Ex ante assessment of the cost-effectiveness of Agri-Environmental Schemes promoting compost use to sequester carbon in soils in Guadeloupe

Blazy, J-M.* Subervie, J.† Paul, J.‡ Causeret, F.§ Guindé, L.¶ Moulla, S.‖ Thomas, A.** Sierra, J.††

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Abstract

In this article, we provide an ex-ante assessment of the cost-effectiveness of a series of innovative Agri-Environmental Measures (AEM) that subsidize the use of compost. To do so, we ran a choice experiment in the western islands of French Polynesia where the soil organic carbon content is extremely low. 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 fertilizers 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 AES 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 easily reached through most cost-effective measures even if only half of the farms were enrolled in the program.

Keywords: soil carbon, compost, climate change, choice experiment, Guadeloupe.

*INRAE, UMR ASTRO, Guadeloupe
†INRAE, UMR CEE-M, Montpellier
‡INRAE, UMR ASTRO, Guadeloupe
§INRAE, UMR ASTRO, Guadeloupe
¶INRAE, UMR ASTRO, Guadeloupe
‖INRAE, UMR ASTRO, Guadeloupe
**INRAE, TSE, Toulouse
††INRAE, UMR ASTRO, Guadeloupe

1 Introduction

Maintaining soil organic matter is critical to tackling climate change because soil organic matter is rich in carbon. Soil carbon 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 carbon stocks have been decreasing for more than a century, 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 fertilizers. Faced with this problem, what instruments should governments use to encourage farmers to improve soil carbon on their farms?

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] However, farmers' participation in these schemes is often low and their effectiveness has not always been demonstrated (Behaghel, Macours, and Subervie, 2019; Kuhfuss and Subervie, 2018; Arata and Sckokai, 2016; Chabé-Ferret and Subervie, 2013; Pufahl and Weiss, 2009). 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, Barreiro-Hurlé, and Ruto, 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 have rarely been undertaken so far.

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. The proposed analysis includes (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 extrapolating environmental gains and economic costs in order to rank the AEM considered according to their cost-effectiveness. 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.

We ran a choice experiment in the western islands of French Polynesia where the soil organic carbon content is extremely low. The farmers who participated were asked to choose one of several AEM that offer financial support in exchange for using compost in their farming activities. In addi-

[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.

tion to financial support, we studied three potential levers for improving farmers' participation rates in the AEM encouraging compost use: free technical assistance, a collective financial bonus, and the possibility of combining chemical fertilizers 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 find that the 4 per 1000 target launched by France at the 2015 United Nations Climate Change Conference (Minasny et al., 2017) could be easily reached through most cost-effective measures even if only half of the farms (specifically the largest ones) were enrolled in the program.

A number of studies have run *ex-post* evaluations of the impact of environmental programs in developed countries (Lynch, Gray, and Geoghegan, 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, Shapiro, and Sims, 2012; Alix-Garcia, Sims, and Yanez-Pagans, 2015; Costedoat et al., 2015; Sims et al., 2014; Jayachandran et al., 2017), to cite only some of them. 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, Swallow, and Adamowicz (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, something we aim to do in this paper. One exception is Gillich et al. (2019), who combine choice modeling estimates and stochastic simulations to assess the potential of new crop adoption in Southwestern Germany.

The rest of the paper is organized as follows. Section 2 presents the methodology and the data used for the analysis; Section 3 provides the results on participation levers, simulated participation rates at the territory level, simulated carbon sequestration in soil and simulated ex-ante cost-effectiveness of each AEM considered. Section 4 discusses the results and concludes.

2 Methodology and Material

2.1 Surveys

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. 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.

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 is 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).

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 experiments, 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 experiment began. To help them understand how the experiment would be conducted, farmers were presented with a test card. In order to avoid any order effects, choice cards were presented in a different order from one farmer to another. A pilot of the questionnaire was carried out with 20 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.

2.2 Statistical model to predict participation in AEM

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:

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

We estimated this model by maximum simulated likelihood using Halton draws (Hole, 2007), assuming that all of the parameters except the monetary attribute follow a normal distribution. 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, Ferrini, and Willis, 2005). 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.

2.3 Design of the choice experiment

In Guadeloupe, AEMs for soil composting practices have been offered to farmers since 2007, but they have not been widely adopted because of the complexity of the contracts offered, inadequate compensation and the onerous requirement to reduce chemical fertilisation. We proposed new AEM profiles containing four attributes to address each of these constraints (see Table 1). The first attribute is a free administrative and technical support. It is a service to help with the assembly of the AEM file and technical advice. The second attribute imposes a 20 percent reduction in chemical fertilization. The third attribute offers a bonus of 300 €per hectare and per year conditional on having at least 50 percent of the whole sector (banana, sugar cane or fruit and vegetable gardening) enrolled into the AEM. Finally, the last attribute is a conditional payment (in €per hectare and per year), i.e. the amount received each year by the farmer for each hectare on which soil composting is practised. This amount is supposed to cover the purchase price of the compost, its transport and spreading. This attribute can take on three different values (600, 800 or 1000 €per ha and per year). One of the originalities of this experiment with respect to the existing literature is that it combines an individual incentive, namely the standard AEM monetary attribute, with a collective incentive through a final bonus conditional on collective success, the sum of which is paid to individuals. This premium is expected to play the role of what is referred to as a nudge in the behavioural economic literature (Thaler and Sunstein, 2009).

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 6 profiles distributed in 6 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 1. Farmers were asked to choose between two AEMs and the status quo option, i.e. neither of the proposed profiles.

2.4 Estimation of carbon sequestration in soil

We then 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, Causeret, and Chopin (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. The model was initialized with the mean C content observed for each soil and cropping system combination in Guadeloupe (SOC year 0 in Table 5).

It is well known 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, Schumacher, and Freibauer, 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. We moreover compared our results to the four per thousand target. Results are displayed in Table 5.

2.5 Computation of AEM's cost-effectiveness

We estimated the ex ante cost-effectiveness of all of the AEMs that could be generated from our experimental design (the combination of all attribute levels, i.e. $2 * 2 * 2 * 3 = 24$ measures, see Table 6). For each measure, we predicted the adoption decision of each farmer in the sample from the parameters of the ML model. Then, assuming that each participant in the AEM engages all of its land in the chosen scheme, 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 on these areas based on the results of the biophysical model for each of the AEMs. Finally, we calculated the cost of implementing each AEM, including not only the payment per hectare committed, but also the payment of the collective bonus of 300 €(if applicable) and the cost of technical assistance (if applicable), i.e. 50 euros per hectare per year. The ratio of the environmental gain to the cost of the AEM gives us a measure of the AEM cost-effectiveness.

3 Results

3.1 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 7. 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.

3.2 Levers for participation in AEM

Table 8 presents the parameters estimated by the ML model using the choice experiment data collected from the 305 farmers. The lower part of Table 8 indicates that the distribution of attributes have statistically significant variances across the sample, which reflects some heterogeneity in respondents' preferences and can be at least partly attributed to the differences between crops. The results presented in the upper part of the table show that the levers tested (payment, administrative support and collective bonus) all play a significant and positive role in a farmer's decision to participate in an AEM.

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.

The reduction in the use of chemical fertilizers, which we expected to be a barrier to the adoption of "compost" AEMs, was found to have no statistically significant effect on the probability of adoption ($P > |z| = 0.32$), 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 investigate how the probability of choosing an AEM changes when a single element of the AEM changes. We calculate the difference between the predicted probability provided by the mixed logit model when the element is included in the measure, and the predicted probability obtained when it is not. Results are displayed in Table 10. We find that the probability of choosing an AEM changes dramatically if the AEM includes free technical assistance (+31 percentage points) and a collective bonus (+14 percentage points), while including the requirement of reducing chemical fertilization decreases the probability of participation by only 2 percentage points.

3.3 Estimated participation rates

Table 11 shows participation rates simulated from the parameters of the ML model. The results demonstrate heterogeneity in preferences across the three sectors. The adoption rates of each AEM are systematically highest in the banana sector and lowest among fruit and vegetable gardeners. This can be explained by the differences in structuring at the level of the two farming systems. The banana sector is much better organised and has already taken action to promote the practice of organic soil fertilisation within the framework of the so-called sustainable banana development plan (ref).

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 16, which offers a payment of 600 euros per ha per year is equal to the participation rate of measures 20 and 24, which offer higher payments. However, the results show that the removal of these incentives can be partially compensated by a large one-time payment (M11 for example).

3.4 Cost-effectiveness

Table 12 presents the results of the cost-effectiveness calculation for each AEM considered. Cost-effectiveness is estimated by calculating for each measure the ratio of the total cost of the measure to the amount of carbon sequestered, taking into account the estimated participation in the AEM. The results show that the cost of the measure ranges from 293 €(M3) to 649 €per tonne of CO2 sequestered (M24).

One can observe that the measure that sequesters the greatest total amount of carbon (25.824 teqCO2) is also the least cost-effective measure. Similarly, the most cost-effective measure is that which sequesters the least total amount of carbon (8.063 teqCO2). These results indicate that there is a trade-off between the cost-effectiveness of AEM and the total amount of carbon sequestered. This trade-off is depicted in Figure 2, which shows the annual carbon sequestration of AEMs as a function of their total cost of implementation and cost-effectiveness. The most effective measures appear in the upper part of the graph. 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.

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. Finally, 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.

4 Discussion

4.1 Non-cash versus cash rewards

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 12 indeed shows that most of the proposed measures would achieve this objective quite easily. This is likely because farmers tend to overvalue non-cash attributes, as evidenced by the ML model parameter estimates. Because the monetary attribute is assumed to be a fixed parameter in our model, the average value that respondents place on a (non-cash) attribute k – something referred to as the willingness-to-pay (WTP) in the literature – is:

$$E(\mathrm{WTP}^k) = -\frac{E(\beta^k)}{\beta^{\mathrm{money}}}$$

Results for the WTP estimations are displayed in Table 9. They show 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 700 €, i.e. 14 times more than it would cost the policymaker (50 €).

Moreover, the aversion to AEM and the need for support is very strong (as evidenced by a valuation of the status quo of up to 800 €), which corroborates the fact that compensation must be provided in order for farmers to engage in environmentally friendly farming practices. The amount of the payment must be significant in order to remove this initial aversion to joining an AEM. Nevertheless, the economic incentives proposed, if they are cumulated, on average exceed the value that farmers place on the status quo.

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.

4.2 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 re-estimated the cost-efficiency ratios using 100 € and 200 € per ha and per year (resp.) to compute the cost of the AEMs. Results for these estimations are displayed in Figures 3 and 4 (resp.). The ranking of the AEMs holds under these alternative assumptions.

Another concern is that the participation rates estimated from the ML model are overestimated. A major problem with the stated preference approach is that respondents in hypothetical settings may overstate their preferences (List and Gallet, 2001). If overestimation bias were systematic and homogeneous across choices, there would be no statistical issue in relying on stated preferences to establish a ranking of AEMs because the ranking would not be affected by this bias. However, we have no evidence that the bias is homogeneous and no means to test it empirically with our data. As a sensitivity test, we thus re-estimated the cost-efficiency ratios assuming that only half of the respondents who are expected to participate in the scheme (according to the predictions from the ML model) will actually participate. We arbitrarily focused on half of the respondents who have the largest farms. These results are displayed in Table 13. 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 euros). 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 easily 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.

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Table 1. Description of the attributes

Attribute	Definition	
Requirement	20% reduction in chemical fertilization	yes / no
Payment	Cash payment in euro/ha/an	0; 600; 800; 1000
Technical assistance	Administrative support for the submission of the subsidy file and technical support for the application of the compost	yes / no
Collective bonus	Cash payment of 300 euro/ha/an if 50% the sector area are engaged	yes / no

Table 2. Description of alternatives.

	Free administrative and technical support service	Chemical fertilization reduction of 20% (mandatory)	AEM (€/ha/an)	Collective Bonus (€/ha/year)
Profil1	OUI	OUI	1000	0
Profil2	NON	OUI	800	300
Profil3	NON	NON	600	0
Profil4	OUI	OUI	600	300
Profil5	NON	NON	1000	300
Profil6	OUI	NON	800	300

Table 3: Choice cards

	Choice 1	Choice 2
Card 1	2	1
Card 2	4	3
Card 3	6	5
Card 4	3	2
Card 5	5	4
Card 6	1	6

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

Table 4. Representativeness of the sample

Crop	Soil	Sample		Population	
		ha	%	ha	%
Banana	ANDOSOL	646,0	60%	1 062,7	50%
Banana	FERRALITIQUE	321,0	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	140,0	16%	214,2	2%
Sugar cane	FERRALITIQUE	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	FERRALITIQUE	44,0	15%	119,6	14%
Gardening	NITISOL	14,5	5%	81,9	10%
Gardening	VERTISOL	236,1	79%	486,0	59%
	Total	300,5	100%	827,9	100%

Table 5. Assessment of mean carbon sequestration induced by compost application for the different cropping situations

	Banana				Sugar cane			Gardening			
	vertisol	ferralsol	andosol	nitisol	vertisol	ferralsol	andosol	vertisol	ferralsol	andosol	nitisol
SOC year 0 (% SOC)	1,98	1,52	3,51	1,76	2,67	2,23	5,94	1,77	1,36	3,12	1,57
SOC year 30 (% SOC)	2,66	2,16	4,50	2,50	3,26	2,76	6,82	2,31	1,83	3,95	2,12
Stock year 0 (tSOC/ha)	54,55	39,99	70,10	39,66	73,52	58,64	118,74	48,57	35,60	62,40	35,30
Stock year 30 (tSOC/ha)	73,15	56,71	89,96	56,33	89,66	72,52	136,49	63,43	48,16	78,97	47,81
Diff. (tSOC /ha/year)	0,62	0,56	0,66	0,56	0,54	0,46	0,59	0,50	0,42	0,55	0,42
Diff. (% SOC init/ha/year)	0,01	0,01	0,01	0,01	0,01	0,01	0,00	0,01	0,01	0,01	0,01

Note: no sugarcane is grown on nitisol in the sample.

Table 6. Attributes of the different AEM simulated from the adoption model

AEM	Assistance	No chemical fertilization	Collective Bonus	Payment	SQ
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

Table 7. 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	17,70	1	202
Area under property (share of total area)	305	0,30	0,44	0	1
Mechanized soil cultivation (yes=1)	305	0,82	0,30	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	0,50	0	1

Table 8. Results of the mixed model

	Coef.	Std. Err.	z	P>|z|	[95% Conf.Interval]	
Mean of beta						
Requirement on fert. (yes=1)	-0,16	0,16	-1,00	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	0,30	0,48
Collective bonus (yes=1)	1,63	0,18	9,27	0,00	1,28	1,97
SQ (AEM=0; status quo=1)	3,20	0,42	7,54	0,00	2,37	4,03
Standard deviation of beta						
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	0,20	8,26	0,00	1,29	2,09
SQ (AEM=0; status quo=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

Table 9. Estimates of Willingness-to-accept (WTA)

	reducfert	**accomp**	**bonus**	**SQSC**
WTA (€)	-183,41	710,18	384,19	799,66
ll	-0,46	-8,36	-4,58	-9,31
ul	0,83	-5,84	-3,11	-6,69

Note: The wta have been calculated from a mixed logit in which the payment attribute is fixed.

Table 10. Probability of choosing an AEM

Variable	Without	With	Difference
Technical Assistance	0,21	0,53	0,31
Collective Bonus	0,27	0,41	0,14
Requirement on fertilizers	0,35	0,33	-0,02

Table 11. Simulation of adoption rates for the whole population (n = 305)

Variable	Assistance	No chemical fertilization	Collective Bonus	Payment	whole sample (n=305)	Banana (n=99)	Sugar cane (n=105)	Gardening (n=101)
adopt_m02	0	0	0	600	0,39	0,58	0,37	0,24
adopt_m03	0	1	0	600	0,33	0,44	0,30	0,26
adopt_m04	0	0	1	600	0,61	0,82	0,51	0,50
adopt_m05	0	1	1	600	0,56	0,72	0,49	0,48
adopt_m06	0	0	0	800	0,55	0,80	0,45	0,43
adopt_m07	0	1	0	800	0,53	0,71	0,48	0,42
adopt_m08	0	0	1	800	0,66	0,87	0,54	0,57
adopt_m09	0	1	1	800	0,61	0,82	0,52	0,50
adopt_m10	0	0	0	1000	0,60	0,84	0,50	0,48
adopt_m11	0	1	0	1000	0,60	0,80	0,52	0,48
adopt_m12	0	0	1	1000	0,75	0,91	0,69	0,67
adopt_m13	0	1	1	1000	0,64	0,86	0,56	0,51
adopt_m14	1	0	0	600	0,91	0,95	0,90	0,87
adopt_m15	1	1	0	600	0,84	0,90	0,84	0,77
adopt_m16	1	0	1	600	0,94	0,98	0,92	0,92
adopt_m17	1	1	1	600	0,90	0,96	0,88	0,85
adopt_m18	1	0	0	800	0,91	0,96	0,90	0,87
adopt_m19	1	1	0	800	0,87	0,93	0,89	0,78
adopt_m20	1	0	1	800	0,94	0,98	0,93	0,92
adopt_m21	1	1	1	800	0,91	0,96	0,90	0,86
adopt_m22	1	0	0	1000	0,92	0,96	0,90	0,89
adopt_m23	1	1	0	1000	0,88	0,94	0,91	0,79
adopt_m24	1	0	1	1000	0,94	0,98	0,93	0,92
adopt_m25	1	1	1	1000	0,92	0,98	0,92	0,87
adopt_m26	0	0	0	900	0,57	0,81	0,47	0,45
adopt_m27	0	1	0	900	0,55	0,73	0,50	0,43

Table 12. Simulation of the cost-effectiveness at the territory level

AEM	Converted area (total area is 14,145 ha)	Amount of teqCO2 sequestered (extrapolated)	SOC annual average growth rate (compare to 4 ‰)	Total cost of adoption in €/year (extrapolated)	Cost of teqCO2 sequestered (€ / teqCO2)	Mitigation of total emissions from Guadeloupe agriculture (%)
M2	38%	10521	0,003	3 263 881 €	310 €	5%
M3	30%	8063	0,002	2 580 163 €	320 €	4%
M4	55%	15188	0,004	5 385 772 €	355 €	7%
M5	51%	13684	0,004	4 813 848 €	352 €	7%
M6	48%	13313	0,004	5 469 791 €	411 €	6%
M7	49%	13528	0,004	5 595 781 €	414 €	6%
M8	59%	16116	0,005	9 129 788 €	567 €	8%
M9	56%	15333	0,004	8 727 436 €	569 €	7%
M10	53%	14669	0,004	7 540 006 €	514 €	7%
M11	55%	14947	0,004	7 719 868 €	516 €	7%
M12	71%	19347	0,006	12 992 415 €	672 €	9%
M13	60%	16551	0,005	11 091 201 €	670 €	8%
M14	90%	24609	0,007	8 272 985 €	336 €	12%
M15	82%	22398	0,007	7 541 327 €	337 €	11%
M16	94%	25615	0,007	12 581 921 €	491 €	12%
M17	88%	24132	0,007	11 869 447 €	492 €	12%
M18	90%	24625	0,007	10 824 113 €	440 €	12%
M19	87%	23783	0,007	10 450 806 €	439 €	11%
M20	94%	25824	0,008	15 352 541 €	595 €	12%
M21	91%	24771	0,007	14 733 342 €	595 €	12%
M22	90%	24638	0,007	13 378 091 €	543 €	12%
M23	90%	24523	0,007	13 314 476 €	543 €	12%
M24	94%	25824	0,008	18 022 548 €	698 €	12%
M25	94%	25614	0,007	17 864 814 €	697 €	12%
M26	50%	13857	0,004	6 405 938 €	462 €	7%
M27	52%	14167	0,004	6 606 392 €	466 €	7%

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

Table 13: Simulation of the cost-effectiveness at the territory level (sample = biggest farms only)

AES	tSOC	teqCO2	€	€/teqCO2	% sequestration
2	2,104	7,713	2,355,287	305	0.002
3	1,600	5,866	1,866,224	318	0.002
4	2,930	10,744	3,834,212	357	0.003
5	2,669	9,786	3,183,553	325	0.003
6	2,613	9,583	3,877,604	405	0.003
7	2,669	9,787	4,000,451	409	0.003
8	3,102	11,372	5,218,791	459	0.003
9	2,986	10,948	4,976,220	455	0.003
10	2,843	10,423	5,269,922	506	0.003
11	2,880	10,561	5,384,287	510	0.003
12	3,805	13,953	7,732,193	554	0.004
13	3,265	11,970	6,659,676	556	0.003
14	4,820	17,672	5,857,239	331	0.005
15	4,297	15,757	5,240,084	333	0.005
16	5,107	18,725	9,067,479	484	0.005
17	4,789	17,561	8,530,981	486	0.005
18	4,820	17,672	7,659,467	433	0.005
19	4,597	16,857	7,305,101	433	0.005
20	5,164	18,934	11,100,000	586	0.006
21	4,909	18,000	10,600,000	589	0.005
22	4,820	17,672	9,461,694	535	0.005
23	4,755	17,434	9,331,169	535	0.005
24	5,164	18,934	13,000,000	687	0.006
25	5,090	18,663	12,800,000	686	0.005
26	2,741	10,050	4,574,397	455	0.003
27	2,746	10,070	4,640,932	461	0.003

Figure 1. Example of a choice card

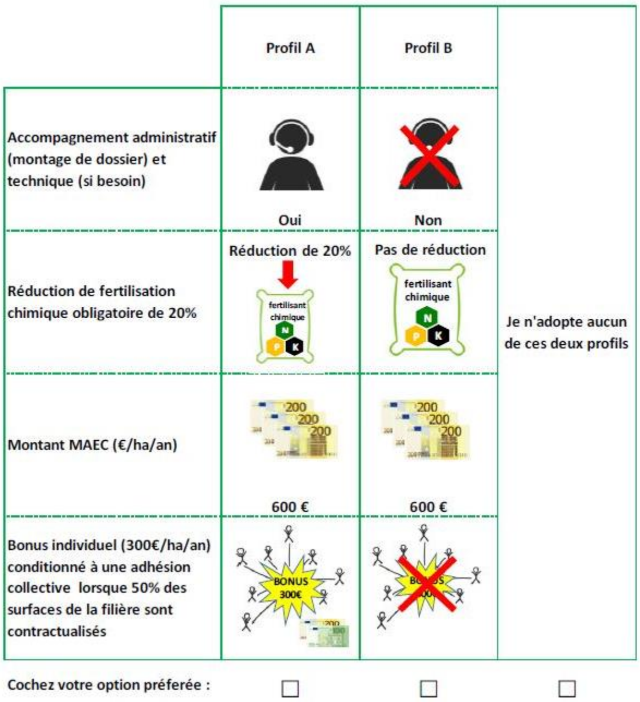
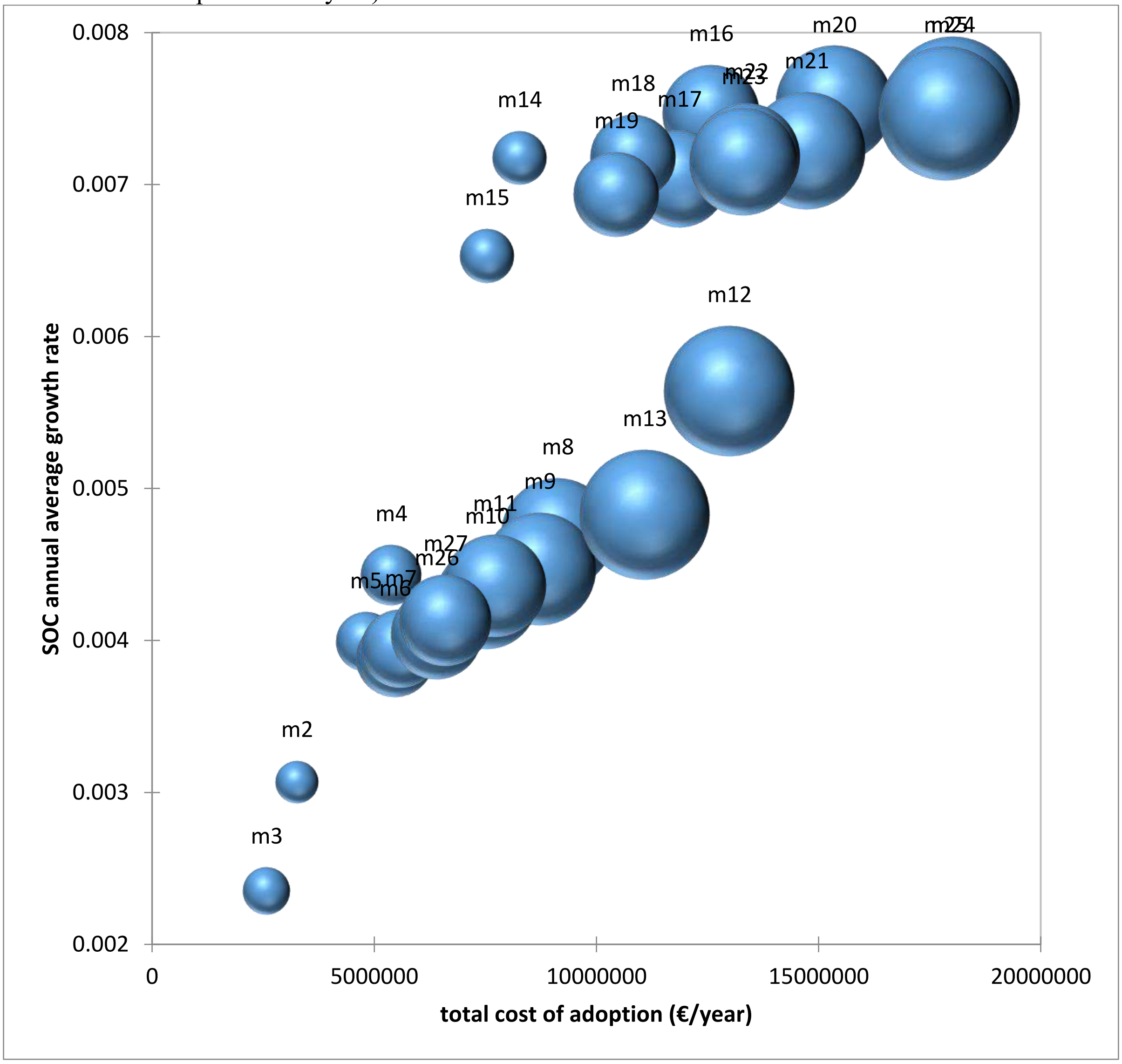
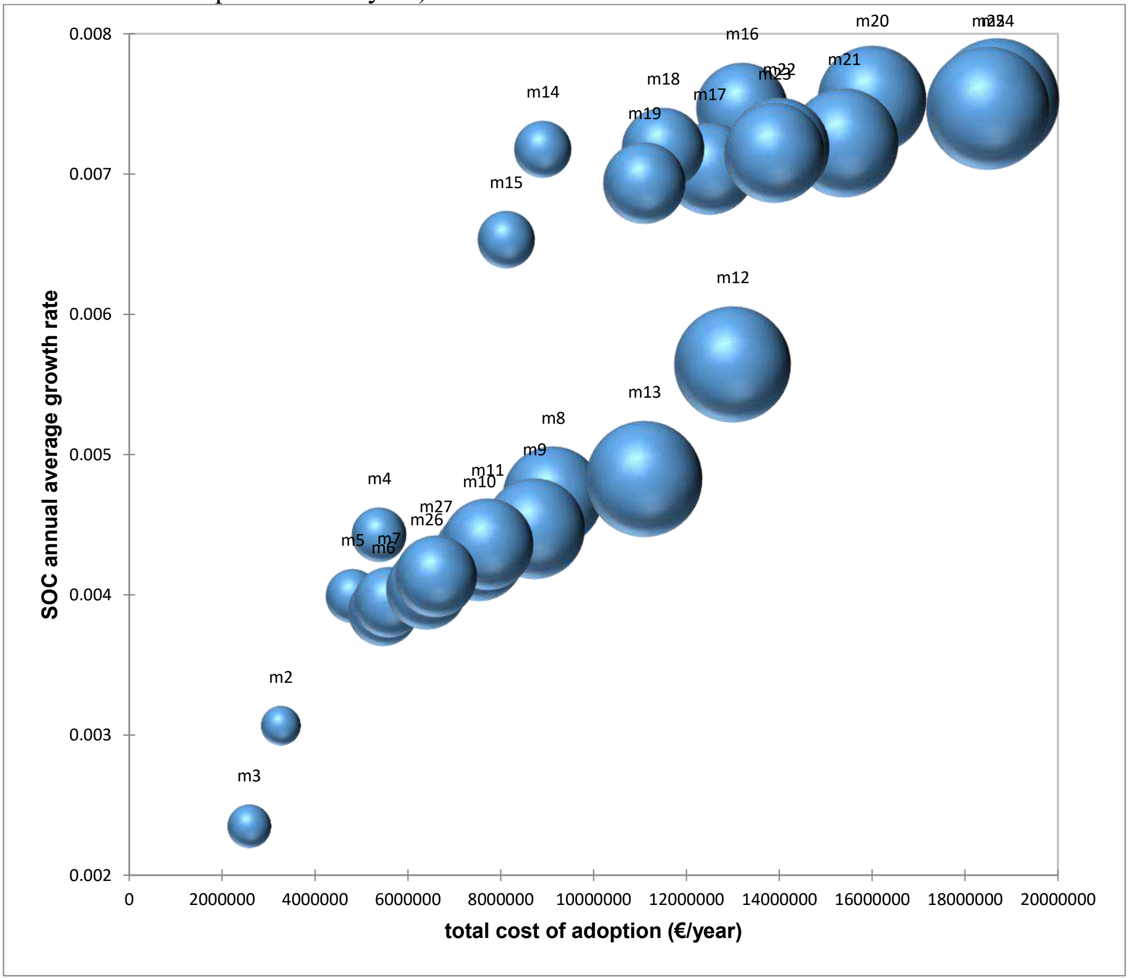


Figure 2. Average annual SOC growth rate according to the total cost of the adoption (technical assistance costs equal €50/ha/year)



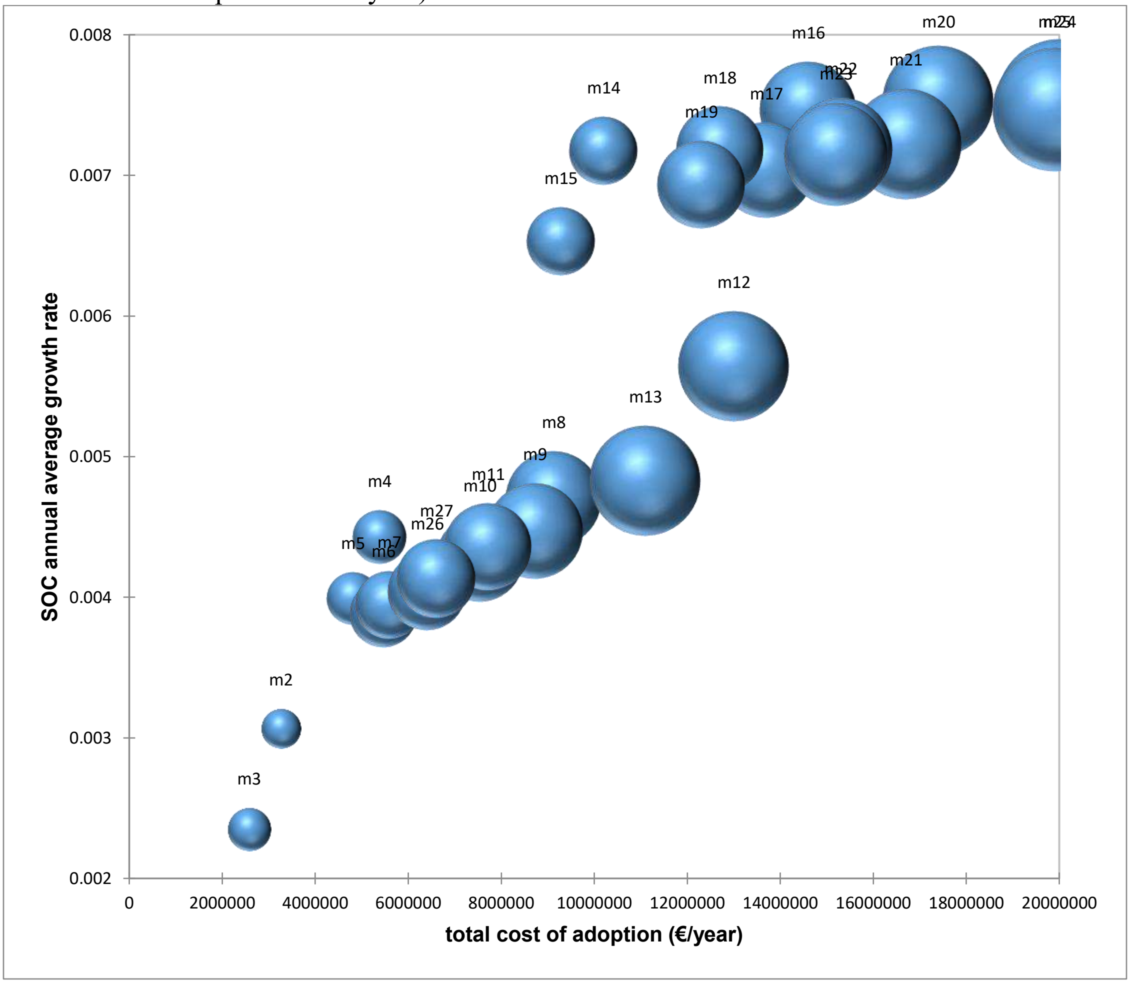
Note: Costs are calculated assuming that technical assistance costs equal €50/ha/year. For each AEM, the diameter of the bubbles is proportional to the average cost of the sequestered teqCO2 (€/teqCO2), so that the smaller the bubble, the more economically efficient the environmental program.

Figure 3. Average annual SOC growth rate according to the total cost of the adoption (technical assistance costs equal €100/ha/year)



Note: Costs are calculated assuming that technical assistance costs equal €100/ha/year. For each AEM, the diameter of the bubbles is proportional to the average cost of the sequestered teqCO2 (€/teqCO2), so that the smaller the bubble, the more economically efficient the environmental program.

Figure 4: Average annual SOC growth rate according to the total cost of the adoption (technical assistance costs equal €200/ha/year)



Note: Costs are calculated assuming that technical assistance costs equal €200/ha/year. For each AEM, the diameter of the bubbles is proportional to the average cost of the sequestered teqCO2 (€/teqCO2), so that the smaller the bubble, the more economically efficient the environmental program.

Figure 5: