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# **Agricultural production and pollutant runoffs in Québec's Chaudière river watershed: what are the potential environmental gains?**

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## **Résumé**

Malgré l'imposition de normes environnementales strictes au Québec, l'impact des activités agricoles sur la qualité de l'eau demeure préoccupant notamment dans la région de Chaudière-Appalaches. Cette région est intensive en productions animale et végétale, ce qui entraîne des surplus de phosphore, d'azote et de sédiments. Cette étude analyse l'efficacité environnementale des producteurs agricoles du bassin de la rivière Chaudière localisé au Sud de la ville de Québec. Nous adoptons une approche stochastique paramétrique appliquée aux fonctions de distance. Les données utilisées portent sur 210 fermes agricoles et les résultats obtenus montrent qu'en moyenne, les producteurs engagés en productions animales sont plus efficaces que ceux en productions végétales. De plus, lorsque l'on considère les émissions de phosphore et d'azote, les efficacités environnementales des producteurs sont proches à 0,804 et 0,820 respectivement. Ce n'est pas le cas pour les sédiments, l'efficacité environnementale étant en moyenne plus faible à 0,736. Globalement, les producteurs agricoles du bassin Chaudière auraient pu réaliser des gains de productivité de plus de 20% tout en réduisant leurs émissions de matières polluantes.

*Mots clés:* Fonction de distance hyperbolique; Frontières stochastiques; Efficacité technique; Efficacité environnementale.

## **Abstract**

Despite imposition of strict environmental standards in Quebec, the impact of agricultural activities on water quality remains a concern, particularly in the Chaudière-Appalaches region. This region's intensive animal and plant productions lead to excess phosphorus, nitrogen and sediments. This paper analyzes the environmental efficiency of agricultural producers in the Chaudière river watershed, located south of Quebec City. We adopt a stochastic approach applied to parametric distance functions to data collected from 210 farms. Results show that, on average, crop producers are more efficient than livestock producers. In terms of emissions of phosphorus and nitrogen, the environmental efficiencies of producers are similar, at 0.804 and 0.820 respectively. For sediment runoff, however, the environmental efficiencies are lower on average, at 0.736. Overall, the agricultural producers from this watershed could have achieved productivity gains in excess of 20%, while simultaneously reducing their emissions of pollutants.

*Keywords:* Hyperbolic distance function; Stochastic frontier analysis; Environmental efficiency.

*JEL classification :* C23, D24, L94.

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## **Agricultural production and pollutant runoffs in Québec's Chaudière river watershed: what are the potential environmental gains?**

### **1 Introduction**

As in other Canadian provinces, the growth of agricultural productivity in Québec was done through mechanization, increased farm acreages and intensive use of fertilizers (nitrogen & phosphorus), pesticides and herbicides (Korol, 2002). The massive use of inputs and changes in farming practices have contributed to increased production, but have also had negative impacts on the environment (Boutin, 2004). In the province of Québec, intensification of livestock and crop production has produced excess phosphorus, nitrogen and sediments that have contaminated both ground and surface water (Gangbazo and Le Page, 2005). Consequently, many programs and regulations were implemented in Québec since the 1990s in an effort to mitigate environmental externalities while keeping the agricultural sector competitive.

The analysis of Technical Efficiency (TE) in agricultural production has a long and rich history (e.g. Farrell, 1957), but its linkage to Environmental Efficiency (EE) is fairly recent (Reinhard, Lowell and Thijssen, 1999; Cuesta, Zofio and Lowell, 2009). Econometric studies<sup>1</sup> analyzing efficiencies involve three main parametric approaches, namely deterministic, probabilistic and stochastic frontiers. However, the first two approaches for estimating the production frontier do not take into account that the performance of a farm can be due to several

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<sup>1</sup> Alternatively, technical efficiency can be analyzed using data envelopment analysis (DEA), as first suggested by Farrell (1957). The DEA approach can generate biased results when the data are not random, but it has been used in many agricultural applications (e.g., Galanopoulos et al. (2006), Lansink and Reinhard (2004), Chih-Ching, Ching-Ming-Kai and Miin (2008) and Singbo and Lansink (2010)).

factors, such as weather, unexpectedly poor performance of machinery, input shortages, diseases and other exogenous factors (Reinhard et al, 1999). Stochastic Frontier Analysis (SFA) is most useful when production processes are subject to such random shocks (Battese, 1992; Coelli et al, 2005). This approach was proposed by Aigner, Lowell and Schmidt (1977) and is most often used in empirical studies on technical efficiency (e.g., Mosheim and Lovell, 2009; Yélou, Larue and Tran, 2010; Tamini, Larue and West, 2012; Singbo and Larue, 2015). However, the stochastic frontier approach could also be used when analyzing environmental efficiency.<sup>2</sup> Reinhard et al. (1999) and Fernandez, Koop and Steel (2000, 2002) introduce good and bad outputs in a stochastic production frontier and computed environmental efficiency scores. Reinhard and Thijssen (2000) use a cost function with an implicit price for nitrogen to measure both technical and environmental efficiencies. Tamini et al. (2012) apply a stochastic frontier approach to estimate an input distance function. An aggregate output is modelled as a technology shifter of the production function for a pollutant (phosphorus)<sup>3</sup> and the results are used to compute environmental performance indicators.

The objective of this study is to evaluate the environmental efficiency of agricultural producers in the Chaudière River basin, located south of Québec City. We rely on the stochastic frontier approach applied to parametric distance functions proposed by Cuesta et al (2009) and

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<sup>2</sup> DEA approaches have also been applied to environmental efficiency studies. See for example Lansink and Reinhard (2004), Chi-Chang et al (2008) or Manello (2012, 2013).

<sup>3</sup> Also see Atkinson and Dorfman (2005) for an application of distance function.

perform a decomposition of environmental inefficiencies in terms of farms characteristics and sociodemographic attributes of producers.<sup>4</sup>

Our results will help determine the extent of heterogeneity in the environmental performances of farms and possibly to identify factors that might explain differences in their performances while considering three different pollutants.<sup>5</sup> These factors can be used to segment farms and target interventions to improve their performances. The next section of this paper, Section 2, presents the context of the study and Section 3 explains the methodological approach. Section 4 describes the empirical data while Section 5 focusses on the interpretation of the results. The sixth and final section summarizes our results and discusses their implications.

## **2 Context of the study**

Within an area of 15,128 km<sup>2</sup> located south the St. Lawrence Seaway, the Chaudière-Appalaches region faces many environmental challenges because of the intensity with which agriculture is practiced (BAPE, 2003).<sup>6</sup> The quality of groundwater and surface water is at high risk due to nitrogen, phosphorus and sediment runoff. In fact, the norm for phosphorus (0.03mg P/l) as set by provincial authorities is often exceeded in this region (Gangbazo and Le Page,

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<sup>4</sup> The goal of Cuesta et al. (2009) was to compare various distance functions with an application to U.S. electric generation units.

<sup>5</sup> Relying on a cost function, Ghazalian, Larue and West (2010) analyzed nitrogen runoff while Tamimi et al. (2012) uses an input distance function to analyze phosphorus runoff.

<sup>6</sup> In 2014, around 30% of Québec hog production was located in the Chaudière-Appalaches region (see at <http://www.leseleveursdeporcsduquebec.com/lorganisation-fr/centre-de-documentation/les-documents-corporatifs.php> Accessed 2015 06 12).

2005).<sup>7</sup> The threat of eutrophication, whereby excess nutrients, like phosphorus, stimulate excessive plant and algae growth in lakes and streams, can harm all aquatic life, impede leisure activities, and deteriorate the quality of drinking water.<sup>8</sup>

For several years now, Quebec authorities have encouraged farmers to adopt environmental Best Management Practices (BMPs) to reduce pollution levels.<sup>9</sup> BMPs can be defined as a set of sustainable management practices that maintain or improve the quality of surface water or groundwater, soil, air and biodiversity (AAC, 2000; Martel et al, 2006). The suite of BMPs includes the management of chemical and organic inputs, the control of erosion and runoff and the use of protective screens and buffer crops to prevent contaminant runoff (AAC, 2000). Michaud et al (2006) and Rousseau et al (2013) show that BMPs can indeed reduce pollution, but that their capacity to abate varies, depending on which BMPs are used, how they are implemented and where. In this context, it has been difficult to determine how to allocate resources to achieve environmental targets at a minimum cost. It is hoped that a better understanding about the incidence of BMPs on environmental efficiency will help producers, regulators and policymakers to make better decisions.

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<sup>7</sup> Tamini and Larue (2012) addressed the implications of manure surplus in terms of public policies.

<sup>8</sup> See at [http://www.msss.gouv.qc.ca/sujets/santepub/environnement/index.php?algues\\_bleu-vert](http://www.msss.gouv.qc.ca/sujets/santepub/environnement/index.php?algues_bleu-vert).

<sup>9</sup> Ghazalian, West and Larue (2009) analyzed the determinants of adoption of BMPs while Tamimi (2011) looked at the impact of agri-environmental advisory activities.

### 3 Methodological approach

#### 3.1 Theoretical considerations

Distance functions are particularly useful in the analysis of multi-output technologies when only data on outputs and inputs are available. There are different types of distance function. An output (input) orientation is most appropriate when firms can adjust their outputs more (less) easily than their inputs. Accordingly, the output distance function indicates how production can increase while keeping the vector of inputs and the bad output unchanged. To be more specific, let us define by  $x$  the bundle of inputs used in a multi-output production process in which  $y$  denotes the good outputs (“*goods*”),  $b$  stands for a pollutant (“*bad*”) and by  $F$  is the frontier of the production technology. The output distance function is defined as:

$$(1) \quad D(x, y, b) = \inf\{\theta > 0: (x, y/\theta, b) \in F\}$$

with  $0 < D(x, y, b) \leq 1$ . It is homogeneous of degree 1 in outputs, non-decreasing in the “*goods*” and non-increasing in the “*bad*” and in the inputs (Cuesta et al., 2009). As suggested by Paul and Nehring (2005), the linear homogeneity property can be imposed by setting  $\theta = 1/y_1$ .

An alternative distance measure allowing for a symmetric treatment of good and bad outputs has been proposed to include environmental gains. Cuesta et al, (2009: p 2234) argue that the hyperbolic distance function simultaneously assesses the maximum amount of the vector “*goods*” and the minimum amount of “*bad*” needed to stay on the production frontier  $F$  without changing the amount of inputs. It can be used to measure environmental efficiency. More specifically, the hyperbolic output distance function is defined as follows:

$$(2) \quad D'(x, y, b) = \inf\{\theta > 0: (x, y/\theta, b\theta) \in F\}$$

The distance function defined by equation (2) is defined in the interval ]0,1]. It is quasi-homogeneous of degree 1 in “goods”, of degree -1 in the “bad”, non-decreasing in “goods” and finally non-increasing in the “bad” and in inputs (Lau, 1972; Cuesta et al, 2009). Using  $\theta = 1/y_1$  the distance function given by equation (2) becomes:

$$(3) \quad D^{EE} \left( x, \frac{y}{y_1}, by_1 \right) = D^{EE}(x, \tilde{y}, \tilde{b})$$

Environmental efficiency indicators can be estimated by exploiting the interactions between “goods” and “bad” given a fixed bundle of inputs (Cuesta et al, 2009). However, the exact definitions of these indicators are conditional on the specification of an empirical model which begins by choosing a functional form.

### 3.2 Functional form

The distance function is most commonly approximated using a Translog function:

$$(4) \quad -\ln y_{1f} = \gamma_0 + \sum_q \gamma_q r_{qf} + \sum_m \gamma_m \ln x_{mf} + \left(\frac{1}{2}\right) \sum_n \sum_m \gamma_{nm} \ln x_{mf} \ln x_{nf} + \\ \sum_{i=2}^{i-1} \gamma_i \ln \tilde{y}_{if} + \left(\frac{1}{2}\right) \sum_{i=2}^{i-1} \sum_{j=2}^{j-1} \gamma_{ij} \ln \tilde{y}_{if} \ln \tilde{y}_{jf} + \sum_{i=2}^{i-1} \sum_m \gamma_{im} \ln \tilde{y}_{if} \ln x_{mf} + \\ \sum_z \gamma_z \ln \tilde{b}_{zf} + \left(\frac{1}{2}\right) \sum_s \sum_z \gamma_{zs} \ln \tilde{b}_{zf} \ln \tilde{b}_{sf} + \sum_m \sum_z \gamma_{mz} \ln x_{mf} \ln \tilde{b}_{zf} + \\ \sum_{i=2}^{i-1} \sum_z \gamma_{iz} \ln \tilde{y}_{if} \ln \tilde{b}_{zf} + \zeta_f$$

In equation (4),  $\ln x_{mf}$  is the log transformation of input  $x_m$  used by farm  $f$  and  $r_{qf}$  represents one of  $q$  management practices or BMPs implemented on the farm. From the above theoretical



considerations,  $\tilde{y}_i \equiv y_i \cdot \frac{1}{y_1}$ ,  $\tilde{b}_z \equiv b_z \cdot y_1$  and we denote by  $d^{EE} \equiv \ln\left(\frac{1}{y_1}\right)$  the distance function used to analyze the environmental efficiency. We assume that error term has two components: a purely random component normally distributed with zero mean ( $v_f$ ) and a half-normally distributed inefficiency component  $u_f$ :

$$(5) \quad \zeta_f = v_f - u_f$$

Time-invariant farm-specific hyperbolic efficiency estimates can be obtained by computing  $\exp(-u_f)$ .

### 3.3 *Economic performance measures*

#### *Inputs elasticities*

First-order elasticities (equation (6)) and second-order elasticities (equation (7)) are given by:

$$(6) \quad \varepsilon_m^{EE} = \partial d^{EE} / \partial \ln x_m$$

$$(7) \quad \psi_{m,l}^{EE} = \partial \varepsilon_{y,m}^{EE} / \partial \ln x_l$$

The second-order elasticities indicate how the first-order elasticities change in percentage in response to a 1% increase in an input, while keeping constant all other inputs and outputs. In interpreting the second-order effects, Cuesta et al (2009, p.2238) exploit the fact that  $\psi_{m,l}^{(\cdot)}$  is a share-weighted<sup>10</sup> version of the marginal product elasticity  $\partial \ln MP_m / \partial \ln x_l$ . The elasticity of the marginal product of input  $m$  with respect to input  $l$  is positive (negative) if inputs are

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<sup>10</sup> The first derivatives of the Translog distance with respect to inputs give input shares.

complementary (substitute), but because the dependent variable of the estimated equation is negative (see equation (4)), the signs of the cross derivatives are inverted. The complete measure of the share elasticity shows how an increase in input l impacts on the contribution of input m to production (Morrisson-Paul, Johnson and Frengley, 2000; Cuesta et al, 2009):

$$(8) \quad \xi_{m,l}^{EE} = \psi_{m,l}^{EE} \times \ln x_l = \gamma_{ml} \times \ln x_l$$

*Elasticities of substitution between “goods” and “bads”*

The elasticities of substitution between “goods” and “bads” are given by:

$$(9) \quad \varepsilon_{y,i}^{EE} = \partial d^{EE} / \partial \ln y_i = \partial d^{EE} / \partial \ln \tilde{y}_i$$

$$(10) \quad \varepsilon_{b,z}^{EE} = \partial d^{EE} / \partial \ln \tilde{b}_z$$

Equations (9) (equation (10)) represents the effect of an increase in a “good” (“bad”) on the distance function while keeping everything else unchanged. Using the conditions of quasi-homogeneity, Cuesta et al (2009) show that:  $\varepsilon_y^{(\cdot)} = 1 + \varepsilon_b^{(\cdot)}$ . Thus the ratio of elasticities, measuring the substitutability between “goods” and “bads” are as follows:

$$(11) \quad \tau_{y,b}^{EE} = \varepsilon_y^{EE} / \varepsilon_b^{EE}$$

A more negative (higher in absolute value) ratio is indicative of a higher opportunity cost of “goods” in terms of the “bads”.

*Shadow price of the “bads”*

Let define profit function as:

$$(12) \quad \pi(x, p, q) = \max_{y,b} \{py/qb : D^{EE} \leq 1\}$$

where  $p$  and  $q$  are the prices of “goods” and “bads”, respectively. Profits maximization implies that  $\tau_{y,b}^{EE} = \varepsilon_y^{EE} / \varepsilon_b^{EE} = -1$  (Cuesta et al, 2009). The quasi-homogeneity property of the hyperbolic distance function implies  $\varepsilon_y^{EE} - \varepsilon_b^{EE} = 1$ . Combining these two results,  $\varepsilon_y^{EE} = -\varepsilon_b^{EE} = 0.5$  and the shadow price of the “bad” is:

$$(13) \quad q = py \cdot (0.5 \cdot D^{EE} \cdot b)^{-1}$$

#### 4 Data

The database consists of a cross-section of 210 observations. The “goods” include animal (cattle, dairy cows, pigs) and crop (hay, alfalfa, beans, corn, and other grains) productions. The sample is dominated by livestock producers since 77.1% of all producers reported an animal production as their main production. The variables *Crop* and *Animal productions* represent the gross revenue derived from crop and animal production. They are both expressed in thousands of Canadian dollars. The quantities of phosphorus, nitrogen and sediment are highly correlated; 0.975 between phosphorus and nitrogen, 0.866 between phosphorus and sediment and 0.832 between nitrogen and sediments. To avoid a serious multicollinearity problem, we estimate three separate distance functions with the same two good outputs, but with a different bad output. Runoffs are computed through simulations that estimate the amount of chemical leached from individual Relatively Homogeneous Hydrological Units (RHHUs). RHHUs correspond to small areas whose drainage structures are derived from a relatively high resolution Digital Elevation Model (DEM).

The inputs are labor expressed in hours, fertilizers and herbicides in kg/ha and capital proxied by the value of machinery, including tractors, trucks and other equipment. A high correlation between fertilizers and herbicides (0.916) induce collinearity problems in the estimation process and prevented us from combining these two inputs. Only fertilizers are used in the estimation.<sup>11</sup>

Five BMPs are considered: crop rotation, liquid and solid manure injection into the soil within 24 hours after the initial spread, reduced dosage of herbicides and the establishment and maintenance of a buffer strip of at least a one meter in width. These variables take the value 1 if the management practice is adopted and 0 otherwise. We also hypothesize that belonging to an agro-environmental club and having an educational certificate for organic production will condition the distance functions.

We assume that the inefficiency terms can be explained by a vector of explanatory variables and use the following decomposition scheme:

$$(14) \quad u_f = \sum_{s=2}^4 \delta_{1,s} size_s + \sum_{e=2}^4 \delta_{2,e} education_e + \delta_3 telecom + \delta_4 gender + \delta_5 residence + \delta_6 crop + \sum_{a=2}^3 \delta_{7,a} age_a$$

The binary variables *size*, are introduced to reflect a potential relationship between the inefficiencies and the value of agricultural production. Based on total revenue from crops and livestock, the sample is divided into 4 classes of size. The effect of education (*education*) is

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<sup>11</sup> Usually, it is best to combine two or more inputs by constructing a quantity index. However, the high degree of correlation between fertilizer and herbicides made the use of an aggregator pointless.

specified using binary variables allowing for five different levels: primary school (reference group), secondary school, technical school, college and university. The variable *telecom* is expressed in thousands of dollars and is the producer's annual expenditure on telecommunications. This captures their access to information. The variables *gender* and *residence* take respectively the value of 1 if the producer is a female and if the producer lives on the farm. The variable *production* is set to 1 if the value of crop production is higher than that of animal production and it is set to 0 otherwise. Finally, producers are divided in 3 groups based on their *age*: 17 to 39, 40 to 54, 55 to 81.

Table 1 presents some descriptive statistics for the variables of interest of this study.

<<< *Table 1 about here* >>>

## **5 Results and discussion**

### *5.1 General results*

Table 2 presents results obtained from the estimation of the distance functions given by equation (4) and for phosphorus, nitrogen and sediment. The table allows us to determine the magnitude and significance of the direct partial elasticities. For the studied pollutants, the first order coefficients related to “goods” ( $\gamma_{Good}$ ) are positive which is expected, as is the negative first-order estimated coefficients of the “bads” ( $\gamma_{Bad}$ ). The cross-effect coefficients between “goods” and “bads” are positive and significant implying a “complementarity” between the two types of outputs. The similarities in the reported coefficients across pollutants are not surprising in light of the high degree of correlation between phosphorus, nitrogen and sediments.

The coefficients related to crop rotation, solid manure management and belonging to an environmental club are negative and statistically significant at the 5% level, implying an upward shift of the environmental frontier. These results indicate that farms that have adopted these specific BMPs or are member of an environmental club were able to increase their production while lowering their pollutant runoff. These results are similar to those found by Tamini (2011) regarding the incidence of advisory/extension activities and those by Tamini et al (2012) about the impact of BMPs. The coefficients of the remaining management variables are not significant at 5%.

<<< *Table 2 about here* >>>

As presented in Table 3, the first-order elasticity of the “*bad*” is negative, while it is positive for the “*goods*”, reflecting the fact that, at the sample mean, the distance functions are non-increasing in the “*bad*” and non-decreasing in the “*goods*”. The relatively low values of the substitutability between the “*bad*” and the “*goods*” relative to those reported by Custa et al., (2009) indicate that policies for controlling the production of a “*bad*” through the use of reduction targets or quotas are likely to be effective.<sup>12</sup> At -6.038, the substitutability between nitrogen and the “*goods*” is the lowest, indicating a lower opportunity cost (See Table 3).

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<sup>12</sup> For high values (50 to 200 in absolute value), Cuesta et al (2009: p. 2239) concluded that « ... *economic incentives aimed at attaining an efficient control of pollution by way of taxes, or permits related to “cap and trade” schemes, as well as incentives to invest in cleaner production technologies, are favored by economic regulators worldwide.*». In our study, regulated pollution reductions would also bring about reductions in good outputs, but not nearly of the same order.

Because 77.1% of the farms included in our data had livestock as their main production, the higher opportunity cost (and complementarity) for phosphorus was expected.

<<< *Table 3 about here* >>>

When statistically significant, the first-order elasticities of input are negative (see Table 4) reflecting the fact that, at the sample mean the distance function are non-increasing in input, an outcome that is consistent with a theoretical property of distance functions. For the 3 pollutants considered in this study, the first order-elasticity is highest for labor.

<<< *Table 4 about here* >>>

As mentioned before, negative (positive) second order elasticity indicates that inputs are complements (substitutes). Our results indicate that capital and labor tend to be substitutes, as are capital and fertilizers. The second order elasticities regarding fertilizers and labor are consistently non-significant. Increasing the use of labor does not seem to have an impact on the marginal effect of fertilizers and *vice-versa*.

## 5.2 *Environmental efficiencies*

The coefficients related to farm size are statistically different from zero at the 5% level, but in a non-monotonic way (Table 5). Farms belonging in group 3 are more efficient than those in group 4 (the reference group), while there is no difference between groups 1, 2 and 3. When significant, advancing in age has a positive impact on efficiency. This is the case for phosphorus and sediments for producers in the third class when compared to the reference group, class 1. The impact is higher when the *bad* is phosphorus. The positive sign of the coefficient for the

*crop* variable indicates that farms that have crop production as their main production are less efficient, which is particularly the case for the inefficiency term for sediments. In contrast, residence on the farm reduces the inefficiency term for sediments, while it has no impact when the *bads* are phosphorus and nitrogen. Intuitively, highly educated producers should have an advantage in terms of acquisition and assimilation of new information. The results in Table 5 suggest that there is no significant gain in environmental efficiency beyond a high school diploma.

<<< *Table 5 about here*>>>

The empirical distributions of the environmental efficiency scores for the three *bads* are displayed in Figure 1. Table 6 shows that mean efficiency is lowest for sediments, at 0.736, while mean environmental efficiency for phosphorus and nitrogen are 0.804 and 0.820 respectively. The distribution of efficiency scores for phosphorus displays higher dispersion than that for nitrogen, but less than that for sediments.

<<< *Figure 1 about here* >>>

<<< *Table 6 about here* >>>

Like Tamini et al (2012), the mean environmental efficiency statistic is lower for farms whose main source of revenues is livestock production. This is true across all three *bads*. This suggests that allocating relatively more resources to extension services targeting livestock production could be a cost-effective strategy to improve the productivity performance of



“goods”, especially for phosphorus and sediments (see Table 7).<sup>13</sup> As indicated in Table 7, there is a potential for increasing productivity, while simultaneously reducing the production of “bads”. Farms can increase productivity in the production of “goods” by 24.38%, while simultaneously reducing phosphorus runoff by 19.60%. The policy implication of this result is that higher agricultural productivity – and higher production levels – can be achieved while reducing discharges of pollutants in streams, lakes and river. Higher agricultural productivity and output levels need not simultaneously reduce water quality.

<<< Table 7 about here >>>

### 5.3 Shadow prices of the “bads”

Our calculations of shadow prices are reported in Table 6. The average shadow price related to the emission of a kilogram of phosphorus is \$745.142 CAN. This shadow price is interpreted as the value of total production (animal and plant) to be sacrificed in order to reach the efficiency frontier (Färe et al, 2005). Tamini et al (2012) found that a 10% reduction in phosphorus runoff costs on average \$461.24 CAN. Using their reported mean for phosphorus, we can compute an implied price of phosphorus runoff of \$725.905 CAN/kg which is close to our estimate. The shadow price is lower for nitrogen, with a value of \$259.72 CAN/kg, while it is higher for sediments, at \$1,114.19 CAN/kg. Ghazalian et al (2010) found that the average cost associated with a 10% reduction in nitrogen emissions was \$324.10 CAN, which is

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<sup>13</sup> The mean efficiency statistics in this study are higher than those found in Tamini et al (2012) Their mean environmental efficiency statistics for crops and livestock are 0.504 and 0.380. Murty, Kumar and Paul (2006) obtained an average environmental efficiency of 0.853 for Indian sugar companies and Lansink and Reinhard (2004) reported a mean efficiency of 86% for Dutch hog farms producing excess phosphorus and ammonia.

equivalent to a cost of \$218.25 CAN/kg. Shadow costs are higher for farms primarily involved in livestock production, for all three “*bads*”. This is not so surprising because environmental regulations pertaining to livestock productions in Quebec were tightened in the wake of a moratorium on hog production imposed in 2002 and lifted in 2005. If the regulations were significantly stricter, then there would have been less room for heterogeneity in environmental efficiency amongst livestock producers.

## **6 Conclusion**

The study has evaluated environmental efficiencies of agricultural producers of the Chaudière watershed in Québec by following the approach proposed by Cuesta et al (2009) featuring the hyperbolic distance function. Three “*bad-specific*” distance functions were estimated to measure environmental performance indices for phosphorus, nitrogen and sediments runoffs. Environmental efficiency was decomposed in terms of farms characteristics and producers sociodemographic attributes. Our results show that farm size, age group, type of production and on-farm residence each had an impact on environmental inefficiencies. Mean efficiency was lower for all three “*bads*” for farms deriving their revenues mainly from livestock production. For these farms, there is much room to increase productivity in the production of agricultural “*goods*” while decreasing the “*bads*” by-product. This is especially true for phosphorus and sediment. Overall, there is a potential for increasing productivity while simultaneous reducing the production of “*bads*”. The corollary to this result is that policies that require agricultural producers to reduce the negative by-products of their agricultural activities on water quality do not necessarily reduce their productivity.

The relatively low values of the substitutability between each “*bads*” and the “*goods*” indicate that regulations directly controlling the production of “*bads*”, like reduction targets or quotas, are likely to be effective. However, reducing “*bads*” is more costly for some farms than others. The shadow costs associated with the reduction of “*bads*” were consistently higher across “*bads*” for farms deriving most of their farm income from crop production.

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## List of Tables

**Table 1:** Descriptive statistics of variables

<b>Variables</b>	<b>Mean</b>	<b>Standard Error</b>	<b>Minimum</b>	<b>Maximum</b>
Crop production (x\$1000)	6.557	22.159	0.010	260.000
Livestockproduction (x\$1000)	103.091	325.414	0.150	2,696.165
Nitrogen (kg)	14.846	12.512	0.234	46.980
Phosphorus (kg)	6.354	5.635	0.002	20.549
Sediments (kg)	1.516	1.384	<0.001	6.131
Labor (number of hours)	27.556	91.587	0.028	730.097
Herbicides (kg/ha)	0.561	0.676	0.003	4.987
Fertilizer (kg/ha)	1.159	1.390	0.006	10.907
Capital (x\$1000)	137.772	115.104	1.787	784.500
Liquid manure management (=1 if yes)	0.419	0.495	0.000	1.000
Crop rotation (=1 if yes)	0.700	0.459	0.000	1.000
Riparian buffer (=1 if yes)	0.557	0.498	0.000	1.000
Herbicides control (=1 if yes)	0.381	0.487	0.000	1.000
Solid manure management (=1 if yes)	0.129	0.336	0.000	1.000
Age (years)	49.357	10.100	17.000	81.000
Gender (=1 if women)	0.038	0.192	0.000	1.000
Residence on farm (=1 if yes)	0.571	0.319	0.000	1.000
Education (order variable)	2.286	1.051	1.000	5.000
Belonging to an environmental club (=1 if yes)	0.595	0.492	0.000	1.000
Biological/organic certificate (=1 if yes)	0.029	0.167	0.000	1.000
Livestock as main production (=1)	0.771	0.421	0.000	1.000
Crops as main production (=1)	0.229	0.421	0.000	1.000
Telecommunication expenditure (x\$1000)	1.102	0.812	0.050	4.000
Size (total gross revenue in \$1000)	158.465	563.532	0.584	5,835.288

**Table 2.** Estimated coefficients of the distance functions

<b>Parameters</b>	<b>Phosphorus</b>		<b>Nitrogen</b>		<b>Sediments</b>	
<i>Y<sub>Good</sub></i>	0.481	(0.067)	0.453	(0.076)	0.481	(0.071)
<i>Y<sub>GoodXGood</sub></i>	0.070	(0.023)	0.083	(0.027)	0.084	(0.025)
<i>Y<sub>Bad</sub></i>	-0.256	(0.037)	-0.288	(0.049)	-0.247	(0.051)
<i>Y<sub>BadXBad</sub></i>	-0.002	(0.008)	0.009	(0.016)	-0.002	(0.011)
<i>Y<sub>BadXGood</sub></i>	0.026	(0.012)	0.037	(0.018)	0.032	(0.015)
<i>Y<sub>Capital</sub></i>	-0.384	(0.077)	-0.271	(0.085)	-0.460	(0.080)
<i>Y<sub>Labor</sub></i>	-0.793	(0.112)	-0.635	(0.127)	-0.914	(0.114)
<i>Y<sub>Fertilizers</sub></i>	-0.145	(0.087)	-0.152	(0.099)	-0.118	(0.088)
<i>Y<sub>CapitalXCcapital</sub></i>	0.183	(0.032)	0.144	(0.031)	0.212	(0.033)
<i>Y<sub>CapitalXLabor</sub></i>	0.212	(0.062)	0.162	(0.059)	0.269	(0.064)
<i>Y<sub>CapitalXFertilizers</sub></i>	0.082	(0.031)	0.096	(0.029)	0.068	(0.036)
<i>Y<sub>LaborXLabor</sub></i>	0.067	(0.040)	0.074	(0.041)	0.119	(0.042)
<i>Y<sub>LaborXFertilizers</sub></i>	0.070	(0.043)	0.077	(0.044)	0.054	(0.043)
<i>Y<sub>FertilizersXFertilizers</sub></i>	-0.022	(0.022)	-0.016	(0.021)	-0.011	(0.023)
<i>Y<sub>CapitalXGood</sub></i>	0.038	(0.015)	0.025	(0.015)	0.041	(0.019)
<i>Y<sub>LaborXGood</sub></i>	-0.007	(0.023)	-0.035	(0.029)	-0.021	(0.024)
<i>Y<sub>FertilizersXGood</sub></i>	-0.001	(0.021)	-0.000	(0.022)	-0.006	(0.021)
<i>Y<sub>CapitalXBad</sub></i>	0.031	(0.012)	0.034	(0.013)	0.026	(0.016)
<i>Y<sub>LaborXBad</sub></i>	0.005	(0.015)	-0.016	(0.021)	-0.009	(0.017)
<i>Y<sub>FertilizersXBad</sub></i>	-0.020	(0.016)	-0.011	(0.018)	-0.021	(0.017)
<i>Y<sub>Crop rotation</sub></i>	-0.152	(0.051)	-0.130	(0.049)	-0.152	(0.052)
<i>Y<sub>Riparian buffer</sub></i>	-0.035	(0.045)	-0.029	(0.044)	-0.041	(0.044)
<i>Y<sub>Herbicides control</sub></i>	-0.013	(0.049)	-0.011	(0.047)	0.010	(0.050)
<i>Y<sub>Solid manure management</sub></i>	-0.176	(0.079)	-0.158	(0.077)	-0.189	(0.082)
<i>Y<sub>Liquide manure management</sub></i>	-0.001	(0.053)	-0.023	(0.050)	-0.005	(0.054)
<i>Y<sub>Environmental club</sub></i>	-0.125	(0.045)	-0.109	(0.044)	-0.109	(0.046)
<i>Y<sub>Organic certificate</sub></i>	0.011	(0.134)	-0.025	(0.131)	0.071	(0.142)
Log likelihood	-39.919		-31.826		-49.160	
Number of observations	210		210		210	

Standard errors are reported in parentheses.



**Table 3.** Substitutability between “goods” and “bads”

	Phosphorus	Nitrogen	Sediment
First order elasticity of the “goods” ( $\epsilon_y^{EE}$ )	0.778	0.782	0.770
First order elasticity of the “bads” ( $\epsilon_b^{EE}$ )	-0.112	-0.129	-0.110
Substitutability between “goods” and “bads” ( $\tau_{y,b}^{EE}$ )	-6.926	-6.038	-6.984

**Table 4.** Estimated inputs elasticities

<b>Phosphorus</b>	Capital		Labor		Fertilizers	
Estimated coefficients ( $\gamma_m$ )	-0.384	(0.077)	-0.793	(0.112)	-0.145	(0.087)
First order elasticities ( $\epsilon_m^{EE}$ )	0.046	(0.054)	-0.639	(0.074)	-0.050	(0.049)
Second order elasticities ( $\xi_{m,l}^{EE}$ )						
Capital	0.231	(0.053)	0.268	(0.102)	0.104	(0.051)
Labor	0.357	(0.124)	0.113	(0.081)	0.117	(0.086)
Fertilizers	-0.039	(0.031)	-0.033	(0.043)	0.010	(0.022)
<b>Nitrogen</b>	Capital		Labor		Fertilizers	
Estimated coefficients ( $\gamma_m$ )	-0.271	(0.085)	-0.635	(0.127)	-0.152	(0.099)
First order elasticities ( $\epsilon_m^{EE}$ )	0.085	(0.051)	-0.637	(0.076)	-0.045	(0.045)
Second order elasticities ( $\xi_{m,l}^{EE}$ )						
Capital	0.182	(0.051)	0.205	(0.097)	0.121	(0.048)
Labor	0.274	(0.118)	0.125	(0.083)	0.130	(0.089)
Fertilizers	-0.046	(0.029)	-0.037	(0.044)	0.007	(0.022)
<b>Sediments</b>	Capital		Labor		Fertilizers	
Estimated coefficients ( $\gamma_m$ )	-0.460	(0.080)	-0.914	(0.114)	-0.118	(0.088)
First order elasticities ( $\epsilon_m^{EE}$ )	0.008	(0.058)	-0.722	(0.080)	-0.034	(0.051)
Second order elasticities ( $\xi_{m,l}^{EE}$ )						
Capital	0.268	(0.055)	0.340	(0.106)	0.086	(0.059)
Labor	0.453	(0.129)	0.201	(0.084)	0.091	(0.086)
Fertilizers	-0.033	(0.036)	-0.026	(0.043)	0.005	(0.024)

Standard errors are reported in parentheses. These elasticities are obtained from the Delta method. They are reported at their respective average.

**Table 5.** Estimated coefficients of the inefficiency terms

Parameters	Phosphorus		Nitrogen		Sediments	
$\delta_{Gender}$	-2.717	(2.475)	-3.155	(3.040)	-2.256	(1.449)
$\delta_{Telecom}$	-0.08	(0.202)	-0.068	(0.207)	-0.019	(0.151)
$\delta_{Size_1}$	-1.765	(1.018)	-1.944	(1.035)	-0.658	(0.679)
$\delta_{Size_2}$	-0.494	(0.582)	-0.608	(0.615)	-0.223	(0.458)
$\delta_{Size_3}$	-1.266	(0.484)	-1.075	(0.481)	-1.008	(0.405)
$\delta_{Age_2}$	-0.451	(0.418)	-0.501	(0.429)	-0.109	(0.354)
$\delta_{Age_3}$	-3.96	(1.959)	-4.472	(2.751)	-1.893	(0.563)
$\delta_{Crop}$	1.825	(0.547)	1.135	(0.624)	2.124	(0.466)
$\delta_{Education_2}$	-1.024	(0.509)	-1.139	(0.515)	-0.77	(0.375)
$\delta_{Education_3}$	-0.178	(0.571)	-0.329	(0.587)	0.05	(0.439)
$\delta_{Education_4}$	-0.569	(0.601)	-0.711	(0.591)	-0.168	(0.452)
$\delta_{Education_5}$	-1.722	(1.362)	-1.196	(1.230)	-1.68	(1.463)
$\delta_{Residence\ on\ farm}$	-0.642	(0.476)	-0.529	(0.468)	-0.975	(0.387)
$\sigma_u$	0.235	(0.019)	0.230	(0.019)	0.203	(0.027)

Standard errors are reported in parentheses.

**Table 6.** Efficiencies scores and the shadow price of the bad

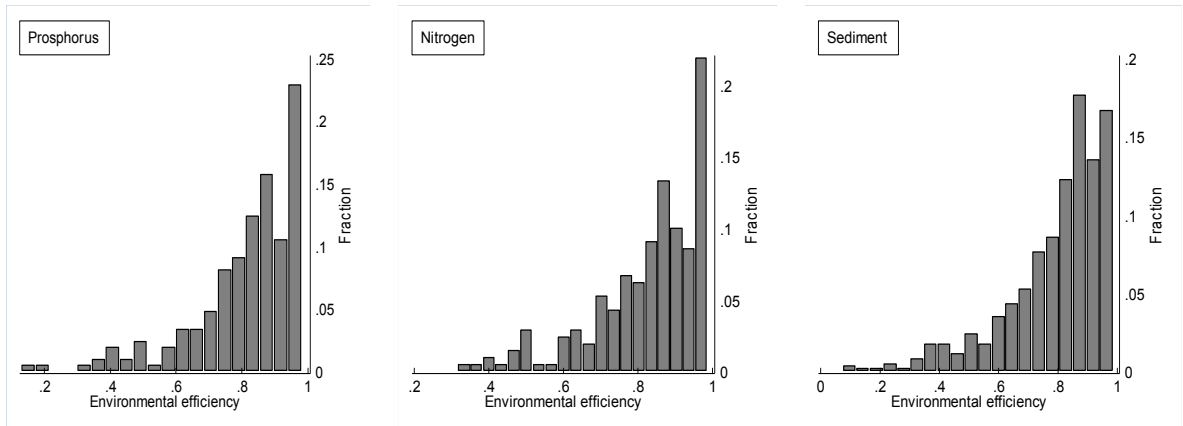
	Phosphorus		Nitrogen		Sediment	
	EE	Shadow price	EE	Shadow price	EE	Shadow price
All productions	0.804	745.142	0.820	259.716	0.736	1114.192
	(0.163)	(320.040)	(0.148)	(126.153)	(0.183)	(264.723)
Livestock production	0.555	1290.329	0.642	1317.133	0.426	3720.684
	(0.047)	(388.629)	(0.041)	(590.708)	(0.048)	(1180.717)
Crop production	0.833	684.243	0.840	135.976	0.773	821.485
	(0.010)	(312.010)	(0.009)	(70.535)	(0.011)	(245.944)

Standard errors are reported in parentheses.

**Table 7. Potential for productivity and environmental gains**

	<u>All productions</u>	<u>Livestock production</u>	<u>Crop production</u>
<b>Phosphorus</b>			
Potential for increasing productivity performance of “goods” [= $(1 / EE - 1) * 100$ ]	24.38%	80.18%	20.05%
Potential for –simultaneous- reduction of “bads” production [= $(1 - EE) * 100$ ]	19.60%	44.50%	16.70%
<b>Nitrogen</b>			
Potential for increasing productivity performance of “goods” [= $(1 / EE - 1) * 100$ ]	21.95%	55.76%	19.05%
Potential for –simultaneous- reduction of “bads” production [= $(1 - EE) * 100$ ]	18.00%	35.80%	16.00%
<b>Sediment</b>			
Potential for increasing productivity performance of “goods” [= $(1 / EE - 1) * 100$ ]	35.87%	134.74%	29.37%
Potential for –simultaneous- reduction of “bads” production [= $(1 - EE) * 100$ ]	26.40%	57.40%	22.70%

## List of figures



**Figure 1.** Predicted environmental efficiencies distribution