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Abstract

Soil organic carbon stocks have been declining for more than a century, mostly in the tropics. Maintaining soil organic matter is critical to tackling climate change and controlling soil health. One way to address this problem is to encourage farmers to improve soil carbon on their farms. We provide an ex-ante assessment of the cost-effectiveness of innovative Agri-Environmental Measures (AEM) that subsidize the use of compost. To do so, we ran a choice experiment in Guadeloupe, in the northeastern Caribbean, where there is an urgent need to preserve soil organic matter levels. The 305 farmers who participated were asked to choose one of several AEM that offer financial support in exchange for using compost in their farming activities, as well as free technical assistance, a collective financial bonus, and the possibility of combining chemical fertilisers with composts. We found that offering free technical assistance increases the participation rate by 30 percentage points and offering a collective bonus increases it by 14 percentage points. In contrast, including a requirement on the reduction of chemical fertilization would decrease the probability of participation by only two percentage points. We then estimated the amount of carbon that would be sequestered in the soil using compost as prescribed under each of the AEM proposed. We found that the most effective AEM would sequester up to 25,000 teqCO2 per ha and per year and that the most cost-effective scheme would reach this target at a cost of about 500 euros per teqCO2. Finally, we find that the so-called 4 per 1000 target could be reached through AEM under a variety of scenarios.
Keywords: soil carbon, compost, climate change, choice experiment, Guadeloupe.

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Significance statement

Maintaining soil organic matter is critical to tackling climate change and controlling soil health. In this article, we study the effectiveness of a series of innovative Agri-Environmental Measures (AEM) that subsidize the use of compost in Guadeloupe, in the northeastern Caribbean. We combined estimates of the likelihood of farmers adopting agri-environmental measures, with biophysical simulations of the effects of adopting these measures on soil carbon sequestration. We find that measures incorporating non-monetary incentives such as free technical assistance for the choice and use of compost, administrative support for the preparation of the application file, or a collective bonus that would compensate large groups of voluntary farmers could be used to achieve the 4 per 1000 target. This suggests that such incentives should be included in future AEM to improve soil carbon.

1 Introduction

Maintaining soil organic matter is critical to tackling climate change because soil organic matter is rich in carbon. Soil organic matter is also the keystone element controlling soil health, which enables soils to be resilient as droughts and intense rainfall events increasingly occur (Lynch, 2014, 2019). Yet, soil organic carbon stocks have been decreasing for more than a century, mainly in the tropics, due notably to an increase in agricultural land, the intensification of deforestation, the shortening of fallow periods, the increasing use of agricultural heavy machinery and the decrease in organic fertilisers (Lal, 2019). Faced with this problem, the choice of the most efficient instrument to encourage farmers to improve soil carbon is a central issue.

For several years now, the European Union's Common Agricultural Policy (CAP) has implemented Agri-Environmental Measures (AEM), to encourage ecologically friendly practices such as adding compost to the soil.[1] This is a crucial concern in the small island states of the Caribbean where there is an urgent need for recycling solid wastes because of the collapse of landfill sites. However, farmers' participation in these schemes is often low and their effectiveness has not always been demonstrated (Behaghel et al., 2019; Kuhfuss and Subervie, 2018; Arata and Sckokai, 2016; Chabé-Ferret and Subervie, 2013; Pufahl and Weiss, 2009; Blazy et al., 2015).

The determinants of farmers' adoption of innovative, sustainable agricultural systems have been a central question of research in agricultural economics for a long time (Sunding and Zilberman, 2001). The challenge is to identify the obstacles to the adoption of the most innovative agri-environmental techniques on the one hand, and the public policy instruments that can remove these obstacles on the other (Espinosa-Goded et al., 2010). In the context of a limited EU budget, high priority should be placed on the cost-effectiveness of public schemes. For this reason, ex-ante evaluation of the cost-effectiveness of environmental programs – i.e. determining the maximum environmental benefit for a fixed cost or the minimum cost of achieving a specific environmental outcome – has become a central concern of public authorities in the last ten years (Thoyer and Préget, 2019; Colen et al., 2016; Smismans, 2015). However, such evaluations are generally lacking in the literature on environmental programs.

In this article, we perform an ex-ante evaluation of the cost-effectiveness of a series of innovative AEM designed to promote the use of organic soil enrichments containing compost among farmers in Guadeloupe. Our objective is to determine which types of AEM could significantly improve soil carbon in Guadeloupe farms and at what cost. To do so, we make use of an original methodological procedure, combining a choice experiment involving 305 volunteer farmers with biophysical simulations of the effects of the adoption of the proposed measures on soil carbon sequestration in Guadeloupe. The proposed analysis includes three steps: (i) predicting the participation rate of farmers in each AEM, (ii) simulating the environmental impacts of the adoption of each AEM in areas with possibly heterogeneous land uses and pedoclimatic conditions, and (iii) computing and extrapolat-

[1] AEMs are one of the major tools of the 2nd pillar of the Common Agricultural Policy (CAP). The CAP has two objectives: to facilitate changes in agricultural practices in order to reduce pressure on the environment and to maintain environmentally favourable agricultural practices. Under this scheme, farmers sign a contract with the State in which they commit to environmentally friendly practices, in return for which they receive payment for the environmental and climatic services rendered.

ing environmental gains and economic costs in order to rank the AEM considered according to their cost-effectiveness.

The farmers who participated in the choice experiment were asked to choose among several AEM that offer both monetary and non-monetary incentives to use compost in their farming activities. In addition to financial support, we studied three potential levers for improving farmers' participation rates in the AEMs encouraging compost use: free technical assistance, a collective financial bonus, and the possibility of combining chemical fertilisers with composts. We found that offering free technical assistance increases the participation rate by 30 percentage points and offering a collective bonus increases it by 14 percentage points. In contrast, including a requirement on the reduction of chemical fertilization would decrease the probability of participation by only 2 percentage points. We then estimated the amount of carbon that would be sequestered in the soil using compost as prescribed under the AEMs proposed. We found that the most effective measure sequesters up to 25,000 teqCO2 per ha and per year and that the most cost-effective measure reaches this target at a cost of about 500 euros per teqCO2. Finally, we found that AEM could be used to reach the 4 per 1000 target launched by France at the 2015 United Nations Climate Change Conference (Minasny et al., 2017).

A number of studies have run *ex-post* evaluations of the impact of environmental programs in developed countries (Lynch et al., 2007; Lynch and Liu, 2007; Pufahl and Weiss, 2009; Chabé-Ferret and Subervie, 2013; Arata and Sckokai, 2016; Kuhfuss and Subervie, 2018) and developing countries (Robalino and Pfaff, 2013; Arriagada et al., 2012; Alix-Garcia et al., 2012, 2015; Costedoat et al., 2015; Sims et al., 2014; Jayachandran et al., 2017). Apart from a few exceptions (Chabé-Ferret and Subervie, 2013; Jayachandran et al., 2017), no study has attempted to translate the additional effects on land use into environmental gains in order to compare them with the costs of the program. In the literature that focuses on *ex-ante* evaluation of environmental programs, a growing number of studies rely on choice experiments to estimate farmers' willingness to provide ecosystem services (see for example Kaczan et al. (2013) and references therein, Villanueva et al. (2017), or Latacz-Lohmann and Breustedt (2019) for more recent references). However, very few attempt to then use these estimated participation rates in broader frameworks that would allow for an estimation of the cost-effectiveness of the program under study,[2] something we aim to do in this paper.

The remainder of the paper is structured as follows. We outline the statistical model and the empirical strategy used to estimate participation in AEM in Section 2. We present the original data collected in the study area and the estimations of carbon sequestration used to compute cost-effectiveness in Section 3. We present the results in Section 4 and discuss them in Section 5. We conclude with policy implications of our study in Section 6.

[2] One exception is Gillich et al. (2019), who combine partworth coefficients obtained from choice modelling and stochastic simulations to assess the potential of new crop adoption in Southwestern Germany.

2 Economic Model

2.1 Statistical model to predict participation in AEM

In order to predict participation in AEM, we use a standard theoretical framework of choice modelling, based on the random utility theory (Marschak, 1960; Thurstone, 1927). We use the framework developed by Revelt and Train (1998), in which N respondents can choose from among J alternatives (here, AEMs for adding compost to the farmland) on T choice occasions. A farmer is assumed to choose an AEM if the net utility from choosing that alternative is greater than choosing either no AEM or any of the competing AEMs. The utility that farmer n derives from choosing alternative j is given by $U_{nj} = V_{nj} + \epsilon_{nj}$, where U_{nj} denotes the overall utility of respondent n for AEM j, which consists of an observed systematic component of utility V_{nj} and an unobserved random component ϵ_{nj}. The observed component of utility of respondent n is a linear additive function of the variables X_{njk} for $k = [1,...,K]$ attributes that describe AEM j, each weighted with a coefficient β_{njk}:

$$V_{nj} = \sum_{k=1}^{K} X_{njk}\beta_{njk}$$

The probability P_{nj} that an individual n chooses alternative j from among the set C of alternatives reflects the probability that alternative j gives him the greatest utility:

$$P_{nj} = P[V_{nj} + \epsilon_{nj} > V_{ni} + \epsilon_{ni}], \forall i \in C, i \neq j$$

Different discrete choice models are obtained from different assumptions about the distribution of the random term ϵ. We used a mixed logit (ML) model, which overcomes several drawbacks of the standard logit model by allowing for heterogeneity in tastes, correlation in unobserved factors over repeated choices made by each individual, and the complete relaxation of the independence of irrelevant alternatives (IIA) assumption (Train, 1998; Greene and Hensher, 2003).

The model assumes that the coefficients β_{jk} vary among respondents with a density function $f(\beta)$. This density is characterized by the parameters θ of the mean and the variance of β in the population. The ML model also takes into account the fact that choices are repeated by respondents in different choice situations (Revelt and Train, 1998). The ML choice probability is given by:

$$P_{nj} = \int \frac{\exp(x'_{nj}\beta)}{\sum_{i=1}^{I}\exp(x'_{ni}\beta)} f(\beta|\theta)\, d\beta$$

Our model also includes an alternative specific constant (ASC) that takes the value of one if the status quo alternative describing the current situation is chosen and zero otherwise (Adamowicz et al., 1998; Scarpa et al., 2005). We estimated this model by maximum simulated likelihood using Halton draws (Hole, 2007), assuming that all of the parameters follow a normal distribution. We estimated this model from our survey data using STATA software (StataCorp, 2013), and the model was implemented using the mixlogit command.

We then used the estimated value of the model parameters to simulate the probability of adoption of a series of innovative AEMs. In practice, we used the predicted value of each coefficient β_{njk} to compute the utility that each farmer n derives from choosing AEM j. When this utility was greater than the utility of the status quo, we deduced that the farmer would have chosen the AEM. From there, we compiled the adoption rate of the 26 possible AEM.

2.2 Attributes of the AEM

We first identified the attributes relevant to addressing the research question and we then defined possible levels for each of these attributes (Hensher et al., 2005). Since the levels chosen should reflect the range of situations that respondents might expect, we conducted a focus group to select relevant levels. Such a survey is likely to increase the accuracy of the parameter estimates (Hall et al., 2004). The attributes that were chosen correspond to the levers that we wanted to study in order to remove the constraints to adoption identified through a consultation with experts from the Guadeloupean agricultural extension services.

More precisely, our objective was to assess the relevance of a certain number of economic levers aimed at subsidizing the practice of soil amendment with compost, within the framework of so-called Agro-Environmental and Climate Measures (AEM). In Guadeloupe, this system has existed since 2007 for the practice of soil amendment with composts, but it has been extremely little adopted so far (with an adoption rate of less than 0.1 percent). Among the probable reasons for this failure, the administrative complexity of the contracting procedure, the sometimes insufficient payment amount or even the reduction of chemical fertilization as an additional obligation included in the requirements are most often reported. For the present choice experiment, we therefore constructed AEM profiles made up of four attributes to overcome these constraints. They are described in Table 1.

The first attribute is a free technical and administrative and assistance service, provided for free to the participant, to help with the preparation of the AEM application file and technical advice. The inclusion of such support can be expected to increase the likelihood of adopting the measure. The second attribute refers to the requirement of reduction of chemical fertilization by 20 percent. When included in the AEM, a 20 percent reduction in chemical fertilization from the recommended fertilization rates is required. Although this reduction can be compensated by the addition of compost, it can be expected that the introduction of this constraint in the contract will decrease the chances of adoption of the measure. The third attribute is the standard monetary allocation provided by an AEM. It is the amount received each year by the participant, in exchange for the implementation of the practice, per hectare enrolled. This amount is expected to cover the purchase price of the compost, its transport and its spreading. Knowing that in the past (from 2007 to 2013), the amount offered to farmers in a measure of this type was of the order of 900 €/ha/year, we considered three levels for this attribute in our setting: 600, 800 and 1,000.

One of the original characteristics of our experience of choice is to associate an individual incentive, namely the standard monetary remuneration, with a collective incentive, in the form of a bonus, paid individually, but conditional on the participation of other farmers from the same sector. In practice, this means that the participant receives 300 €/ha/year, as soon as 50 percent of the agricultural areas of the sector to which he belongs (banana, sugar cane or fruit and vegetable gardening) are under AEM contract. This collective bonus is expected to play the role of what is referred to as a nudge in the behavioural economic literature (Thaler and Sunstein, 2009).

3 Data

3.1 Surveys

The surveys were carried out over three months by two interviewers who received training on composting methods and on survey administration, including choice experiments specifically. The questionnaire was presented in paper form and consisted of three parts. The first part elicited the socio-economic profile of the farmers and included questions to establish an initial assessment of farmers' practices, knowledge and perceptions of composting. The second part of the questionnaire contained the choice experiment. The interviewers organised appointments with the farmers, which mainly took place on their farms. Once on site, the interviewers provided farmers with a letter explaining the interview process, as well as a brochure describing the project.

Before starting the choice experiment, the interviewers described each of the attributes to the respondents, which were also provided as a handout that could be consulted at any time during the experiment. In particular, the participants were informed that the proposed AEMs involved either the application of 10 tonnes of compost per hectare per year for 5 years or the application of 50 tonnes per hectare once every 5 years, at an average cost of 600 € per hectare per year.

Farmers were also given the opportunity to ask questions before the choice experiment began. To help them understand how the choice experiment would be conducted, the farmers were given a test card, presenting a trivial trade-off. These cards also enabled us to check the respondent's understanding and identify possible "yea-saying" phenomenon. This test revealed that only three farmers did not understand the objective of the experiment. We removed these individuals from the sample.

In order to avoid any order effects, choice cards were presented in a different order from one farmer to another. A pilot survey was carried out with twenty farmers who varied by location and individual characteristics. This test made it possible to validate the attribute levels used and to verify that the questionnaire and the choice experiment were easily understandable.

3.2 Design of the choice experiment

We followed a D-efficient design approach to construct the choice sets, using prior information we had about the sign and relative values of the attribute coefficients, based on the pilot survey. This allows for a small number of choice option profiles and combinations of these profiles while remaining as close as possible to an orthogonal factorial design.

Tables 2 and 3 present the incomplete D-Optimal design selected for the study. This design was constructed with XLSTAT software (Addinsoft 2013) and includes six profiles distributed in six choice sets, without any trivial sets and a good balance in terms of attribute levels used. An example of a choice set is depicted in Figure 3. Farmers were asked to choose between two AEMs and the status quo option, i.e. neither of the proposed profiles.

3.3 Sample

The surveys were conducted by targeting the three agricultural sectors that present the greatest challenges in terms of compost adoption in Guadeloupe, namely banana, sugar cane and fruit and vegetable gardening. The banana sector is characterised by the highest adoption rate and consumes most of the compost produced in Guadeloupe. An increase in the doses used and/or the frequency of the spreading of compost on banana plantations could significantly increase the development of the composting sector. On the other hand, the sugarcane sector consumes little compost but represents almost 50 percent of the territory's agricultural area. An increase in the amount of land using compost would thus have a very significant impact on the local demand for compost (Paul et al., 2017). Finally, the use of compost in the gardening sector is relevant to food security insofar as it has the greatest need for organic fertilization due to the progressive soil degradation this type of agriculture can cause (Sierra et al., 2017).

Our sample consists of 305 farmers, among which 99 banana producers, 105 sugar cane producers and 101 fruit and vegetable crop producers. These farmers were randomly selected from a database covering most of the territory of Guadeloupe (Chopin et al., 2015), according to a stratification strategy aiming for representativeness in the diversity of soil types in each sector (Table 4). This stratification was important for measuring cost-effectiveness on a territorial scale, since the amount of carbon sequestered depends on the type of cropping system and the nature of the soil (Sierra et al., 2015).

3.4 Carbon sequestration in soil

We estimated the extent of carbon sequestration induced by each AEM considered via the MorGwanik model (Sierra et al., 2015). MorGwanik is a model designed to simulate changes in soil organic carbon (SOC) at the plot scale, as a function of annual carbon inputs (e.g., crop residues, including roots, and organic amendments, including compost) and carbon outputs (e.g., SOC mineralization). Both carbon inputs and outputs are affected by pedoclimatic conditions (e.g., soil type and local climate) and farming practices (e.g., rotation, soil tillage, management of crop residues, type and rate of organic fertilisers).

The model was calibrated and tested for the agro-ecological regions of interest and most cropping systems in Guadeloupe. Further detail on the model can be found in Sierra et al. (2015). We used parameter values reported for the soils, the crops and the compost by Sierra et al. (2015) and Sierra et al. (2017). The parameter values for compost were 0.5 kg kg^{-1} for the water content, 0.33 kg C kg^{-1} for the C content, and 0.51 kg C kg C^{-1} for the coefficient of humification. The rate of compost used in simulations was 50 Mg ha^{-1} every 5 yr for sugarcane and bananas, and 10 Mg ha^{-1} yr^{-1} for vegetable crops, in line with what was proposed to the participants in the choice experiment. The model was initialized with the mean C content observed for each soil and cropping system combination in Guadeloupe (SOC year 0).

It is well established now that carbon sequestration is not a linear process but it tends towards an equilibrium (or asymptote) over time, where the amount of SOC diminishes as time elapses (Don et al., 2011). To take this into account, we performed simulations for a period of 30 years and the rate of carbon sequestration was expressed as the mean annual SOC increase over that period (e.g., in Mg C ha^{-1} yr^{-1}). In this way, we were able to get the mean impact of compost application on C sequestration in the long term, which agrees with the proposal of the IPCC (IPCC, 2006).

4 Results

4.1 Descriptive statistics

Descriptive statistics of the farms owned or managed by the survey respondents as well as their main socioeconomic characteristics are shown in Table 5. Only 9 percent of farmers have a poor perception of composting, 33 percent of farmers think that composting is beneficial, and 58 percent are not aware of the issue. Finally, 71 percent of farmers are aware of the existing European AEM scheme. With respect to socio-economic variables, the average age of farmers in the sample is 50 years and the average area farmed is 12 ha, 30 percent of which is fully owned by the farmer. Farmers' plots are generally able to be farmed using machinery (82 percent). Most farmers are members of a group of producers (76 percent), which can be a potential lever for technical and administrative support, as well as collective action.

4.2 Levers for participation in AEM

Table 6 presents the parameters estimated by a model of participation in the AEM, using the choice experiment data collected from the 305 farmers. We used data from our sample to fit a mixed logit (ML) model, which gives the relative importance of the attributes in the decision to participate in the AEM and can then be used to predict the probability of each farmer's participation in each AEM. The lower part of the table indicates that the distribution of the coefficients have statistically significant variances across the sample, which reflects some heterogeneity in respondents' preferences. The results presented in the upper part of the table show that the levers tested (payment, administrative and technical support and collective bonus) all play a (statistically) significant and positive role in a farmer's decision to participate in an AEM, as p-values indicate strong evidence against the null hypothesis of no effect.

The estimate of the alternative-specific constant (SQ) also has a significant positive sign, which means that respondents derive more utility from not participating in an AEM than participating in one. This could be due to delays in the payment of European subsidies that they may have experienced from previous participation. On the contrary, the reduction in the use of chemical fertilisers, which we expected to be a barrier to the adoption of an AEM, was found to have no statistically significant effect on the probability of adoption on average ($P \geq |z| = 0.32$), which may reflect farmers' indifference to chemical fertilization in the context of subsidized compost; it could at least reflect the considerable variability of respondent preferences for this attribute.

From the coefficients of the ML model, we then investigated how the probability of choosing an AEM changes when a single element of the AEM changes.[3] We found that the probability of choosing

[3] We estimated the marginal effect of offering technical assistance (or a collective bonus) by taking the difference between the predicted probability provided by the mixed logit model when technical assistance (or bonus) is included in the measure, and the predicted probability obtained when it is not. In practice, we used the mixlpred command after the mixlogit command under STATA software.

an AEM changes dramatically if the AEM includes free technical assistance (+31 percentage points) or a collective bonus (+14 percentage points), while including the requirement of reducing chemical fertilization decreases the probability of participation by only 2 percentage points.

4.3 Estimated participation rates

We estimated participation in all of the AEMs that could be generated from our experimental design: the combination of all attribute levels, i.e. 26 measures (Table 7). For each measure, we predicted the adoption decision of each farmer in the sample from the parameters of the ML model. Table 8 shows participation rates simulated from the parameters of the ML model for the different AEM, constructed from the different values of the four attributes. Unsurprisingly, the lowest adoption rate is observed for the M02 measure (39 percent) which is the most restrictive and includes the fewest incentives. The highest adoption rate is obtained for measures M16, M20 and M24 (94 percent), which include technical assistance and a collective bonus and do not require the reduction of chemical fertiliser use. It is interesting to note that the participation rate of measure M16, which offers a payment of 600 euros per ha per year is equal to the participation rate of measures M20 and M24, which offer higher payments.

4.4 Carbon sequestration and cost-effectiveness

Assuming that each participant in the AEM would engage all of its land in the chosen scheme,[4] we extrapolated the amount of land that would be engaged throughout the territory, taking into account the representativeness of each farm in the sample in terms of crop (banana, cane, fruit and vegetable gardening) and soil type (andosol, vertisol, nitisol, and ferralsol). We then estimated the amount of carbon sequestration that would take place in these areas based on the results of the MorGwanik model for each of the AEMs. Table 9 provides the average carbon sequestration induced by compost application for the different cropping situations.

We then calculated the cost of implementing each AEM, including not only the payment per hectare enrolled in the AEM, but also the payment of the collective bonus of 300 € (if applicable) and the cost of technical assistance (if applicable), i.e. 50 € per hectare per year. This figure is an approximation based on the total cost of hiring a technical assistant in Guadeloupe.

The ratio of the average carbon sequestration induced by compost application to the cost of the AEM gives us a measure of the AEM cost-effectiveness. Table 10 presents the results of the cost-effectiveness calculation for each AEM considered. The results show that the cost of an AEM ranges from 293 € (measure M3) to 649 € per tonne of CO2 sequestered (measure M24). This cost includes the amount paid as direct conditional payments, the amount paid as collective bonuses (if there are any), and the cost of technical assistance that is offered in the AEM.

[4]The theory of innovation adoption suggests that farmers often go through a test phase in which they try out the innovation on a small area of their farm, before adopting it on their entire farm, or abandoning it completely. Since our study aims to enlighten policy makers on the sequestration potential of a variety of long-term scenarios, we take a long-term perspective, in which farmers who would have accepted an AEM would ultimately have applied the compost to all their farmland.

One can observe that M24, the AEM that sequesters the greatest total amount of carbon (25,824 teqCO2), is also the least cost-effective measure (698 € per ton). The most cost effective AEM is M2 (310 €per ton), which is also the second to last in total sequestered carbon (i.e., 10,521 teqCO2). This is not very surprising, since increasing participation in AEMs requires increasing incentives. However, the relationship between efficiency and cost is not necessarily linear because farmers may have different preferences for technical assistance or collective bonus type incentives, and are endowed with different carbon sequestration capacities, depending on the nature of their soil.

Figure 1 shows the annual carbon sequestration of the AEMs as a function of their total cost of implementation and cost-effectiveness. For each AEM, the diameter of the bubble is proportional to the average cost of the sequestered teqCO2 (in € per teqCO2), so that the smaller the bubble, the more economically efficient the environmental program. The most effective measures appear in the upper part of the graph. Table 10 moreover shows that four measures sequester a quantity of carbon greater than 25,000 teqCO2 (M16, M20, M24, M25) but only one (M16) does so for a cost lower than 500 € per ton. This figure is much higher than the estimated carbon value provided by Quinet (2019) for the year 2019 (87 € per ton); it however ranges between the value estimated for 2020 (250 € per ton) and the value estimated for 2030 (775 € per ton).

Interestingly, we observe that the cost-effectiveness of M16, which offers the lowest payment but includes all the three of the other participation levers, is very close to that of M10, which offers the highest payment but none of the other levers of participation. However, M16 outperforms M10 by far, as it sequesters more than 25,000 teqCO2 while M10 sequesters less than 15,000 teqCO2. The measure M17 is also of interest insofar as it achieves a level of sequestration very close to that of M16 while also reducing the amount of pollution generated by the use of chemical fertilisers.

Finally, the SOC annual average growth rate displayed in the fourth column suggests that the AEMs could be used to reach the 4 per 1000 target launched by France at the 2015 United Nations Climate Change Conference (Minasny et al., 2017).

4.5 Sensitivity tests

One concern with our findings is that they are driven by the price we used to compute the costs of technical assistance that is offered in the AEMs (50 € per ha and per year). We thus recalculated the cost-efficiency ratios using 100 € per ha and per year to compute the cost of the AEMs. Results for these estimations are displayed in Figure 2. The ranking of the AEMs holds under these alternative assumptions.

Another concern is that the estimate of the total number of hectares enrolled into AEM relies upon the assumption that all the farmers in the three sectors would have been offered to participate in an AEM. We re-estimated the cost-efficiency ratios assuming that only half of the respondents would be offered to participate in an AEM. We arbitrarily focused on half of the respondents who have the largest farms. These results are displayed in Table 11. We found that the most effective measures make it possible to sequester more than 18,000 tons of carbon (M16, M20, M24, M25, just as when we use the whole sample). Again, we found that only one measure achieves this at a relatively low cost (484 €). As before, it is M16, which offers the lowest payment but includes all of the three other incentives to participate. Again, we found that the 4-per-1000 goal could be reached with this measure. This result supports our conclusion that incentives for participation, such as technical assistance and a collective bonus, are likely to significantly improve the efficiency of composting measures in the pursuit of the 4 per-1000 goal.

5 Discussion

5.1 Farmers' willingness-to-pay

Our results suggest that including non-cash incentive elements in agro-environmental schemes offering AEMs can contribute to the pursuit of ambitious environmental goals such as the 4 per 1000. Table 10 indeed shows that most of the proposed measures would achieve this objective quite easily. Computing the average value that respondents place on each non-cash attribute – something referred to as the willingness-to-pay (WTP) in the literature[5] –, we found that participants value the opportunity to receive a collective bonus of up to 380 € as much or even slightly more than receiving the same amount as a certain payment. The participants also value technical assistance at 710 €, i.e. 14 times more than it would cost the policy-maker.

Moreover, the aversion to AEMs in general (the so-called preference for the status quo) is very strong, as evidenced by a valuation of the status quo of up to 800 €. This corroborates the fact that significant compensation, although not necessarily monetary, must be provided in order for farmers to engage in environmentally friendly farming practices. The provision of administrative support for the preparation of the AEM file is valued highest by farmers. Including this element in future AEMs therefore seems essential to promoting their uptake in the field. The collective bonus also plays an important role, since when added to the basic payment, it compensates for the attractiveness of the status quo.

5.2 Compost supply

Some studies have pointed out that while demand for compost could be stimulated, increasing the supply of compost to meet this new demand could face certain obstacles, at least in the short term (Arrouays et al., 2002; Mondini et al., 2018). To assess the extent to which the supply of compost in Guadeloupe could meet the increase in compost demand associated with the implementation of AEM, we compared the current compost production and the amount of compost needed to effectively implement the AEM proposed. The last can be calculated using the rate of compost (e.g. average 10 Mg ha^{-1} yr^{-1}), the participation rate for each AEM, and the land area occupied by the cropping systems. We calculated that the amount of compost needed to implement AEM at the territory scale varied from 42,435 Mg yr^{-1} for AEM 3 to 132,963 Mg yr^{-1} for AEM 25. A recent study carried out in Guadeloupe indicates that the current production of composts is around 26,000 Mg yr^{-1} and could

[5]These willingness-to-pay estimates have been computed from the estimates of a mixed logit model where the price is assumed to be a fixed parameter, and for which we have the convenient result that $E(\mathrm{WTP}^k) = -\frac{E(\beta^k)}{\beta^{\mathrm{money}}}$. The estimates of this model are however very similar to those displayed in the main specification in Table 10.

reach 70,000 Mg yr^{-1} with better management of organic resources derived from agro-industrial factories, green wastes and water treatment plants (Paul et al., 2017).

These figures suggest that, although the current compost supply is not sufficient to cover the need of the proposed AEM, the production potential, which is important in this sector, may well meet the demand for compost that would result from the implementation of measure M1 to measure M13. In the more conservative the scenario in which only half of the farms would actually enrol in the proposed AEM, however, the production potential would meet the demand for compost under any of the proposed AEM.

6 Conclusion

In this study, we sought to show that certain types of Agri-Environmental Measures (AEM) are likely to improve soil carbon at a lower cost. We designed an original framework coupling a mixed logit model to perform an ex-ante assessment of the adoption of AEM devoted to promote compost use, with a biophysical model describing soil carbon dynamics to establish the impact of AEM adoption on carbon sequestration in tropical soils. This approach was useful to assess a variety of scenarios combining monetary and non-monetary incentives in terms of their cost-effectiveness, and to identify the land area where the so-called 4-per-1000 target for carbon sequestration could be reached using compost. This should help policy makers to design new AEM for the tropics that are more environmentally and economically appropriate than previous schemes.

One of the main conclusions of the study is that non-monetary incentives, such as technical assistance provided for the choice and use of compost, and administrative support for the preparation of the application file, can play a key role in farmers' perception of the cost of participation in the scheme, and should therefore be included in future AEMs to improve adoption. This would be particularly important for the very conservative rural population studied here, which is characterized by a relatively high level of aversion to AEMs, as evidenced by a high valuation of the status quo (800 €/ha/year) compared to the amount of proposed subsidy (from 600 to 1000 €/ha/year).

Despite the relatively high rates of carbon sequestration obtained for most of the tested AEM, the cost of the carbon sequestration unit is quite expensive, on average 500 €/teqCO2, which is much greater than the values reported in studies carried out in Europe. This is mainly associated with the level of subsidy payments, which should offset the high cost of the practice in Guadeloupe (product, transport and application of the product). Indeed, the AEMs proposed to promote the use of compost should be considered as a policy tool offering several simultaneous benefits in addition to carbon sequestration, such as the reduction of pollution risks linked to the overuse of mineral fertilizers, the recycling of organic wastes, and the restoration of degraded tropical soils. In this sense, the framework proposed in this study seems appropriate to assess the cost-effectiveness of these additional environmental services in future research.

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Figures and tables

Table 1: Description of the attributes in the AEMs

Attribute	Definition	
Requirement	20 percent reduction in chemical fertilization	yes/no
Payment	Cash payment (€/ha/an)	600; 800; 1000
Technical assistance	Administrative support for the submission of the application file and technical support for compost use	yes/no
Collective bonus	Cash payment of 300 €/ha/an if at least 50 percent of the sector is enrolled	yes/no

Table 2: Description of the AEMs proposed

	Free administrative and technical support service	Chemical fertilization reduction of 20%	Payment (€/ha/an)	Collective Bonus (€/ha/year)
Profile 1	yes	yes	1000	0
Profile 2	no	yes	800	300
Profile 3	no	no	600	0
Profile 4	yes	yes	600	300
Profile 5	no	no	1000	300
Profile 6	yes	no	800	300

Table 3: Choice cards

	AEM 1	AEM 2
Choice card 1	Profile 2	Profile 1
Choice card 2	Profile 4	Profile 3
Choice card 3	Profile 6	Profile 5
Choice card 4	Profile 3	Profile 2
Choice card 5	Profile 5	Profile 4
Choice card 6	Profile 1	Profile 6

Note: The number refers to the alternative displayed in Table 2.

Table 4: Representativeness of the sample

Crop	Soil	Sample ha	Sample %	Population ha	Population %
Banana	Andosol	646	60	1 062.7	50
Banana	Ferralsol	321	30	304.8	14
Banana	Nitisol	78.5	7	594.7	28
Banana	Vertisol	32.6	3	177.9	8
	Total	1 078.0	100	2 140.0	100
Sugar cane	Andosol	140	16	214.2	2
Sugar cane	Ferralsol	255.2	29	3 720.0	33
Sugar cane	Vertisol	474.7	55	7 212.6	65
	Total	869.9	100	11 146.8	100
Gardening	Andosol	5.9	2	140.5	17
Gardening	Ferralsol	44	15	119.6	14
Gardening	Nitisol	14.5	5	81.9	10
Gardening	Vertisol	236.1	79	486	59
	Total	300.5	100	827.9	100

Table 5: Characteristics of the sample

Variable	Obs	Mean	Std. Dev.	Min	Max
Banana grower (yes=1)	305	0.32	0.47	0	1
Sugar cane producer (yes=1)	305	0.34	0.48	0	1
Vegetable grower (yes=1)	305	0.33	0.47	0	1
Already apply compost (yes=1)	305	0.26	0.44	0	1
Believes compost is good (yes=1)	305	0.33	0.47	0	1
Believes compost is bad (yes=1)	305	0.09	0.29	0	1
Believes nothing about compost (yes=1)	305	0.58	0.49	0	1
Knows what an AEM is (yes=1)	305	0.71	0.46	0	1
Age	305	50	9	24	74
Education (college level=1)	305	0.29	0.45	0	1
Total area (ha)	305	12.12	17.7	1	202
Area under property (share of total area)	305	0.3	0.44	0	1
Mechanized soil cultivation (yes=1)	305	0.82	0.3	0	1
Member of SICA (yes=1)	305	0.76	0.43	0	1
Member of CUMA (yes=1)	305	0.18	0.39	0	1
Family labor (yes=1)	305	0.75	0.32	0	1
Location (Basse Terre South-West =1)	305	0.06	0.24	0	1
Location (Basse Terre North =1)	305	0.17	0.38	0	1
Location (Basse Terre South-East =1)	305	0.28	0.45	0	1
Location (Grande Terre =1)	305	0.49	0.5	0	1

Table 6: Results of the mixed logit model

Mean of β coef.	Coef.	Std. Err.	z	$P>\lvert z\rvert$	[95% Conf.Int.]	
Requirement on fert. (yes=1)	-0.16	0.16	-1	0.32	-0.48	0.16
Technical assistance (yes=1)	3.27	0.25	12.85	0.00	2.77	3.76
Payment (0; 600; 800; 1000)	0.39	0.05	8.27	0.00	0.3	0.48
Collective bonus (yes=1)	1.63	0.18	9.27	0.00	1.28	1.97
Status Quo (yes=1)	3.2	0.42	7.54	0.00	2.37	4.03
Standard deviation of β coef.						
Requirement on fert. (yes=1)	1.83	0.22	8.23	0.00	1.39	2.26
Technical assistance (yes=1)	2.23	0.26	8.55	0.00	1.72	2.74
Payment (0; 600; 800; 1000)	0.34	0.04	8.93	0.00	0.27	0.42
Collective bonus (yes=1)	1.69	0.2	8.26	0.00	1.29	2.09
Status Quo (yes=1)	-0.97	0.63	-1.52	0.13	-2.21	0.28

Number of obs is 5490; LR chi2(5) = 426.05 ; Log likelihood = -1299.0035 ; Prob > chi2 = 0.0000; For the sake of readability, the coefficients of the payment attribute have been divided by 100.

Table 7: Description of the attributes of all AEMs considered

AEM	Technical Assistance	Requirement on fertilizers	Collective Bonus	Payment	Status Quo
M1	0	0	0	0	1
M2	0	0	0	600	0
M3	0	1	0	600	0
M4	0	0	1	600	0
M5	0	1	1	600	0
M6	0	0	0	800	0
M7	0	1	0	800	0
M8	0	0	1	800	0
M9	0	1	1	800	0
M10	0	0	0	1000	0
M11	0	1	0	1000	0
M12	0	0	1	1000	0
M13	0	1	1	1000	0
M14	1	0	0	600	0
M15	1	1	0	600	0
M16	1	0	1	600	0
M17	1	1	1	600	0
M18	1	0	0	800	0
M19	1	1	0	800	0
M20	1	0	1	800	0
M21	1	1	1	800	0
M22	1	0	0	1000	0
M23	1	1	0	1000	0
M24	1	0	1	1000	0
M25	1	1	1	1000	0
M26	0	0	0	900	0
M27	0	1	0	900	0

Note: "Technical assistance" refers to a free administrative and technical support service for the submission of the AEM application file and the use of compost, "Requirement on fertilizers" refers to a reduction in chemical fertilization of 20 percent, "Collective bonus" refers to a monetary compensation conditional on the participation of other farmers from the same sector, "Payment" refers to the standard monetary compensation paid individually. The value of 1 means that the proposed AEM includes the attribute, while zero indicates that it does not.

Table 8: Simulation of adoption rates for the whole sample

AEM	Technical assistance	Requirement on fertilizers	Collective Bonus	Payment	Adoption
M02	0	0	0	600	0.39
M03	0	1	0	600	0.33
M04	0	0	1	600	0.61
M05	0	1	1	600	0.56
M06	0	0	0	800	0.55
M07	0	1	0	800	0.53
M08	0	0	1	800	0.66
M09	0	1	1	800	0.61
M10	0	0	0	1000	0.6
M11	0	1	0	1000	0.6
M12	0	0	1	1000	0.75
M13	0	1	1	1000	0.64
M14	1	0	0	600	0.91
M15	1	1	0	600	0.84
M16	1	0	1	600	0.94
M17	1	1	1	600	0.9
M18	1	0	0	800	0.91
M19	1	1	0	800	0.87
M20	1	0	1	800	0.94
M21	1	1	1	800	0.91
M22	1	0	0	1000	0.92
M23	1	1	0	1000	0.88
M24	1	0	1	1000	0.94
M25	1	1	1	1000	0.92
M26	0	0	0	900	0.57
M27	0	1	0	900	0.55

Note: "Technical assistance" refers to a free administrative and technical support service for the submission of the AEM application file and the use of compost, "Requirement on fertilizers" refers to a reduction in chemical fertilization of 20 percent, "Collective bonus" refers to a monetary compensation conditional on the participation of other farmers from the same sector, "Payment" refers to the standard monetary compensation paid individually. The value of 1 means that the proposed AEM includes the attribute, while zero indicates that it does not.

Table 9: Carbon sequestration induced by compost application

Cropping system	Annual change in carbon stock compared to initial stock (%yr^{-1}) Vertisol	Ferralsol	Andosol	Nitisol
Banana	1.1	1.4	0.9	1.4
Sugarcane	0.7	0.8	0.5	(a)
Gardening	1	1.2	0.9	1.2

(a) No sugarcane is grown on nitisol in the sample.

Table 10: Simulation of the cost-effectiveness at the territory level (whole sample)

AEM	Amount of teqCO2 sequestered (extrapol.)	SOC annual average growth rate	Total cost of adoption (€/year extrapol.)	Cost of teqCO2 sequestered (€/teqCO2)
M2	10,521	3.07	3,263,881	310
M3	8,063	2.35	2,580,163	320
M4	15,188	4.43	5,385,772	355
M5	13,684	3.99	4,813,848	352
M6	13,313	3.88	5,469,791	411
M7	13,528	3.94	5,595,781	414
M8	16,116	4.70	9,129,788	567
M9	15,333	4.47	8,727,436	569
M10	14,669	4.28	7,540,006	514
M11	14,947	4.36	7,719,868	516
M12	19,347	5.64	12,992,415	672
M13	16,551	4.83	11,091,201	670
M14	24,609	7.17	8,272,985	336
M15	22,398	6.53	7,541,327	337
M16	25,615	7.47	12,581,921	491
M17	24,132	7.04	11,869,447	492
M18	24,625	7.18	10,824,113	440
M19	23,783	6.93	10,450,806	439
M20	25,824	7.53	15,352,541	595
M21	24,771	7.22	14,733,342	595
M22	24,638	7.18	13,378,091	543
M23	24,523	7.15	13,314,476	543
M24	25,824	7.53	18,022,548	698
M25	25,614	7.47	17,864,814	697
M26	13,857	4.04	6,405,938	462
M27	14,167	4.13	6,606,392	466

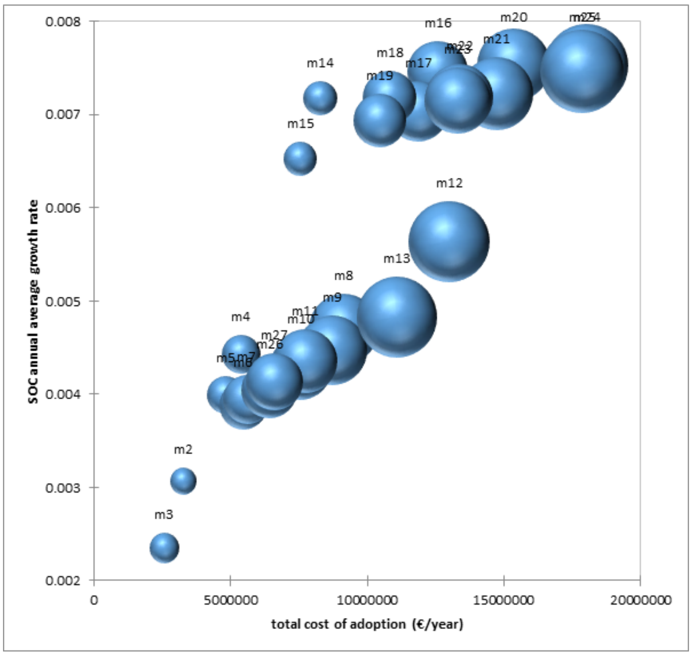
Note: Costs are calculated assuming that technical assistance costs equal €50/ha/year.

Table 11: Simulation of the cost-effectiveness at the territory level (using half of the farms in the sample)

AEM	Amount of teqCO2 sequestered (extrapol.)	SOC annual average growth rate	Total cost of adoption (€/year extrapol.)	Cost of teqCO2 sequestered (€/teqCO2)
M2	7,713	2.25	2,355,287	305
M3	5,866	1.71	1,866,224	318
M4	10,744	3.13	3,834,212	357
M5	9,786	2.85	3,183,553	325
M6	9,583	2.79	3,877,604	405
M7	9,787	2.85	4,000,451	409
M8	11,372	3.32	5,218,791	459
M9	10,948	3.19	4,976,220	455
M10	10,423	3.04	5,269,922	506
M11	10,561	3.08	5,384,287	510
M12	13,953	4.07	7,732,193	554
M13	11,970	3.49	6,659,676	556
M14	17,672	5.15	5,857,239	331
M15	15,757	4.59	5,240,084	333
M16	18,725	5.46	9,067,479	484
M17	17,561	5.12	8,530,981	486
M18	17,672	5.15	7,659,467	433
M19	16,857	4.91	7,305,101	433
M20	18,934	5.52	11,100,000	586
M21	18,000	5.25	10,600,000	589
M22	17,672	5.15	9,461,694	535
M23	17,434	5.08	9,331,169	535
M24	18,934	5.52	13,000,000	687
M25	18,663	5.44	12,800,000	686
M26	10,050	2.93	4,574,397	455
M27	10,070	2.94	4,640,932	461

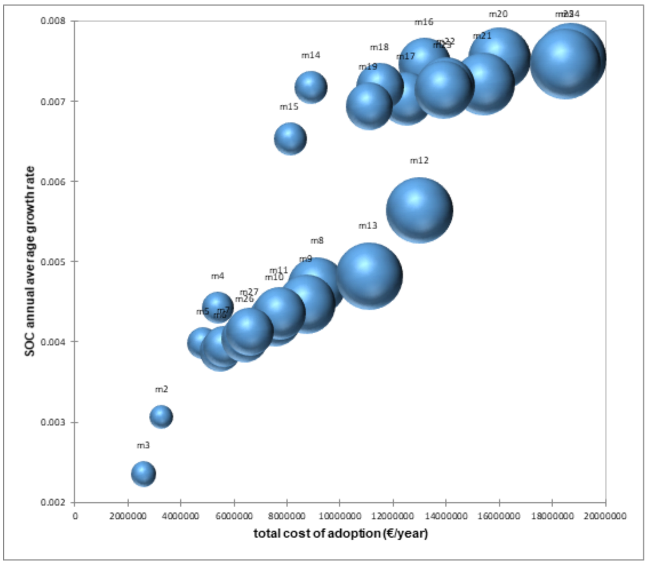
Note: Costs are calculated assuming that technical assistance costs equal €50/ha/year.

Figure 1: Average annual SOC growth rate according to the total cost of the adoption (technical assistance costs equal €50/ha/year)



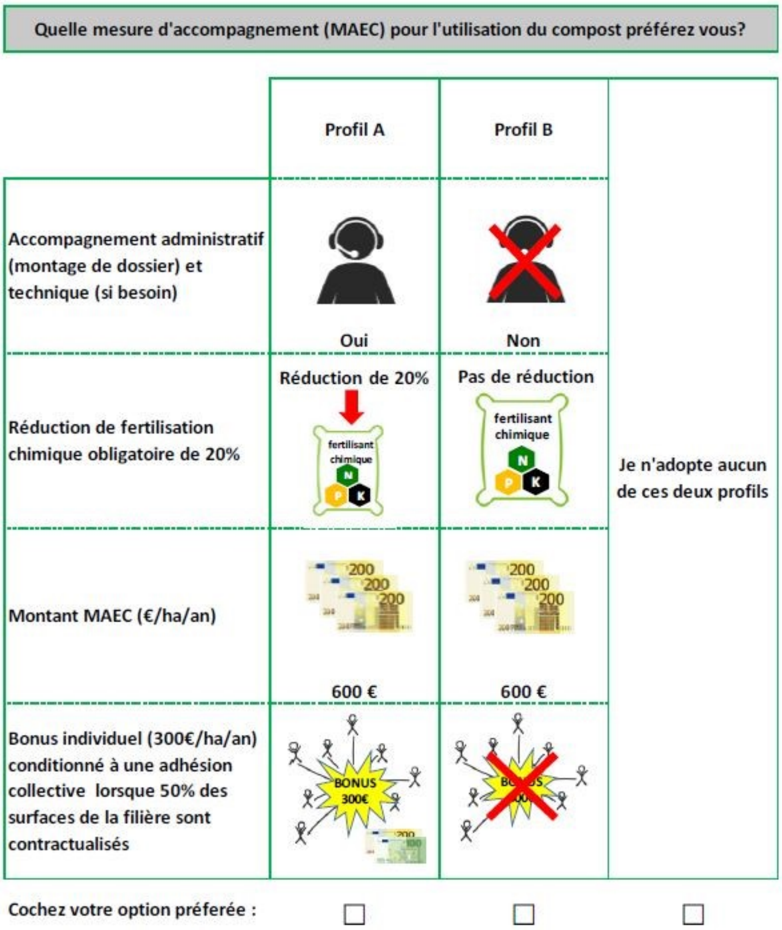
Note: For each AEM, the diameter of the bubble is proportional to the average cost of the sequestered teqCO2 (in €per teqCO2), so that the smaller the bubble, the more economically efficient the environmental program.

Figure 2: Average annual SOC growth rate according to the total cost of the adoption (technical assistance costs equal €100/ha/year)



Note: For each AEM, the diameter of the bubble is proportional to the average cost of the sequestered teqCO2 (in €per teqCO2), so that the smaller the bubble, the more economically efficient the environmental program.

Figure 3: Example of a choice card



Quelle mesure d'accompagnement (MAEC) pour l'utilisation du compost préférez vous?

	Profil A	Profil B	
Accompagnement administratif (montage de dossier) et technique (si besoin)	Oui	Non	Je n'adopte aucun de ces deux profils
Réduction de fertilisation chimique obligatoire de 20%	Réduction de 20%	Pas de réduction	
Montant MAEC (€/ha/an)	600 €	600 €	
Bonus individuel (300€/ha/an) conditionné à une adhésion collective lorsque 50% des surfaces de la filière sont contractualisés	BONUS 300€	BONUS 300€	
Cochez votre option préferée :	☐	☐	☐