion of the former Beauce-Appalaches agricultural region located between Québec City and the USA-Québec border, and is mainly devoted to swine and dairy production (Statistic Canada, Census 2001). The former Beauce-Appalaches agricultural region was chosen because available soil survey reports coincide with its limits. It has an area of 10,301 km² of which 17% is occupied by farmland, 77% by forest, and 6% by urban land. Its altitude varies from 230 to 700 m AMSL. Latitude ranges between 45°13'N and 46°41'N, and longitude between 70°09'W and 71°52'W. From a sensitivity analysis standpoint, such an area is

Table 1. The P-Index adapted by Beaudet et al. (1998).

Site characteristic	Weighting factor	Very low (1)	Low (2)	Moderate (4)	High (8)	Very high (16)
Transport						
Erosion (t ha^{-1} y^{-1})	4	0 - 3	3.6	6 - 12	12 - 18	> 18
Runoff (see Table 2)	4					
Preferential flow (see Table 3)	1.5					
Subsurface drain spacing (m)	1.5	not present	> 35	25 - 35	15 - 25	< 15
Source						
Saturation P/A1 (%)	6	0 - 2.5	2.5 - 5	5 - 10	10 - 20	> 20
Soil P content (kg P/ha)	6	0 - 60	60 - 150	150 - 250	250 - 500	> 500
Total phosphorus (kg P$_2$O$_5$/ha)	3	< -20	-20 - 0	0 - 20	20 - 40	> 40
Organic phosphorus (%)	2	< 50	50 - 100	100 - 150	150 - 200	> 200
Mineral phosphorus (%)	1	< 50	50 - 100	100 - 150	150 - 200	> 200
Phosphorus management (see Table 4)	7					
P-Index		36 - 55	55 - 109	109 - 222	222 - 433	433 - 576

Table 2. Vulnerability level for Runoff (Beaudet et al. 1998).

Slope (%)	Curve number for AMCII*				
	< 50	50 - 60	60 - 70	70 - 80	> 80
< 1	Very low	Very low	Very low	Very low	Moderate
1 - 2	Very low	Very low	Very low	Low	Moderate
2 - 4	Very low	Very low	Low	Moderate	Moderate
4 - 8	Very low	Very low	Moderate	High	High
8 - 16	Very low	Low	Moderate	Very high	Very high
> 16	Very low	Low	High	Very high	Very high

* SCS (1969) curve number for an antecedent moisture content of II.

Table 3. Vulnerability level for Preferential flow by soil texture (Beaudet et al. 1998).

Vulnerability level				
Very low	Low	Moderate	High	Very high
Sandy loam	Loam Silty loam	Clay loam Silty-clay loam	Medium sand Clay	Coarse sand Heavy clay

Table 4. Vulnerability level for Phosporous management (Beaudet et al. 1998).

Application timing	Application method			
	Incorporation	After ploughing	Surface application of solid fertilizer	Surface application of liquid manure
Pre-sowing	Low	Low	High	Moderate
Growing season	Very low	Very low	Moderate	High
Post-harvest	Low	Moderate	Very high	Very high

large enough to provide adequate variability in the various input variables, and at the same time, it is not so small that results would be very site specific. Soils are tills, alluvial deposits, and fluvio-glacial deposits. According to soil surveys, half of the agricultural area is of the gleysol order, followed by podzol (29%), and brunisol (18%). Organic soils and luvisols represent less than 1% of the area. The mean annual temperature is 3.9ºC, and total annual precipitation is 1237 mm, of which 928 mm is rainfall. The crops are mostly forage (56.6%) and pasture (25.0%), and the remainder is cereals (10.5%), corn (7.5%), vegetables and fruits (MAPAQ 2003).

Description of the phosphorus index

The adapted P-Index model of Beaudet et al. (1998) is presented in Table 1. For the sake of clarity, a capital letter will be used to identify the input variables and site characteristics. The site characteristic Erosion is calculated with RUSLEFAC (Wall et al. 2002), a version of RUSLE (Renard et al. 1997) adapted for Canada. Soil P content and Saturation P/Al (ratio of P to Al) were obtained from Mehlich-3 extraction of P and Al (CRAAQ 2003). Total phosphorus refers to the amount of organic and mineral P applied to the field minus that removed (CRAAQ 2003). Organic phosphorus is the ratio of the organic P applied to the field over crop removal from the field. The same definition applies to Mineral phosphorus. The relationships between vulnerability levels and site characteristics of Runoff, Preferential flow and Phosphorus management were determined mostly by professional judgment and presented in Tables 2, 3, and 4, respectively. Subsurface drain spacing

Table 5. Input variables and their probability distribution characteristics.

Input variable	n[†]	Scale[‡]	Distribution type	Distribution function
Sand%	539	Interval	Continuous	Normal
Clay%	539	Interval	Continuous	Gamma
Silt%	539	Interval	Continuous	Beta General
Organic matter content	n.a.*	Interval	Continuous	Normal
Field slope	35,870	Interval	Continuous	Lognormal
Field length	200	Interval	Continuous	Beta General
P/A1 ratio	14,051	Interval	Continuous	Inverse Gausian
P Mehlich-3	14,051	Interval	Continuous	Inverse Gausian
Rainfall erosivity	38	Interval	Continuous	Beta General
Organic P application	3089	Interval	Discrete	Empirical
Mineral P application	2835	Interval	Discrete	Empirical
Hydrological soil group	n.a.	Ordinal	Discrete	Empirical
Subsurface drain spacing	n.a.	Ordinal	Discrete	Empirical
Application method	3106	Nominal	Discrete	Empirical
Application timing	3106	Nominal	Discrete	Empirical
Crop type	n.a.	Nominal	Discrete	Empirical
Ploughing method	n.a.	Nominal	Discrete	Empirical

† - number of observations used to fit the pdf
‡ - measurement scale
* - not applicable

reflects the increased possibility of P reaching surface water, via the subsurface drainage system, by closer drain spacing. The adapted P-Index of Table 1 is composed of 10 site characteristics, six for the source of P and four for its transport. The P-Index is easily calculated once the value of each of the 10 characteristics is known, which in turn must be determined from the corresponding input variables.

Data sources and probability density functions

Seventeen input variables are required for the calculation of the ten site characteristics and are listed in Table 5. The sensitivity analysis of the adapted P-Index method requires the pdf of all 17 input variables in order to calculate the pdf of the 10 site characteristics and ultimately the pdf of the P-Index. For interval scale variables (e.g. Sand%), the distributions were fitted with a continuous pdf function. However, discrete input variables are measured either on an ordinal scale (e.g. Hydrological soil group) or a nominal scale (e.g. Crop type) which precludes the use of continuous pdf, but allows empirical
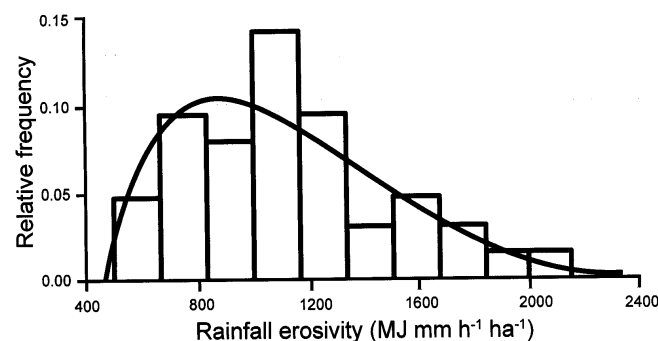

Fig. 1. Empirical (bars) and fitted (continuous line) for pdfs for Rainfall erosivity.

distributions. The pdf's were fitted to the observed values of the continuous input variables using the distribution fitting function of @RISK Version 4.5 (Palisade Corporation, Newfield, MA). The adequacy of the resulting pdf was examined with the Chi-square statistic, the probability plot, and the quantile plot. Table 5 shows the distribution type, and the continuous distribution function that was fitted to each input variable. An extensive set of data was needed to determine the pdf of each input variable over the study area. The data sources and methods for determining the pdf of the input variables are summarized below.

Rainfall erosivity was calculated based on the 1945 – 1982 daily rainfall and temperature records from the Québec City airport using the method of Richardson et al. (1983) and Selker et al. (1990) adapted for snowmelt conditions in the province of Québec (Madramootoo 1988). This analysis yielded 38 annual Rainfall erosivity values from which a beta pdf was determined. Because Québec City is located at the northern end of the study area (46°48'N, 71°15'W), the Rainfall erosivity pdf was also determined from the 1941 – 1982 record of the Disraéli station (45°54'N, 71°21'W), at the southern end of the study area. A Kolmogorov-Smirnov test showed that the two Rainfall erosivity empirical distributions were not significantly different (p < 0.05). The empirical pdf from the Québec airport was, therefore, used for the study area because of the greater reliability of its observations. As an example of a continuous input variable, Fig. 1 shows the empirical and fitted pdf of Rainfall erosivity.

Fractions of sand, silt, and clay were obtained from soil survey reports for each soil series within the four counties covering the study area: Mégantic (Laflamme et al. 1989), Dorchester (Pageau 1974), Beauce (Ouellet et al. 1995), and Frontenac (Dubé and Camiré 1996). To improve the fitted pdf of these three soil fractions, additional sampled values for the same soil series were obtained by using data from adjacent counties: Lotbinière (Baril and Rochefort 1957), Bellechasse (Baril and Rochefort 1979), Lévis (Laplante 1963), Compton (Cann and Lajoie 1943), Nicolet (Chouinière and Laplante 1948), Arthabaska (Rompré et al. 1984), and Wolfe (Ouellet and Rompré 1998). This procedure resulted in total values of sand, silt, and clay percentages from which the pdf were determined. To account for the variation in the area covered by each soil series, the fraction values were weighted according to the relative area of each soil series within the study area. The relative area of a given soil series was obtained by dividing the area of that series by the total area, both areas referring to the cultivated area. All cultivated areas were determined by superimposing the soil maps on the LANDSAT 5 TM image (DBSQ 1996) and by using additional information from the Québec Ministry of Agriculture database (MAPAQ 2003). Values of Organic matter content, published in the soil survey reports previously cited, vary from 0.24 to 43%, an upper bound

unrealistic for the mineral agricultural soils considered in this study. Since published soil fraction values were given on a soil series basis only, i.e. without reference to land use, it was not possible to differentiate between agricultural and forested areas. Therefore, in consultation with professionals from the area, we determined that Organic matter content could be best represented by a normal distribution with a mean of 4%, and minimum and maximum values of 2 and 6%, respectively.

The 1996 LANDSAT 5 TM image was used to identify 16 140 fields composing the study area. Because the determination of Field length for each field would be time consuming, Field length was calculated from a random sample of 200 fields using MapInfo Professional version 6.5 (MapInfo Corporation, Troy, NY). Since the average field size was found to be 14 ha, the study area was divided into 375 m square cells superimposed onto a Digital Terrain Model created from the contours lines and spot heights a the scale of 1:20,000 from the Québec Ministry of Natural Resources, and for each cell within an agriculture area, field slope was calculated as the maximum slope of the cell. Spot checks showed that using a square grid, instead of actual fields, did not introduce any bias in the slope distribution.

Based on soil characteristics (drainage, permeability, soil texture, structure, depth) found in the four soil survey reports covering the study area, a value of A, B, C, or D of the Hydrological soil group (SCS 1969) was assigned to each soil series. The probability of occurrence of a given Hydrological soil group was taken as the ratio of the surface area of all series pertaining to that group to the total cultivated area. Although there are no recent statistics on subsurface drain spacing in the study area, it was estimated that drain spacing is always less than 15 m and that only 20% of the agricultural area is installed with subsurface drains (Association des entrepreneurs en drainage agricole du Québec, Ste-Martine, QC). The various crops grown in the study area were determined based on data provided by the farmers to the Québec Ministry of Agriculture: cereals, grain and silage corn, forage, pasture, vegetables and fruits. Discrete pdf for the phosphorus management factors of fertilizer Application method and Application timing (Table 4) were based on a survey of 3106 farmers in the study area (BPR-GREPA 2000). BPR-GREPA (2000) also provided the discrete pdf for Ploughing method with 83% of the annual crops under conservation tillage and 17% under mouldboard ploughing. For perennial crops only, no-till is practiced.

Probability distributions of the P/Al ratio and P Mehlich-3 input variables were based on 14051 values from the upper 200 mm of the soil profile (1995 - 2004). Mineral P applications were estimated, on a farm basis, from fertilizer sales, and included 2835 farms. The use of mineral fertilizer is not widespread in this area considering that it is mostly devoted to animal production. Organic P applications were determined from 3089 farms in the study area and was calculated, on a farm basis, from the amount of manure produced, crop yield, and soil fertility. All aforementioned data were provided by the Québec Ministry of Agriculture (Beaudet P., agr. MAPAQ, Québec). Farms were either in excess or in deficit of manure with extremes going from swine production with no spreading land to cash crop producers without manure, respectively. To simulate the actual practice, the amount of manure from farms in excess was equally distributed to those in deficit; this resulted in a probability distribution with a large proportion of the observations in the lowest and highest classes, and relatively few in the middle.

Sensitivity analysis procedure

The sensitivity analyses were done with the commercial software @RISK Version 4.5 add-in for Microsoft EXCEL 2000 (Microsoft Corporation, Cambridge, MA). The adapted P-Index model of Beaudet et al. (1998) was completely specified in an EXCEL spreadsheet and Monte Carlo simulations were run within EXCEL.

When a correlation exists between two or more input variables and the sensitivity analysis does not consider it, results of the analysis might be biased (Hession et al. 1996b). To avoid this, @RISK allows the specification of a correlation matrix incorporating some or all of the input variables. In our case, this correlation matrix was incomplete because not all variables are dependent upon one another (e.g. Organic matter content and Subsurface drain spacing), or because financial restrictions made impossible the incorporation of interactions between all variables in the P-Index model. In this study, a correlation coefficient was assigned to each input variable pair for which a correlation appeared obvious. The correlation matrix included Field slope, Sand%, Silt%, Clay%, P/Al ratio, and P Mehlich-3. Correlation values were determined based on 275 soil samples from the province of Québec (Pellerin 2005), and correlation coefficients ranged between -0.59 (Sand% and Clay%) and 0.62 (P/Al ratio-P Mehlich-3). However, preliminary results showed that the inclusion of the correlation matrix had no effect on the results from the sensitivity analyses and, therefore, correlation between input variables was not considered in the two MC simulations described in this study.

To make sure the sum of Clay%, Silt%, and Sand% was 100%, an equation was built-in in the model to correct the sampled values of these three input variables.

$$FR_{cj} = FR_{sj} \frac{100}{\sum_{k=1}^{3} FR_{sk}} \qquad (4)$$

where:

FR_{sj} = sampled value of fraction j,
FR_{cj} = corrected value of fraction j, and
j, k = indices for Sand%, Silt% and Clay%.

For the results of an MC simulation to be valid, two requirements must be met (Haan and Skaggs 2003): 1) input and simulated correlation matrices must be equal, and 2) input and simulated variables pdf must be similar. For the first requirement, examination of the a posteriori correlation matrix showed all entries to be zeros except for Sand%, Silt% and Clay%, for which the correlation coefficients ranged from -0.22 to -0.83. These non-zero correlations between soil fractions are observed despite the null input correlation matrix that was specified. This was expected because of the ties imposed by Eq. 4. In addition, results of the MC simulations showed that the stepwise regression, used for determining which input variables impacted most the P-Index, excluded some of these variables that were correlated, such that results are valid despite these non-zero values in the *a posteriori* correlation matrix.

Table 6. Standardized weights and regression coefficients for the two sensitivity analyses.

Site charcteristic	P-Index		With WF[†]		Without Wf		
	Scaled[‡] WF	Rank	Standard coefficient	Rank	Standard coefficient	Rank	Partial R^2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Transport							
Erosion	0.111	5	0.120	5	0.103	5	0.039
Runoff	0.110	4	0.023	9	0.020	10	0.002
Preferential flow	0.042	9	0.023	10	0.051	9	0.014
Subsurface drain spacing	0.042	8	0.065	7	0.151	2	0.117
Source							
Saturation P/A1	0.167	2	0.143	2	0.082	7	0.035
Soil P content	0.167	3	0.135	3	0.077	8	0.030
Total phosphorous	0.083	6	0.125	4	0.144	3	0.074
Organic phosphorous	0.056	7	0.098	6	0.158	1	0.587
Mineral phosphorous	0.028	10	0.028	8	0.097	6	0.038
Phosphorous management	0.194	1	0.240	1	0.117	4	0.043

† - weighting factor
‡ - scaled coefficients

The second requirement was met because each simulation consisted of a large number of iterations. In this study, a sensitivity analysis consists of a single simulation and a simulation consists of a certain number of iterations. During an iteration, each input variable is sampled taking into account its own pdf, so that if the number of iterations is large enough the sampled pdf reproduces the input pdf. In our case, 20,000 iterations were specified, such that 20 values of percentiles (0%, 5%, … 95%, 100%), the mean, and the standard deviation of the sampled and input pdf did not differ by more than 1.5%. The probability distribution of each of the 17 input variables was specified as either continuous or discrete, and sampling of all pdf was done by the Latin Hypercube technique, a refinement of the MC sampling (Tarantola et al. 2002). Results of a simulation provided 20,000 values for each variable required in the calculation of the P-Index, i.e. 17 input variables, 10 site characteristics, the P-Index and all other intermediate variables. These 20,000 values formed the database from which the sensitivity of the P-Index could be determined.

The effect of an input variable, or a site characteristic, on the P-Index, was evaluated by multiple stepwise regressions, which yielded regression coefficients standardized to be comparable to each other. The stepwise procedure kept a variable in the model if it was statically significant ($p < 0.05$). The importance of an input variable was also quantified by providing its partial R^2. Because site characteristics are based on an ordinal scale (the vulnerability categories), results of the MC simulations involving site characteristics were analyzed with the stepwise regression tool provided by @RISK. For input variables, however, the regression included interval as well as ordinal scale variables, but nominal scale variables could not be dealt with by @RISK. Consequently, the regression for input variables was handled by procedure REG (SAS Version 9.1, Raleigh, NC), and regression coefficient estimates were standardized by multiplication with the ratio of the standard deviation of the input variable to that of the P-Index. Ordinal variables were transformed into interval variables by assigning to each value a numerical equivalent. For example, the four Hydrological soil group were assigned their mean infiltration values as defined by the SCS (1969), i.e. A = 9.53 mm/h, B = 5.71 mm/h, etc. The four nominal variables were introduced into the regression model using dummy variables, i.e. a nominal variable with c classes was represented by c-1 dummy variables with the last level taken as the reference (Neter et al. 1985). For all regressions, the normality assumption was verified with the Shapiro-Wilk test, and the homogeneity of variance was confirmed visually from the residual plots.

Two MC simulations were performed: one with the weighting factors (*WF*) and the other without any weighting. The sensitivity analysis, with the *WF* shown in Table 1, evaluated the adapted P-Index method as presented by Beaudet et al. (1998). Because the *WF* have an important effect on the P-Index, and because of their arbitrary nature (Lemunyon and Gilbert 1993), we decided to investigate a situation for which all *WF* were set to 1.0, i.e. the P-Index was calculated by:

$$PI = \sum_{i=1}^{n} PLRV_i \qquad (5)$$

The motivation to include that simulation was prompted by the *WF* not having the physical significance of the input variables, and by field results of the same model (Goulet et al. 2006) where the correlation between the calculated P-Index and measured P losses was increased from 0.63 to 0.73 by using weighting factors of 1.0 instead of those of Table 1. Therefore, deleting the *WF* is thought to estimate the direct effect of the input variables on the P-Index, and might help experts to assign improved *WF* values.

RESULTS and DISCUSSION

Simulation with weighting factors

Results of the sensitivity analysis using the weighting factors are presented in columns (3) and (4) of Table 6. To compare the

Table 7. Standard regression coefficients and partial R² for the input variables.

Input variable[†]	Standard coefficient	Partial R²	Model R²
Crop type	n.a.[‡]	0.464	0.464
Cereals	-0.154	n.a.	n.a.
Corn - grains	-0.204	n.a.	n.a.
Corn - silage	-0.205	n.a.	n.a.
Forage	-0.934	n.a.	n.a.
Pasture	-0.188	n.a.	n.a.
Vegetables	-0.053	n.a.	n.a.
Fruits	0.000	n.a.	n.a.
Subsurface drain spacing	0.348	0.120	0.584
Organic P application	0.331	0.109	0.693
Application timing	n.a.	0.036	0.729
Pre-sowing	-0.231	n.a.	n.a.
Growing season	-0.214	n.a.	n.a.
Post-harvest	0.000	n.a.	n.a.
P/A1 ratio	0.181	0.033	0.762
P Mehlich-3	0.167	0.028	0.790
Mineral P application	0.331	0.028	0.818
Application method	n.a.	0.024	0.842
Incorporation	-0.098	n.a.	n.a.
After ploughing	-0.125	n.a.	n.a.
Surface application - solid	0.019	n.a.	n.a.
Surface application - liquid	0.000	n.a.	n.a.
Field slope	0.053	0.003	0.845
Hydrological soil group	-0.042	0.002	0.847
Clay%	-0.047	0.002	0.849
Rainfall erosivity	0.021	<0.001	0.849
Sand%	-0.014	<0.001	0.849
Field length	0.011	<0.001	0.849
Organic matter content	-0.006	<0.001	0.849

† - Silt% and Ploughing method were not significant at the 5% level
‡ - not applicable

weighting factors and the standardized regression coefficients, the former were scaled such that their sum was equal to unity, as shown in column (1). The column (4) presents the rank of each site characteristic: a value of 1 was assigned to the site characteristic most influencing the P-Index, i.e. the one showing the largest coefficient, and 10 to the one with the least influence. The rank represents the order of importance of the regression coefficients in column (3). This sensitivity analysis shows that Phosphorus management was the most influential characteristic, followed by Saturation P/Al, Soil P content, and Total phosphorus. In fact, site characteristics pertaining to the Source group had the highest influence on the P-Index, with an average rank of 4.0 whereas the influence of the Transport group was less, with an average rank of 7.8.

It is interesting to compare the ranks derived from this simulation to the corresponding ranks of the adapted P-Index method, i.e. columns (4) and (2) of Table 6. Both ranks are in positions close to one another, except for Runoff, Total phosphorus, and Mineral phosphorus. Despite these differences, the general pattern of the P-Index ranks is similar to that of the sensitivity analysis, which averages a rank of 4.8 for the Source group and 6.5 for the Transport group. The *WF* values in Eq. 1 greatly modify the P loss rating values (*PLRV*) and the resulting

P-Index. Therefore, the arbitrary nature of the *WF* may mask the physical nature of the phenomena represented by the *PLRV*, and a second analysis was performed by setting all *WF* to 1.0.

Simulation without weighting factors

Effect of site characteristics Results of the sensitivity analysis performed with the *WF* set to 1.0 are presented in Table 6. Columns (5), (6), and (7) present the standard regression coefficients, corresponding ranks, and partial R², respectively. The model R² for this regression is 0.979. The comparison between ranks of column (6) with those of column (4) shows that the site characteristics affecting most the P-Index are different; only Erosion has the same rank. This observation confirms the importance of the *WF* in the results of the sensitivity analysis and the importance of selecting them cautiously. The most influential site characteristics are Organic phosphorus, Subsurface drain spacing, Total phosphorus, and Phosphorus management. The Erosion site characteristic comes in fifth position. Considering that this site characteristic explains only 3.9% of the P-Index variation (partial R² of 0.039), its presence in the adapted P-Index model might be questioned for the study area because the Erosion site characteristic is the most demanding in terms of amount of data and computation. For the source-group site-characteristics, the average rank is 4.8 and the sum of the partial R² is 80.7%, compared to 6.5 and 17.2%, respectively, for the transport group site-characteristics. Leyten et al. (2003) also observed the predominance of source-group site-characteristics in their P-Index model.

One single site characteristic, Organic phosphorus, explains 58.7% of the P-Index variation, whereas the second most important, Subsurface drain spacing, explains 11.7%. The great sensitivity of the P-Index to Organic phosphorus and Subsurface drain spacing might be explained by the form of the discrete pdf observed for these input variables. The discrete distribution of Organic phosphorus application has a high relative frequency for the low class (10.0-10.5 kg P/ha) and the high class (42.5-43 kg P/ha), whereas Subsurface drain spacing is characterized by a discrete pdf with only two classes: 20% of the agricultural area has a tile drainage system with a spacing < 15 m, and 80% has no subsurface drains. In the extreme case of Subsurface drain spacing, each iteration sampled a drain spacing that corresponded either to a very high or a very low vulnerability category. Variables with a pdf showing important variations will impact more on the P-Index than those with a uniform distribution. In regions with large differences in organic phosphorus application or a wide range of subsurface drain spacing, results of the sensitivity analysis might be different and the ranks of the site characteristics might vary. Therefore, results of a sensitivity analysis will be influenced not only by the P-Index model selected, but also by the distribution of the various input variables.

Effect of input variables Results from the simulation without weighting factors were used to investigate the sensitivity of the P-Index to each input variable presented in Table 5. In Table 7, input variables are ordered as they were introduced into the
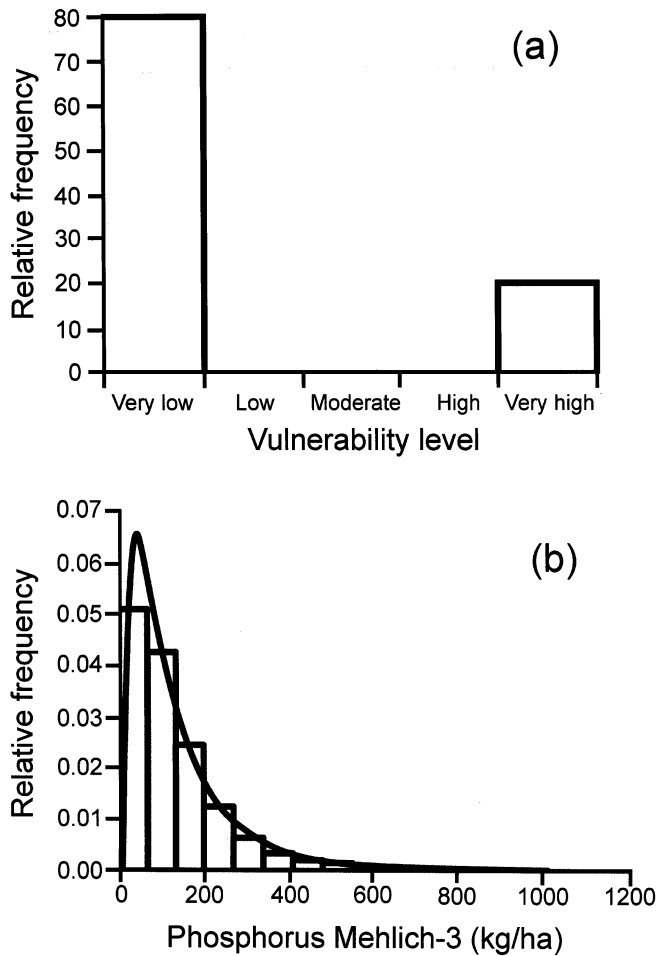
Fig. 2. Probability distribution of (a) Subsurface drain
spacing and (b) P Mehlich-3.

with thousands of fields, it is worthwhile spending resources to collect accurate information on crop types. For the three nominal variables included in the regression model (Crop type, Application timing, and Application method), the use of dummy variables allowed determination of the standard coefficients (Table 7) which can be seen as correlation coefficients, i.e. larger absolute values mean more impact on the P-Index, and the sign indicates an increase or a decrease of the P-Index. For Crop type, forage has the greatest negative effect on the P-Index (-0.934), i.e. forage is the crop which contributed most to reduce the P-Index in the study area. At the other end, fruits showed no effect on the P-Index. The negative values of the standard coefficients for different crops of the Crop type variable are closely related to the phosphorus uptake from the soil, which reduces the risk of transporting P to surface waters, a risk represented by the P-Index. The magnitude of this reduction is related to that of P uptake by the crop: 21.67 kg P/ha for forage, 7.84 kg P/ha for grain corn, and only 1.06 kg P/ha for fruits, with standard coefficients of -0.934, -0.204 and 0.000, respectively. Crops contributing most to decrease the P-Index do not provide much insight regarding the P-Index sensitivity to input variables, but show that this P-Index model is coherent with the accepted knowledge that phosphorus losses are inversely related to the crop P uptake.

The next most important input variables are Subsurface drainage and Organic P application, with standard coefficients of 0.348 and 0.331, respectively, and partial R^2 of 0.120 and 0.109 (Table 7). As opposed to the Crop type variable, these standard coefficients are positive, i.e. they contribute to increase the value of the P-Index. The partial R^2 for Subsurface drain spacing is almost the same for the input variables analysis (0.120) and the site characteristics analysis (0.117) because there are no intermediary calculations between the input variable and its corresponding site characteristic. As mentioned above, the relative importance of Subsurface drain spacing may be explained by a reduced number of classes. In addition, since there are only two classes of subsurface drainage spacing in the study area, very low and very high (Fig. 2), the positive standard coefficient indicates that the presence of subsurface drains increases the P-Index. In fact, Sims et al. (1998), Gächter et al. (1998) and Jamieson et al. (2003) observed that as much as 50% of annual P losses took place by subsurface drains. Organic P application has an impact almost similar to Subsurface drain spacing in terms of both standard coefficient and partial R^2. The positive standard coefficient of 0.331 (Table 7) implies a higher contamination risk to surface waters with increasing amounts of organic P applied to the field. The number of site characteristics affected by Organic P application and Mineral P application is the same for both input variables, i.e. Total P and Organic P for Organic P application, and Total P and Mineral P for Mineral P application. However, the impact of Organic P application on the P-Index is greater than the Mineral P application, with partial R^2 of 0.109 and 0.028, respectively. Since the study area is mostly dedicated to animal production, the predominance of Organic P application over Mineral P application is caused by larger amounts applied (average of 25.8 versus 3.0 kg P ha^{-1} y^{-1}, respectively), and by a greater variability in the applied quantities (standard deviation of 9.6 vs. 3.8 kg P ha^{-1} y^{-1}).

The three input variables discussed above (Crop type, Subsurface drain spacing, and Organic P application) are those

stepwise model. The regression model explained 84.9% of the P-Index variation. Two input variables, Ploughing method and Silt%, were not included because they were not significant (p > 0.05). The low significance of Silt% is explained by the built-in relationship that forces the soil fractions to sum up to 100%, and which resulted in a correlation coefficient of -0.83 between Silt% and Sand% in the *a posteriori* correlation matrix. Sand% was likely selected by the model because it enters in the calculation of two site characteristics, Erosion and Preferential flow, while Silt% only influenced the Erosion characteristic.

Crop type is the input variable that impacted most the P-Index, with a partial R^2 of 0.464, followed by Subsurface drain spacing (partial R^2 = 0.120). The considerable sensitivity of the P-Index to Crop type is clearly due to the use of this variable in the calculation of five of the ten site characteristics. Crop type is used to determine the factor C in RUSLEFAC, i.e. the Erosion characteristic. It is also needed for estimating the curve number and therefore the Runoff site characteristic. In addition, Crop type is required to calculate the crop removal of P from the field, which affects Total phosphorus, Organic phosphorus, and Mineral phosphorus site characteristics. In a situation where the P-Index is calculated for one or a few fields, there is almost no possibility of assigning the wrong crop to a given field. However, if the P-Index method is to be used on a regional basis

impacting most the P-Index, with a model R^2 of 0.693. Considering that the total model R^2 is 0.849 (Table 7) means that most of the information to calculate the P-Index (0.693/0.849 x 100 = 81.6%) could be obtained by gathering good quality information for these three input variables, out of the 17 required by the model of Beaudet et al. (1998). Although information about the 17 input variables is required to calculate the P-Index, results from Table 7 show that a user should concentrate to get accurate values for Crop type, Subsurface drains and Organic P application, while estimated or approximate values could be used for the remaining variables. A similar sensitivity analysis should be performed for areas where the use of a P-Index is planned for identification of the important input variables, and ultimately to determine the human and financial resources needed.

Among the remaining input variables with some importance is the Application timing with a partial R^2 of 0.036. The corresponding standard coefficients of this nominal variable are -0.231 for Pre-sowing, -0.214 for Growing season, and 0.000 for Post-harvest. Hence, both Pre-sowing and Growing season fertilization will decrease the value of the P-Index, compared to Post-harvest fertilization that has no effect. This is coherent with the vulnerability levels defined in Table 4 since, whatever the Application method, the risk to surface water increases from pre-sowing to growing season to post-harvest. Therefore, the sensitivity analysis reflects the structure of the P-Index model used but, in addition, quantifies the effect of the input variables. In a field situation, the sooner the fertilizer is applied, the longer the crop uptake period, and the lesser the potential risk of P transport to surface water.

Similar to Subsurface drain spacing, the site characteristics Saturation P/Al and Soil P content are both described by a single input variable, P/Al ratio and P Mehlich-3, respectively. For this reason, the partial R^2 values of these site characteristics are close to those of the corresponding input variables, with 0.035 and 0.033, respectively, for saturation, and 0.030 and 0.028 for P content (Tables 6 and 7). Both variables have positive standardized coefficients, indicating a value of the P-Index increasing with the value of theses variables, a result that confirms the P-Index model structure. Contrary to Subsurface drain spacing, which also defines a single site characteristic, these input variables do not rank very high as input variables impacting the P-Index. Conceptually, P/Al ratio and P Mehlich-3 are potentially important causes of surface water P contamination. The difference of partial R^2 between Subsurface drainage (0.120) and P Mehlich-3 (0.028) might be partly explained by the difference in these input variables distribution, as mentioned above for Subsurface drain spacing (Table 7). Figure 2 shows the pdf of these two variables, the characteristics of which are potential causes for the difference in partial R^2. In the case of Subsurface drain spacing, not only the pdf is discrete, but the only two classes used are located at the extremities of the distribution. However, the pdf of P Mehlich-3 is continuous and shows a smooth variation which attenuates the impact on the P-Index. Our data show that the P-Index is more sensitive to input variables defined by discrete pdf. In Table 7, six of the eight most important variables, i.e. those with a partial R^2 above 0.01, have discrete pdf, and these six variables explain 64.4% of the P-Index variation, compared to 19.8% for the two variables with a continuous pdf (P/Al ratio and P Mehlich-3).

Discrete pdfs introduce jumps from class to class, which artificially increases the importance of the variable in the sensitivity analysis. This discrete nature of the input variable pdf is compounded by the use of the categorical function, fc_2 in Eq. 3, which reduces interval scale values to ordinal scale values. To avoid this loss of information, Sharpley et al. (2003) suggested a method which does not use categorical functions.

The last two input variables which have some impact on the P-Index are the Mineral P application and the Application method, with partial R^2 of 0.028 and 0.024, respectively (Table 7). For Application method, values for Incorporation and After ploughing have negative signs for the standard coefficients, which means that the use of these methods will reduce the P-Index, whereas Surface application values are either positive or zero, which implies an increase in the P-Index or no effect at all, respectively. In Table 7, input variables with a partial R^2 below 0.01 were statistically significant at $p < 0.05$, but their practical contributions to the variation of the P-Index is insignificant since together these seven variables contribute only 0.7% to the risk of surface contamination by phosphorus.

Results presented in this paper will be of help to calculate P-Index on a field by field basis, or on a regional basis, in the study area. The sensitivity method presented could guide people from other areas to develop their own sensitivity analysis for evaluating the input variables on which most resources should be allocated without significant loss of precision. The software @RISK was useful to perform the different tasks related to the sensitivity analyses, but had the shortcoming of not allowing nominal variables in the regressions. Regression information provided by the procedure REG of SAS proved useful in validating the P-Index model structure.

CONCLUSIONS

Monte Carlo simulations were performed to determine the sensitivity of a P-Index model, adapted to the province of Québec, including ten site characteristics and 17 input variables. Results from the analysis were applied to the 10,301 km² study area located south of Québec City. The following conclusions can be drawn from this study:

1. The results of two sensitivity analyses, with and without weighting factors, showed that the weighting factors applied to the site characteristics had a dominant effect on the P-Index value. To remove this arbitrarily effect from the model, subsequent results refer to the analysis performed without weights.

2. The Erosion site characteristic explained only 3.9% of the P-Index variation, even though it is the most demanding in terms of input data and computation.

3. Site characteristics related to the Organic P budget and Subsurface drain spacing explained 58.7 and 11.7% respectively, of the P-Index variation. The importance of these characteristics is partly due to the high frequency observed at both ends of their discrete distributions.

4. Crop type was the most influential input variable since it explained 46.4% of the P-Index variation. The variable Crop type is important in the model because it contributes to the calculation of five out of the ten site characteristics. The second most important variable was Subsurface drain spacing which explained 12.0% of the P-index variation.

5. Input variables Crop type, Subsurface drain spacing and Organic P application were responsible for more than 80% of the explainable P-Index variations.

6. Input variables modeled by discrete distributions had more impact on the P-Index than those modeled with continuous distributions. Out of the eight most important variables, six had a discrete distribution and explained 64.4% of the P-Index variation, whereas only two had a continuous distribution with a contribution of 19.8% to the P-Index variation. These eight variables contributed 84.2% to the maximum model R^2 of 84.9%.

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