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Estimating the CAP greening effect by machine learning techniques: A big data ex post analysis

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ABSTRACT

Greening payment represents one of the main and controversial novelties of the current Common Agricultural Policy (CAP) 2015–2020 programming period. Such payments bind a portion of farm subsidies to compliance with specified practices, such as crop diversification. Unlike previous ex ante simulations, the present contribution attempts to estimate the ex post impact of greening payments in terms of land use change using a parcel-level constant sample (2011–2017) dataset of approximately 4.5 million observations. First, Markov chains and a weighted χ^2 test detect a discontinuity in farmland transition probabilities only in farms that are initially non-compliant with the greening rules. Such a discontinuity is not observed in farms that are not eligible for or already compliant with the greening rules. This evidence, even if indirect, suggests that the greening payment has induced farmland conversion in farms with a lower degree of crop diversification. The greening impact on farmland allocation in this farm group was subsequently simulated using machine learning techniques. This policy has reduced maize monoculture and increased nitrogen-fixing crops, fallow land and other cereals in the targeted farms. Environmental gains (reduction in greenhouse gas emissions –GHG- and input use) and farm economic losses due to land use change have been derived, providing the first tentative cost-benefit analysis of such policy tool. Due to data limitations, indirect costs and benefits of greening (improvement in pest management, land quality and biodiversity) have not been assessed. More research and detailed environmental monitoring data are required to assess such indirect effects and to provide a more comprehensive cost-benefit ex-post analysis of greening policy

1. Introduction

The Common Agricultural Policy (CAP), implemented in the 1960s, was the first and most relevant sectoral policy of the European Union (EU). Its aims have progressively changed over time with the evolution of the agricultural sector and societal needs. Over time, aspects related to the environmental sustainability of agriculture have assumed greater importance than the traditional objectives of supporting agricultural income and food self-sufficiency. In this context, the greening payment represents one of the main novelties of the current CAP 2015–2020 programming period. It binds a portion of CAP direct payments for farmers to compliance with some environmentally friendly practices, namely, i) arable crop diversification, ii) maintenance of permanent grassland and iii) allocation of a share of farmland to ecological focus areas (EFAs). This payment is meant to influence farmland allocation, transitioning farming systems based on monoculture to a more diversified status. The introduction of the greening payment has been accompanied by a vibrant debate (Hart and Little, 2012; Matthews, 2013a) over various aspects of such novel policy tool. Criticism has been raised based on different, and sometimes opposite, motivations. On the one hand, have been pointed out implementation difficulties and economic losses for farms and bureaucratic burdens due to implementation and monitoring, for national authorities (COPA-COGECA, 2012; Roza and Selnes, 2012). The territorial targeting of greening payment, considering its farm-level enforcement, has also been questioned (Buckwell et al., 2012; Hart and Baldock, 2011). Doubts about the effectiveness in producing significant environmental effects have also been a major criticism of this tool (Hart and Baldock, 2011; Matthews, 2012, 2013b, Westhoek et al., 2013). In the wave of such political debate, a remarkable number of analyses have been conducted to assess various impacts of the greening payment. As this debate has developed over the long legislative process (from first EU Commission proposal to final agreement), related analyses have been based mainly on ex ante simulations. The bulk of existing studies on this topic relies on

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mathematical programming and positive mathematical programming models (Ahmadi et al., 2015; Cortignani and Dono, 2015; Cortignani et al., 2017; Czekaj et al., 2014; Gocht et al., 2017; Louhichi et al., 2018; Solazzo and Pierangeli, 2016; Solazzo et al., 2014, 2015; Solazzo et al., 2016; Cortignani and Dono, 2018, 2019). Such simulation exercises yield the estimated land use change induced by the greening payment as the main result. Some contributions use this input to infer the environmental and/or economic effects of greening (Cortignani and Dono, 2018; Gocht et al., 2017; Louhichi et al., 2018; Solazzo and Pierangeli, 2016). Furthermore, some analyses covered specific crops or specialized farms (tomato farms in Solazzo et al., 2014, arable crop farms in Cortignani et al., 2017). Additionally, the scale of analysis ranges from single regions/areas (Cortignani and Dono, 2015, 2018; Solazzo and Pierangeli, 2016) to whole countries (Czekaj et al., 2014; Cortignani and Dono, 2019) to the entire EU (Gocht et al., 2017; Louhichi et al., 2018).

The current strand of literature relies on sample-based data and ex ante simulation; to date, there is no trace of any ex post analysis on the impact of greening payments based on actual land use data. This paper fills this gap by providing an ex post evaluation of the CAP greening policy on farmland use changes. The actual crop mix during the periods before and after the introduction of CAP greening is used for this purposes. This ex post assessment exploited a dataset of approximately 2 million georeferenced farmland parcels of the Lombardy region in Northern Italy. Time and spatial farmland dynamics were observed over the period 2011–2017, covering the first three years of greening implementation. The present analysis first applied Markov chain modelling of the process and then a model aimed at predicting the crop mix evolution. In particular, crop mix change predictions have been performed using machine learning techniques in a multinomial choice framework (Hastie et al., 2009). This big data approach has been explored and discussed in medicine (Bashir and Carter, 2010; de Jong et al., 2019) and applied economics (Varian, 2014; Storm et al., 2020), exhibiting various advantages with respect to traditional approaches. The present work is the first attempt to employ such techniques for CAP impact analysis.

2. The study area

The analysis has been carried out on the plain and hill portion of the Lombardy Region, located in the North of Italy. Such sub-areas concentrates all arable crops, 85% of UAA, 87% of permanent crops and 17% of permanent grassland of the Region, and are therefore the main target of greening policy. Lombardy holds the highest share of value of agricultural production, among Italian regions (Pretolani and Rama, 2020). The regional agricultural activity in plain areas is intensive, with a dominance of livestock (dairy and pig) and arable crops farms. Maize is the prevalent arable crop, used both as a livestock feed and for grain. As a result of national energy policies, maize production has also been partly allocated to feed biogas plants, inducing a competition with other uses (Bartoli et al., 2016; Demartini et al., 2016). The prevalence of maize coexists with a concentration of other crops in spatially concentrated areas of the region. Relevant examples are rice and vegetable districts (Frisio et al., 2012; Ferrazzi et al., 2017). Such features makes the region a peculiar case study to explore how different sub-areas and farming system reacted to greening rules. Furthermore, before the introduction of greening payment, similar commitments were subsidised through Agri-Environmental Measures of the Rural Development Programme, with a fair degree of uptake by eligible farms (Bertoni et al., 2011). It is reasonable to assume that such farms were among those compliant to greening, before its enforcement.

3. Data

Our analysis exploited the Regional Information Systems dataset, by which the Lombardy region administration collects and manages farmers' applications for CAP payments. Initially, we built a constant sample for 2011–2017 of approximately 730,000 georeferenced farmland parcels located in the plains and the hills of the Lombardy region, representing almost the entire universe (95%) of agricultural land in the reference area. The mountain area was excluded because it was scarcely affected by greening rules due to the low share of arable crops. In the georeferenced dataset, for each farmland parcel, the barycentre in GIS coordinates, its extension in hectares, the farm it belongs to, and the (main) type of crop cultivated each year were registered. Crop typologies were aggregated into 23 different categories, and each parcel was assigned to one of three groups, selected according to the following policy criteria:

1 The eligibility of the farm (and its parcels) to greening commitments: arable crop diversification and EFA. Farms having 10 (30) or more hectares of arable land in 2014 were obliged to have at least two (three) crops (diversification commitment). Farms having more than 15 ha of arable land in 2014 were obliged to devote 5% of it to ecological focus areas (EFA commitments). Farms exceeding the previous thresholds are exempted from greening rules only if they belong to the following categories: organic farms or farms with a high share of forage crops (temporary grassland and herbage) or flooded crops (rice)[1] .
2 In case of eligibility, farm compliance with greening commitments before their enforcement (in 2015) was assessed.

Farms' classification was based on their status in 2014, the last year before the introduction of greening payment. The three groups were defined as follows:

GROUP 1 (non-eligible farms) includes parcels of farms exempted from greening commitments. Parcels in this group sum to 197,960 ha.

GROUP 2 (eligible and compliant farms) includes parcels of farms that were both eligible and compliant to greening commitments in 2014 (total area of 231,128 ha).

GROUP 3 (eligible and non-compliant farms) includes parcels of farms that were eligible for greening rules in 2014 but needed a subsequent adaptation to comply with those obligations (total area of 300,922 ha).

Farmland area was well distributed among the three groups. Thus, our analysis had an almost balanced design, which ensured high statistical power in comparing the results among groups.

4. Methodology

4.1. Weighted χ^2 test of transition discontinuity

As a first step, to test whether farmland use dynamics have changed after greening introduction (2015–2017) with respect to the previous period (2011–2014), we tested the stationarity of transition probabilities by means of a weighted Chi-square test (Micheletti et al., 2019). To perform such a test, the process must be modelled as a Markov chain. In this model, each parcel is seen to evolve over time, from one year to the other, into one of 23 cultivation classes. The evolution is estimated via a transition matrix *P(t)*, and we are interested in a) testing the homogeneity of transitions until the introduction of greening and b) checking whether a significant change is observed in *P(t)* after the year of greening introduction when the time index *t* passes 2014.

As expected, classical tests (Anderson and Goodman, 1957) of stationarity reject homogeneity before 2014 due to the large amount of noise and correlations in the data. This problem has been solved by introducing a new weighted χ^2 type test (Bertoni et al., 2018a; Micheletti et al., 2019) that accounts for the "physiological" variability registered before the new CAP. With this new test, we can identify the correct statistical unit that should be considered to filter out variability before a

[1] Further details on greening rules are provided in Bertoni et al., 2018a

given time in a set of panel data. We rescaled the statistical unit by estimating a parameter u, representing the number of hectares that should be aggregated, in the assumption of time homogeneity of transition probabilities up to 2014.

After reweighting all the data with u, a weighted χ^2 test was applied to test for discontinuities after greening introduction (2015–2017) with respect to the previous period (2011–2014). The test was applied to each combination of groups, crops and annual transitions (before and after greening introduction). In Group 2, and especially in Group 1, we did not expect to detect significant changes in the dynamics of the transitions of arable crops before and after greening introduction. In contrast, such changes were expected in group 3, at least for some of the main arable crops. Confirmation of this hypothesis would imply that the introduction of greening affected farmland allocation in Group 3 parcels. In this case, the analysis would focus on estimating the net effect of greening among Group 3 parcels, using as a counterfactual the behaviour of farmland units in Groups 1 and 2.

4.2. Gini-Simpson index and crop probability matrices

Given the presence of specialized and spatially concentrated agricultural districts in Lombardy, it is useful to highlight how diverse farming systems reacted, or did not react, to the introduction of greening. Consequently, to quantify and visualize farmland use transitions in the period under study, we calculated the Gini-Simpson index for each combination of year, group, and crop and for each geographical grid (spatial resolution of 12 sqkm). This index permits us to spatially visualize where transition probabilities changed after the introduction of the greening policy, discriminating among the abovementioned eligibility and compliance groups (see the example in Fig. 1–3 related to maize). The Gini-Simpson local index $D_i(t)$ may be read as the probability that any two parcels, which are both cultivated with the i-th crop at time t, will move to two different categories in the subsequent year

$$D_i(t) = \left(1 - \sum_{j=1}^{N} \left(p_j(t)\right)^2\right)$$

We then spatially plotted this index for each combination of group and main crops potentially affected by greening for both transition years just before and after CAP introduction. This operation enabled us to highlight which crops were most penalized, or alternatively favoured, by the application of the innovative policy and provides the basis to implement interacting particle models in the future (see Benfenati and Coscia, 2013), which may describe the evolution of the crops taking into account their spatial correlation.

4.3. Estimation of the greening effect by machine learning techniques

The last analysis we provide in this paper estimates the greening net effect on those farmland parcels that have shown a change in transition dynamics (Group 3). This analytical step is performed via machine learning techniques and using parcels belonging to Groups 1 and 2 as a counterfactual.

The whole decision process of farmland use is modelled in a covariate-dependent discrete choice framework. Discrete choice models, or qualitative choice models, aim to describe and predict how choices are made among a set of predefined alternatives. To do so, for each alternative, the utility obtained by a decision maker from different alternatives is theoretically computed based on covariates of each alternative and on individual propensity. The choice among alternatives is made by maximizing the utility of the decision maker. In this context, the decision makers are the farms that allocate crops (among 23 farmland uses) on each parcel to maximize their utility. In practice, the individual propensity is not observed, and each model describes the link between the observed covariates and the probability of choosing each possible farmland use.

In this work, we use multinomial logistic regression, where the probability of choosing each farmland use is proportional to the exponential of the observed quantity of the utility function, based on the covariates. Formally, if we denote by U_{nk} the utility of the *k-th* land use for the *n-th* parcel, we have

- $U_{nk} = O_{nk} + e_{nk}$, where O_{nk} is the observed part, which is linearly dependent on the observed covariates, and e_{nk} is a random error term;
- The probability P_{nk} that the *n-th* parcel is allocated to the *k-th* farmland use is

$$P_{nk} = \frac{e^{O_{nk}}}{\sum_k e^{O_{nk}}}$$

We have previously proven that the choice process was substantially homogeneous until 2014 and that a discontinuity was detected in 2014−2015, which is the first annual transition after greening introduction. The set of possible choices is given by the 23 possible farmland uses, and

$$O_{nk} = f_k\,(\text{starting}_n,\ \text{eligible}_n,\ \text{area}_n,\ \text{time})$$

Here, k identifies each of the possible choices (n = 23), and $starting_n$, $eligible_n$, and $area_n$ are the past farmland use (n = 23), the eligibility of the parcel for greening[2] and the agricultural district[3] of the *n-th* parcel (n = 58), respectively, while time is a dummy variable that indicates whether the choice is made before 2015 or not. We tested 8 different functions of possible interactions among the covariates, and we found that the following two models performed best in predicting the allocation of crops in the ex ante greening period:

$$\textit{Model 5} \quad \forall\, k, starting,\ area \quad O_{nk} = b_{0\ k,starting,\ area,\ eligible} + b_{1\ k,starting,\ area,\ time}$$

$$\textit{Model 7} \quad \forall\, k, starting \quad O_{nk} = b_{0\ k,starting,eligible} + b_{1\ k,starting,\ area,\ time}$$

In Model 5, parameters b_0 estimate the interaction effects between current farmland use (k), previous farmland use (*starting*), the agricultural district (*area*) and the grouping with respect to greening rules (*eligible*). Therefore, the estimated b_0 in Model 5 are $23 \times 23 \times 58 \times 2 =$ 61,364. Such terms render the estimated effect of the eligibility criteria on farmland use choice, computed at the agricultural district level. In Model 5, b_1 estimates the interaction effects between current farmland use (k), previous farmland use (*starting*), the agricultural district (*area*) and the year of farmland allocation choice (*time*). The estimated $b1$ in Model 5 are $23 \times 23 \times 58 \times 2 =$ 61,364. Parameters $b1$ in Model 5 represent the time effects on farmland use choices, computed at the agricultural district level.

In Model 7, parameters b_0 estimate the interaction effects between current farmland use (k), previous farmland use (*starting*), and the grouping with respect to greening rules (*eligible*). Therefore, the estimated b_0 in Model 5 are $23 \times 23 \times 2 =$ 1,058. Such terms represent the estimated effect of the eligibility criteria on farmland use choice, computed at the regional, and not local, level. Parameters b_1 are estimated in the same way as in Model 5.

The large quantity of data and the number of parameters to be estimated suggest exploiting a machine learning framework for big data with penalization. By adopting a SPARK machine, we can estimate all the parameters by minimizing the weighted negative log-likelihood with an elastic-net penalty to control for overfitting and regularization. The weight of each data point is given by the extension of the parcels, while

[2] The variable *eligible* is a dummy that takes value = 1 if the parcel belongs to Group 3 and 0 otherwise.

[3] In the study area, the Italian National Institute of Statistics (ISTAT) identifies 58 Agricultural Districts, classified based on homogeneous physical characteristics and types of farming.

the two parameters that control the elastic-net penalty are chosen to maximize the prediction of the previous year with the same data (big data approach). Once all the parameters are estimated, the probability of each farmland use for each parcel subject to greening is predicted. Then, by aggregating the results, the predicted and observed extension of each farmland use in 2015 are compared. The difference between the predicted and observed values in 2015 represents an estimation of the greening effect, given the assumed parameters.

5. Results

5.1. Weighted χ^2 test of transition discontinuity

Table 1 shows the results of the weighted χ^2 test computed for maize in each of the three greening groups (the same elaborations for the other main crops are available in Annex I). For a correct interpretation of the table, it is necessary to observe that the *p-value* in the fifth column refers to the comparison between pairs of consecutive annual transitions. For example, looking at the first row of Table 1(maize in non-eligible farms), the *p-value* of 0.13375 indicates that in this group, maize transition probabilities did not diverge significantly for the 2011/2012 and the 2012/2013 annual transitions. The same condition is verified for all pairs of consecutive transitions in the reference period in both Group 1 'Non-eligible farms' and Group 2 'Eligible and compliant farms', indicating that in these two groups, the maize transition probability remained homogeneous, even after the introduction of greening. In contrast, in Group 3, 'Eligible and non-compliant farms', a discontinuity emerges when comparing the 2013/2014 and 2014/2015 transitions. The former represents the last transition before greening implementation, and the latter is the first transition potentially affected by greening (in yellow in Table 1). In this case, the *p-value* of zero indicates a decisive shift in the transition probabilities with respect to previous years. After such years, the transition modalities have a stable trend again. The fact that discontinuity emerged in the first year of application of greening and only for farms that had to adapt provides a strong indication, if not a demonstration, that such a shift may be attributable to the new policy and not to other factors.

The analysis presented in Table 1 was repeated for the other crops and for each group (Annex I reports tables on maize for silage, wheat, soybean, alfalfa and fallow land). The results show that in Group 3, for many of the main arable crops (maize, maize for silage, wheat, other cereals, ryegrass, soybean, alfalfa, fallow land and herbages), the spatial heterogeneity and probability of transition changed after the introduction of greening. The same did not occur, or occurred to only a limited extent, in Groups 1 and 2, suggesting that such modifications in farmland transitions were mainly associated with the introduction of the greening policy. Given these results, we decided to estimate the greening effects by machine learning only in Group 3, exploiting the transition dynamics of Group 1 and Group 2 to build a counterfactual simulating Group 3 behaviour in the absence of CAP greening.

5.2. Gini-Simpson index and matrices of transition probabilities

Computing the Gini-Simpson index and its georeferencing permitted us to observe how crop transition modalities have changed in different parts of the region. In Fig. 1–3 , we present the elaborations for maize by comparing the 2013/2014 and 2014/2015 transitions in each of the three groups of parcels. Particularly, in Group 1 'Non-eligible farms', the two figures chromatically overlap. The red coloured areas, concentrated mainly in the central part of the reference area, indicate that a widespread maize monoculture persists after the greening introduction. The same result is observed for Group 2 'Eligible and compliant farms', but in this case, the starting situation shows a good level of diversification that does not change with the new policy. For Group 3 'Eligible and non-compliant farms', we observe that after the introduction of greening, the red zone (the core of maize monoculture in Lombardy) has been partly "eroded", introducing more variability in farmland allocation.

At this point, the existence of possible inhomogeneities in transition probabilities has been detected and georeferenced. To better understand how crop dynamics changed after greening introduction, we calculated how the transition probabilities changed for the main farmland uses potentially affected by greening (maize, maize for silage, wheat, soybean, alfalfa and fallow land). In particular, our comparison was between the first transition after greening introduction (2014/2015) and the transition immediately before (2013/2014). The probability of transition of some farmland uses towards others for each greening group is presented in Annex II.

Generally, in Groups 1 and 2, the self-succession rates of the main

Table 1
Results of the weighted χ^2 test for maize in different farm groups. The test shows homogenous transitions in all the years for Groups 1 and 2, while an inhomogeneity occurred between transitions in 2013-2014 (the last before greening introduction) and 2014-2015 (the first after greening introduction) for Group 3.

Maize in non-eligible farms (Group 1):							
Transitions	Q_t	c	DF	p-value	freq<5	n_i(t-1)	n_i(t)
2011–12 vs 2012–13	13,691	16,919	9	0.13375	0.400	331.8	332.1
2012–13 vs 2013–14	14,426	16,919	9	0.10795	0.350	332.1	299.8
2013–14 vs 2014–15	2178	16,919	9	0.98833	0.300	299.8	290.5
2014–15 vs 2015–16	5705	16,919	9	0.76907	0.300	290.5	260.7
2015–16 vs 2016–17	3217	16,919	9	0.95507	0.300	260.7	230.8
Maize in eligible and compliant farms (Group 2):							
Transitions	Q_t	c	DF	p-value	freq<5	n_i(t-1)	n_i(t)
2011–12 vs 2012–13	8882	19,675	11	0.63279	0.083	447.2	427.4
2012–13 vs 2013–14	13,118	19,675	11	0.28568	0.042	427.4	400.9
2013–14 vs 2014–15	5298	19,675	11	0.91585	0.167	400.9	361.6
2014–15 vs 2015–16	4056	19,675	11	0.96825	0.250	361.6	327.6
2015–16 vs 2016–17	3795	19,675	11	0.97552	0.292	327.6	286.7
Maize in eligible and non-compliant farms (Group 3):							
Transitions	Q_t	c	DF	p-value	freq<5	n_i(t-1)	n_i(t)
2011–12 vs 2012–13	7386	15,507	8	0.49563	0.000	775.5	764.5
2012–13 vs 2013–14	8614	15,507	8	0.37589	0.000	764.5	735.5
2013–14 vs 2014–15	47,455	15,507	8	0.00000	0.000	735.5	706.3
2014–15 vs 2015–16	3072	15,507	8	0.92974	0.000	706.3	575.5
2015–16 vs 2016–17	3934	15,507	8	0.86302	0.000	575.5	514.9

Source: Own elaboration on data from Regional Information Systems of Lombardy Region.

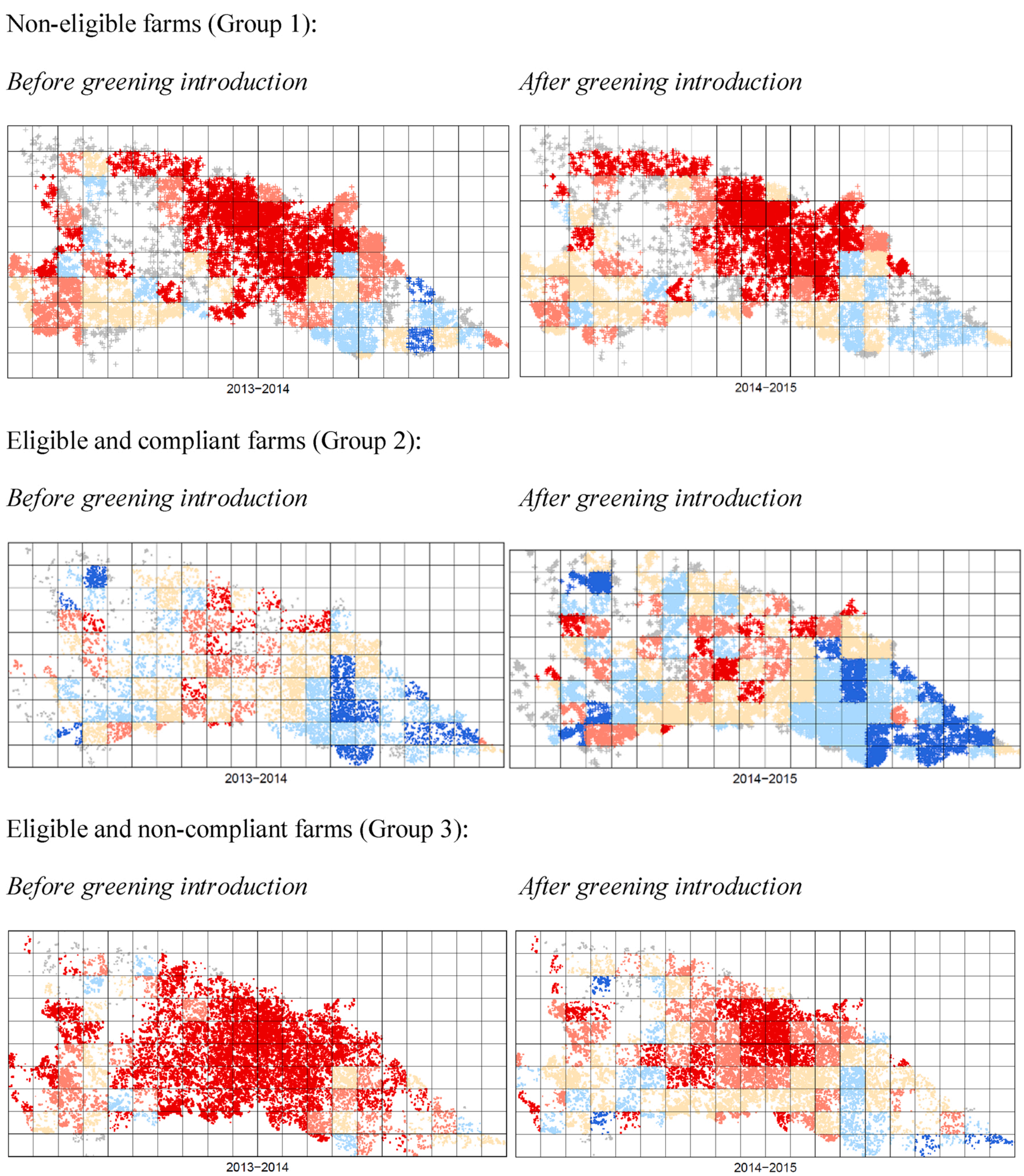

Fig. 1–3. Geographical representation of the transition probability of maize versus other cultivations (Gini-Simpson index) before and after greening introduction in the three groups: red = very small probability (i.e., no change in cultivation), blue = very large probability (i.e., very likely rotation).
Source: Own elaboration on data from Regional Information Systems of Lombardy Region

farmland uses do not vary or vary only slightly after greening introduction. In contrast, in Group 3, the high initial self-succession rates of maize and maize for silage consistently decrease, with a simultaneous increase in transition probabilities towards wheat, other cereals and soybean in particular. Considering those farmland uses that can be used by farmers both to comply with arable crop diversification and EFAs practices (soybean, alfalfa, fallow land), we observed that in Group 3, they considerably increased their self-succession rate.

5.3. Estimation of the greening effect by machine learning techniques

Table 2 reports the results of the greening net effects estimation on farmland allocation using machine learning techniques. In accordance with the preliminary analysis, such effects have been estimated only among Group 3 parcels, as the farmland transition probabilities changed significantly after the introduction of greening only in this cluster. The results of Model 5 and Model 7 do not differ significantly; therefore, we present results from Model 5, in which all relevant parameters are calculated at the detailed agricultural district level, allowing for a greater control of spatial heterogeneity.

According to Table 2, the crops most affected by greening in the Lombardy region are maize and maize for silage, with a remarkable acreage decrease (-14,083 ha and -7,879 ha, respectively). In relative terms, the reductions are 12.1% and 16.4% of the overall area of Group 3 and 7.2% and 10.9% of the whole study area. Interestingly, the effect of greening reinforces a negative trend for maize, while in the case of maize for silage, it counterbalances an expected slight increase. According to the figures in Annex III, the reduction in maize and maize for silage is

Table 2
Estimated effects (Model 5) of greening introduction in 2015 in cropland belonging to Group 3 (eligible and non-compliant farms).

FARMLAND USE	Observed area 2014 (hectares) *a*	Observed area 2015 (hectares) *b*	Change in area 2014–2015 (Δ hectares) *c=b-a*	Predicted area 2015 (hectares) *d*	Estimated greening net effect (Δ hectares) *e=b-d*	Estimated greening net effect (Δ% hectares) *f=e/d*	Estimated greening net effect on all groups (Δ% hectares) *g*
MAIZE	126,850	102,424	−24,426	116,507	−14,083	−12.1%	−7.2%
MAIZE FOR SILAGE	46,495	40,029	−6,466	47,908	−7,879	−16.4%	−10.9%
ROTATION RYEGRASS+MAIZE FOR SILAGE	21,458	25,105	3647	22,281	2824	12.7%	7.1%
WHEAT	20,869	26,794	5925	22,672	4122	18.2%	6.8%
OTHER TEMPORARY GRASSLAND	17,392	16,149	−1,242	17,170	−1,021	−5.9%	−2.2%
RICE	16,325	18,977	2652	18,221	756	4.1%	0.8%
TRITICALE AND OTHER CEREALS	9076	8468	−609	9118	−650	−7.1%	−4.4%
HORTICOLTURE	7433	8206	773	7714	491	6.4%	3.1%
BARLEY	6117	9701	3585	7737	1964	25.4%	12.0%
NON-ELIGIBLE SURFACES	5710	5005	−704	5863	−858	−14.6%	−4.8%
ALFALFA	4839	8863	4024	5364	3499	65.2%	6.6%
SOYBEAN	3840	14,006	10,166	6066	7940	130.9%	26.0%
OTHER ARABLE CROPS	3048	2356	−692	2583	−227	−8.8%	−3.1%
GRASS HERBAGES	2426	1850	−576	1872	−22	−1.2%	−0.4%
LANDSCAPE ELEMENTS	2404	1573	−830	1295	278	21.5%	4.5%
FLOWERS	1627	1693	66	1646	48	2.9%	1.3%
MIXED HERBAGES	1421	997	−424	1551	−554	−35.7%	−13.5%
PERMANENT CROPS	1314	1347	34	1473	−126	−8.5%	−0.5%
PERMANENT GRASSLAND	1246	1382	136	1356	25	1.9%	0.3%
FALLOW LAND	556	3572	3016	1086	2485	228.8%	49.6%
RYEGRASS	344	1270	926	1030	240	23.3%	6.7%
PULSES	119	319	199	317	2	0.6%	0.1%
LEGUME HERBAGES	16	836	821	90	747	832.7%	166.5%

Source: Own elaboration on data from Regional Information Systems of Lombardy Region.

concentrated in the central part of the study area, which is the intensive livestock district of the region. In this area, which is characterized by milk and pig production, feed provision is widely based on maize cultivation (here maize is also utilized as a biogas feedstock – Demartini et al., 2016; Bertoni et al., 2018b).

On the other hand, the introduction of greening promoted the growth of some crops, such as wheat (+4,122 ha), barley (+1964), alfalfa (+3499), and soybean (+7940). Furthermore, an increase in fallow land (+2,485 ha) and in the intra-annual rotation of ryegrass-maize for silage (+2824) was estimated. Such outcomes have an agronomic and economic rationale for farmers forced to overcome maize monoculture. For instance, cereal farmers may have accomplished diversification commitment by introducing wheat into the crop mix. The same applies to pig farms searching for feed crops other than maize (as the increase in wheat is spatially concentrated in the livestock district). Dairy farms may have adopted an intra-annual succession (maize for silage/ ryegrass) for use as livestock feed. In this case, according to greening rules, ryegrass – and not maize for silage - is the arable crop eligible for the crop diversification commitment. Nitrogen-fixing crops, whose areas have been increased by greening (soybean and alfalfa), were probably used to comply with both crop diversification and EFAs practices (as such crops may be used for both commitments). The same applies to fallow land, although it is not a cash crop. Furthermore, farms with more than 75% arable land covered in pastures or other herbaceous forage (such as alfalfa) and/or fallow land are exempted from greening commitments; farms near this threshold likely adjust their crop mix to fall within the exemption limits.

6. Environmental and economic effects of greening: a preliminary estimation

In this section, a rough estimation of the environmental and economic impacts of greening is provided. The computation is derived from the estimated greening net effects in terms of farmland use change. We are aware that an accurate computation of the derived effects of greening would require appropriate economic and environmental indicators at a disaggregated territorial scale (ideally, at the farm or parcel level). Unfortunately, the huge area covered by our sample does not meet such requirements, especially for environmental indicators, which are usually not available at such scales (Primdahl et al., 2003). Furthermore, establishing clear causality between an agro-environmental policy (such as greening) and its related environmental outcomes is not straightforward (Primdahl et al., 2010; Carey et al., 2003). For instance, many effects may be nonlinear, deferred over time and/or spatially differentiated (Primdahl et al., 2003).

Noting these limitations, given the available data, some simplifying assumptions are necessary to conduct a tentative estimation of the environmental and economic impacts of greening.

Therefore, following Bertoni et al. (2020), such an estimation exercise assumes that farmland allocation of a parcel to a use $k = 1$ instead of a use $k = 2$ yields a constant environmental/economic effect, independent of the agronomic and territorial context.

As a first step, using literature and farm accountancy databases, we assigned to each farmland use k a tabulated per-hectare value for each environmental and economic parameter (x_{jk}). Specifically, we gathered information on per-hectare parameters on farm input use (nitrogen and water)[4], emissions[5] (CO_2, N_2O, CH_4, CO_2eq) and gross margins[6] (with and without CAP payments coupled to crops).

Table 3 reports the estimation results. Column *a* reports the baseline situation based on the predicted area for each farmland use in 2015

[4] Data computed using the Farm Accountancy Data Network (FADN) for the Lombardy Region.

[5] We used per hectare emissions for each crop estimated by Solazzo et al. (2016) in their ex ante evaluation of the greening effects in Italy.

[6] Data computed using FADN for the Lombardy Region. A crop's gross margin is the revenue from that crop, minus the specific costs to cultivate and harvest it.

Table 3
Preliminary/tentative estimation of the environmental and economic effects of greening.

	All groups			Treated group (group 3 - eligible and not compliant farms)			
	Baseline (x_j_baseline)	Estimated effect (Δx_j)	Estimated effect ($\Delta\% x_j$)	Baseline (x_j_baseline_gr3)	Estimated effect (Δx_j_gr3)	Estimated effect ($\Delta\% x_j$_gr3)	Reduction cost per unit of effect (€·Δx_j_gr3^{-1})
	a	*b*	*c*	*d*	*e*	*f*	*g*
Inputs							
Nitrogen (kg ha^{-1})	121.4	−0.95	−0.78%	126.0	−2.29	−1.82%	5.5
Water (m^3 ha^{-1})	1041	0.19	0.02%	1085	0.45	0.04%	
Emissions							
CO_2(tons ha^{-1})	0.99	−0.026	−2.64%	1.20	−0.064	−5.30%	198.0
N_2O (tons CO_2eq ha^{-1})	1.25	−0.036	−2.88%	1.52	−0.087	−5.72%	144.5
CH_4 (tons CO_2eq ha^{-1})	0.95	0.008	0.80%	0.44	0.018	4.15%	
CO_2eq(tons ha^{-1})	3.19	−0.055	−1.71%	3.17	−0.132	−4.18%	95.1
Monetary values							
Gross margin (€ ha^{-1})	1356	−5.89	−0.43%	1274	−14.28	−1.12%	
Gross margin + coupled payments (€ ha^{-1})	1375	−5.19	−0.38%	1284	−12.59	−0.98%	

Source: Own elaboration.

(column *d*, Table 2), as follows.

$$x_j baseline = \left(\sum_{i=1}^{n} x_{jk} \times Pred\_area\_2015_k \right) \Big/ total\ farmland$$

The estimated environmental or economic effect (column *b*, Table 3) is computed using the estimated greening net effect for each crop (column *e*, Table 2)

$$\Delta x_j = \left(\sum_{i=1}^{n} x_{jk} \times Green\_net\_effect\_2015_k \right) \Big/ total\ farmland$$

The same computations are then replicated only for farmland parcels of Group 3 (eligible and not compliant farms), which represent the treated group (columns *d* and *e*). Thus, the estimation of the environmental/economic effects of greening pertains only to those farms that adapted to comply with the new policy.

Finally, a reduction cost per unit of effect (column *g*) is estimated only for Group 3. This value is computed by dividing the per-hectare estimated economic effect (-12.59 EUR/ha, including coupled payments) by the per-hectare estimated amount of inputs and emissions. As this result represents the opportunity cost of the policy (the cost for achieving a unit of environmental outcome), it has been attributed only to actually targeted farms.

Per-hectare variations in inputs, emissions and gross margins appear limited, especially when referring to the whole sample. Nitrogen spread per hectare decreases by 0.78% on total farmland (all three groups) and by 1.82% in Group 3 (treated). Water consumption does not change significantly. CO_2 and N_2O emissions fall by 2.64% and 2.88%, respectively (-5.30% and -5.72% in Group 3), while CH_4 increases by 0.80%. Annual per-hectare CO_2eq emissions, as a whole, decrease by 1.71% (-4.18% among Group 3 parcels).

Such environmental gains were obtained at the cost of a reduction in farms' gross margin, quantifiable as 5.19 EUR/ha on the whole sample (-0.38%) and 12.59 EUR/ha (-0.98%) for Group 3. The introduction of CAP payments coupled to some crops (such as soybean or rice) only partially mitigated the gross margin loss, which otherwise would have been 14.28 EUR/ha.

The opportunity cost is estimated considering the environmental gains and economic losses of greening: a 1 kg reduction in nitrogen use cost 5.5 EUR for non-compliant farmers, while 1 ton of CO_2 and 1 ton of N_2O reduction (the last expressed in CO_2eq) cost 198 EUR and 144.5 EUR, respectively. Aggregating variations of the three greenhouse gases results in a reduction cost of approximately 95 EUR per ton of CO_2eq.

7. Discussion

As mentioned in the introduction, this ex post analysis covers a geographical context already examined by some ex ante evaluations of greening effects (Solazzo and Pierangeli, 2016; Solazzo et al., 2016 and Cortignani et al., 2017), enabling a comparison between ex ante and ex post simulations. The former uses farm accountancy sample data and mathematical programming tools, while the latter exploits the universe of Lombardy farmland parcels. As the first two abovementioned ex ante analyses were based on a representative sample of Lombardy farms, the comparability of their results with the present work is assured. The simulation by Cortignani et al. (2017) used a representative sample of Lombardy farms specialized in arable crops; as such typology is among the most represented in the area and is potentially more affected by greening rules, the results may be somehow comparable to the treated farms of Group 3 (eligible and not compliant farms).

It is plausible to ask to what extent our estimations would be biased if the assumption of a sharp land use discontinuity in 2015 would not hold[7] . For instance some farmers may had anticipate change in regulation, while others may had been slower to adapt, expecting imperfect monitoring and enforcement of new regulation. We are quite confident that our estimated effect does not suffer from relevant anticipation or delayed effects, for different reasons:

1) We did not detect any significant farmland transition discontinuity for the main crops in the previous couple of transition years (2013/2014), among eligible and compliant farms, that is the group in which could fall anticipator farms (see Annex I);
2) Greening rules were mainly defined at the EU level, but many operational details have been decided at the national level. For instance, i) the definition of crops asmissible for diversification and ii) the detail of the farmland uses eligible for EFAs were defined by each Member State. Italy has detailed the operational choices late,

[7] We thank the anonymous reviewer that raised this point.

hindering in such way anticipatory behaviours. This is confirmed by specialized reviews of that time[8] ;

3) Since the main discontinuities have occurred on the main arable crops, we can state – by our experience - that in most cases farms have not faced relevant technical adaptations, and related transaction costs. Therefore, it is reasonable to assume that, on average, farmers would had chosen the most profitable crop mix (based on their objective and subjective preferences), changing it only with the enforcement of the policy
4) Concerning the delayed effect, they are possible, but only to a limited extent. In fact, controls about farmland utilization are quite easy. They can be done on the ground or by remote sensing. Consequently, not compliant farms had to be adapted in 2015. However, as showed in the supplementary material (Annex I) the way in which farms adapted partly changed in the transitions after 2015. This is because the availability of more detailed operating rules in later years opened up new solutions for farmers adapting to greening rules.

We first estimated the effects of greening on farmland use change and used the results to assess the consequent environmental and economic effects. The signs of our farmland use change estimates coincide with those of other studies; the same often applies for the magnitude of the estimated effect. In particular, we estimated that the introduction of greening caused a 6.2% reduction in maize area (considering together maize, maize for silage and rotation silage-ryegrass), which is slightly less than the values simulated by Solazzo et al. (2016) - -10%- and Solazzo and Pierangeli (2016) but in line with that of Cortignani et al. (2017). Previsions on wheat and barley (+6.8% and +12%) are comparable to those of Solazzo and Pierangeli (+8.7% and +8%). Compared to the latter contribution, we forecasted a larger increase for soybean (+26% instead of +12.8%) and a smaller increase for alfalfa (+6.6% instead of +20.1%). The estimated effects on fallow land appear to be similar (+49.6% and +40.5%, respectively). Estimations of input use were provided by Cortignani et al. (2017) using FADN data. Exploiting the same data to compute input use for each crop, we estimated a 1.82% decrease in nitrogen use (Group 3), which is comparable to previous nitrogen reduction forecasts (2.2–2.8%). We did not detect any difference in water consumption before and after the introduction of greening.

Our estimated emissions (-2.64% for CO_2, -2.88% for N_2O and -1.71% for CO_2eq) are very close to the forecasts by Solazzo et al. (2016): -3.18% for CO_2, -3.39% for N_2O and -1.96% for CO_2eq. Additionally, the economic estimations are close to those of Solazzo et al. (2016), with a -0.38% gross margin loss (including coupled payments) in the whole sample and -0.98% in treated farms, compared to the previously estimated -0.8% and -2%, respectively. The results are even closer to the estimate of Solazzo and Pierangeli (2016), with a gross margin reduction forecast of 0.9% in the plains and 0.2% in the hills of Lombardy.

Since the results of our ex post analysis are in line with those of ex ante simulations, this comparison may represent a cross-validation of both methodologies.

Unlike previous studies, we provide the economic cost of a unit of environmental gain attained through the greening policy. For simplicity, such estimates are computed assuming that the economic loss is associated with each single category of environmental indicator (greenhouse gas –GHG- emissions or farm inputs).

The estimated cost of carbonabatement (95 Euro per ton of CO_2 equivalent) is far higher than emission trading pricing of carbon. In 2015, the average annual price of a European Union Allowance (EUA) was 7.07 EUR (7.69 US$) risen to 24.5 EUR (US$ 30.14) in 2020[9] . This imply that greening policy is less efficient and more costly (from 10 to 4 times) in mitigating GHG emission, compared to other sectors. On the other hand, carbon abatement cost of greening is lower than the carbon tax of Sweden (110 EUR per metric ton in 2020[10]) that is among the highest in the world. However, GHG abatement is not the primary goal of greening policy, which has been conceived to enhance farmland diversification, with related substantial co-benefits discussed below.

Furthermore, our environmental assessment of greening outcomes multiplies the change in parcel-level land use by fixed regional-level parameters (GHG emissions, input uses). This approach allows us to estimate direct environmental effects of greening land use change but neglects indirect effects associated with the main target of greening policy, that is, farmland diversification. Such indirect effects include improvements in pest management, land quality, and biodiversity. Detailed data from environmental monitoring would be necessary to detect such effects. An improvement and refinement of the present results would be represented by the estimation of direct and indirect environmental effects, accounting for site-specific interactions between land use change induced by greening and local agronomic and territorial conditions.

Additionally, the estimation of the economic impacts of greening presents some limitations, as it accounts only for direct farm gross margin losses due to crop mix changes. The first assumption is the fixed-parameter assumption: we used the same gross margin for each crop in the entire area. The second is to neglect indirect costs of adaptation to greening due to crop diversification and land allocation to EFA. Such indirect costs are due to reduced scope and scale economies and loss of farm efficiency.

8. Conclusions

In the debate around the adoption and definition of CAP greening rules (farmland diversification and EFAs), their effectiveness in improving the environmental sustainability of farming has been questioned by some parts. In particular, the crop diversification commitment has sometimes been identified as ineffective (European Court of Auditors, 2017) and adopted only to formally fulfil environmentalists' concerns. Within this debate, the present contribution provides different evidence: at least in a high-intensity farming region characterized by widespread maize monoculture, such as Lombardy, we detected a significant discontinuity in farmland use transitions for farms eligible and initially non-compliant with greening rules. On the other hand, such discontinuity was not observed (in the same area, over the same period) in farms not eligible or initially compliant with the greening rules. This evidence, even if indirect, suggests that the introduction of greening rules has induced farmland conversion within farms with a lower degree of crop diversification. The extent to which such farmland change is associated with greening rules was estimated using machine learning techniques. To the best of our knowledge, this is the only ex post analysis on CAP impact assessment using such tools.

Using the estimates of farmland use changes induced by greening, we then attempted to broadly quantify the consequent environmental gains and farm economic losses. The plausibility of our results is confirmed by their congruence with the forecasts of previous ex ante simulation analyses. Based on such results, we developed a tentative cost-benefit

[8] Here some examples (in Italian): http://www.confagricolturamantova.it/it/doc-s-31-1094-1-greening%2C_confagricoltura_preoccupata_%C2%ABimprenditori_confusi_e_ministero_assente%C2%BB.aspx https://www.agriforest.it/soia-e-greening-che-confusione/ https://agronotizie.imagelinenetwork.com/agricoltura-economia-politica/2014/11/26/greening-il-parlamento-ue-chiede-di-posticiparlo-al-2016/40969 https://www.risoitaliano.eu/nessun-rinvio-per-pac-e-greening/ https://terraevita.edagricole.it/esperto-risponde/applicare-il-greening-domande-e-risposte/

[9] source: https://carbonpricingdashboard.worldbank.org/map_data

[10] More precisely, SEK 1.190 (EUR 110) in 2020 (currency conversion based on an exchange rate of SEK 10.80 per EUR (source: https://www.government.se/carbontax)

analysis of economic penalties imposed on farmers to obtain an environmental outcome. As this is the first cost-benefit analysis exercise on CAP greening impact, our results may be used as a benchmark for similar future assessments in other agricultural contexts. These results may also be taken into account in designing environmental tools within the current CAP reform.

Author statement

The research has been conceived with the joint contribution of all Authors. In particular Sections 2 and 5 are attributable to DC, Sections 3 and 6 are attributable to DB, Section 7 is attributable to DC and DB, Section 4 is attributable to GA and AM. All Authors have equally contributed to Section 1(Introduction) and to section 8(conclusion).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.envsci.2021.01.008.

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