Highlights

- We integrate remote sensing into ex-post assessment of CAP effects
- We evaluate the effects of CAP greening on soil quality parameters
- Integration of administrative data with remote sensing offers full land coverage
- Membership in greening groups has moderate effects on soil quality
- The approach is reproducible in time and space

Farmland use data and remote sensing for ex-post assessment of CAP environmental performances: an application to soil quality dynamics in Lombardy

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Abstract

With the reform of the European Common Agricultural Policy (CAP) in 2015, subsidies to farms (the so-called green payment or "greening") are now bound to the fulfilment of environmentally friendly measures, such as crop diversification and allocation of a share of their farmland to Ecological Focus Areas. Research on the effects of these policy changes so far have focused mainly on land use transition; however, a detailed investigation of how CAP greening affects the properties of agricultural land is required to assess the actual environmental benefits of the reform. In this study, we present a first attempt to assess the impacts of CAP greening on soil quality dynamics in Lombardy, a populated region in northern Italy where high-intensity agriculture is widespread. We combine high resolution (10/30 m) soil indices from remote sensing based on Landsat-8 and Sentinel-2 data with a regional administrative database covering all agricultural parcels of the region. We then perform a correlation analysis to investigate whether and to what extent greening prescriptions affect the soil quality from 2014, representing pre-greening conditions, to 2017, representing post-greening conditions. Our analysis indicates a high persistence of soil quality indicators and suggests that some crops might have a significant impact on soil quality dynamics, as well as the membership in different groups with respect to CAP greening. Although we identified some uncertainties in the soil indices, by integrating a large volume of data and an efficient processing algorithm our method paves the way for the ex-post environmental performance assessment of agricultural policies.

1. Introduction

Soil health is the foundation of agriculture; it governs food production by supplying the essential nutrients, water, oxygen and root support for food-producing plants (FAO, 2015). Healthy soils also provide a number of additional ecosystem services, including water regulation and the uptake of carbon from the atmosphere (Adhikari and Hartemink, 2016). Soil health is determined by the complex interaction of physical, biological and chemical properties such as organic matter, water content and nutrient availability (Paz-Kegan et al., 2014; Bonfante et al., 2019). Understanding how these properties vary over time and the drivers of variability permits improving agricultural and environmental practices and a more efficient use of resources (Castaldi et al., 2016).

Soil health and quality are affected by agricultural activity through farmland practices and land use choices. Farmer's decisions on crop allocation and land management may be influenced by various factors such as selling prices of agricultural products and cost of inputs (Glenk et al., 2017), pedoclimatic conditions (Leteinturier et al., 2006) along with individual and risk preferences of the farmer itself (Latawiec et al, 2017; Paut et al, 2020). Many of the agricultural drivers that impact, directly or indirectly, on soil management and quality depend, in turn, on external factors, such as agricultural policies (Kremmydas et al., 2018). In Europe, in particular, the Common Agricultural Policy (CAP) has affected and shaped land use choices and land management practices (Topp and Mitchell, 2003; Posthumus and Morris, 2010, Viaggi et al., 2013), depending on the historical phase in which such policy has been implemented. In general, the CAP has shifted over time from productivity-incentive measures toward a more environmentally-friendly regulatory framework. In a first stage, which lasted about 30 years, the CAP was mainly based on interventions aimed at supporting selling prices of agricultural products, in order to stimulate farm productivity and ensure food self-sufficiency of European Countries. Subsequently, the CAP was reshaped in two pillars: the first one where price support has been progressively reduced in favour of per-hectare payments and the second one, providing incentives for environmentally-friendly measures (low-input and organic farming, afforestation). The establishment of first pillar payments inaugurated a process (commonly known as "decoupling") aimed at diminishing the influence of CAP support on farmland use choices (Garzon, 2006; Folmer et al., 2013). Over time, decoupled per-hectare payments (first pillar), have been tied to the fulfilment of practices respectful of the land and the environment, by farms. At a first stage, according to the so-called cross-compliance, farms were obliged to keep their land in Good Agronomic and Environmental Conditions (GAEC) in order to receive CAP payments (Bennett et al., 2006; JRC, 2019a; JRC, 2019b). With the current CAP reform (2015-2020) the requirements to obtain farm payments have increased, with the introduction of the so-called greening payments (European Commission, 2020). Greening payments represent the main part of decoupled payments for farms, provided with the purpose to encourage farmers to make a sustainable use of their land. In order to receive greening payments, farmers are required to respect cross compliance (GAEC), to adopt crop diversification and to devote a portion of their farmland to Ecological Focus Area (for further details, see paragraph 1.2). The ongoing debate on a further future CAP reform (2021-2027) includes two main enhancements in terms of soil and environmental management practices. The first one is the shift from crop diversification (that is a static concept) to crop rotation, as a requirement to receive farm payments. The second and more general innovation implies a shift from compliance-based to performance monitoring of the policy architecture (Rossi, 2018). While so far farm payments have been linked to the compliance to certain practices (GAEC, greening) the reform process binds them to the attainment of certain evidence-based targets. In line with the green evolution of the CAP, it is plausible to expect that such targets will encompass, among others, the effect of sustainable land management practices (such as crop diversification/rotation) on soil quality.

As the CAP has evolved toward more environmentally-friendly targets, there has been a growing interest in measuring and monitoring its effects on land use, coverage and soil properties (Tóth et al, 2013; Orgiazzi et al., 2018; JRC, 2020) and on soil conservation (Borrelli et al, 2016; Borrelli and Panagos, 2020). Referring to soil quality and management, the change of CAP monitoring, from compliance to performance, calls for a stronger integration of available data sources.

While soil properties can be monitored through field sampling and laboratory analysis (see e.g. Paz-Kegan et al., 2014; Orgiazzi et al., 2018), this is a laborious, costly and time-consuming process (Mulder et al., 2011). A more efficient alternative is to combine field sampling with remote sensing to produce spatial maps of soil properties, exploiting the wide area coverage of optical and radar sensors and their ability to monitor the topsoil (Shoshany et al., 2013). Commonly used optical sensors include MODIS (Bouaziz et al., 2011; Poggio et al., 2013; Chen et al., 2014; Pellegrini et al., 2018), Landsat ETM+/OLI (Dehni and Lounis, 2012; Forkour et al., 2017) and more recently, Sentinel-2 MSI (Castaldi et al., 2018). The spectral bands of these sensors are often combined to produce spectral indices, taking advantage of their simplicity and low sensitivity to atmospheric conditions. Several spectral indices have been developed to monitor soil properties, including the normalized multiband drought index (NMDI, Wang and Qu, 2007), which is related to the soil moisture content, the salinity and brightness indices (SI and BI, Dehni and Lounis, 2012), which are related to the soil salinity, and the Normalized Difference Vegetation Index (NDVI). The NDVI, although originally developed and most often used to monitor the health or phenology of vegetation (Primi et al., 2016), has been linked to the organic matter content in soils (Guo et al., 2017; Gholizadeh et al., 2018).

In most studies, spatial maps of soil properties are derived by simultaneously collecting soil samples and acquiring remote sensing data. The soil properties of interest are then measured in the laboratory and a prediction model is built to relate field and remote sensing data, using multivariate regression (Douaoui et al., 2006; Gholizadeh et al., 2018) or machine learning techniques (Bachofer et al., 2015; Castaldi et al., 2019). While this approach can greatly extend the scope of traditional soil surveys, it still relies on accurate field data collection. To overcome this issue, Castaldi et al. (2018) based their prediction model on the LUCAS topsoil database (JRC, 2020), a European-wide effort to produce standardized measurements of soil properties of samples collected across the European Union (EU). Nevertheless, studies such as this produce a static map of soil properties.

In the context of agricultural studies, a more dynamic use of remote sensing datasets is to integrate already existing administrative agricultural data, by increasing their spatial or temporal detail. In fact, remote sensing, such as other digital technologies, could improve different key agricultural policy dimensions, including policy evaluation (Ehlers et al., 2021). Waldhoff et al. (2017) employed medium to high resolution satellites (ASTER, Landsat, Sentinel and SPOT) to produce crop sequences for the North-Rhine Westfalia region in Germany over a period of 8 years; Stumpf et al. (2018) determined land use dynamics from a combination of Landsat satellite images, meteorological and topographic variables. The transition between grassland and cropland was then employed to gain insights into the evolution of organic carbon in Swiss soils. In summary, although remote sensing often forms an integral part of studies on soil properties in agricultural areas, the evolution of soil properties themselves is seldom investigated using this technique (Sheffield and Morse-McNabb, 2015; Dube et al., 2017). Further still, the complexity of the integration between remote sensing and agricultural census data increases with increasing spatial resolution (Zhang, 2010).

Another strand of literature has investigated the economic and environmental impacts of CAP instruments. Detailed scale assessments of CAP environmental effects are usually based on field experiments (Kleijn and Sutherland, 2003; Walker et al., 2007; Ansell et al., 2016), or on ad-hoc surveys carried out on a limited amount of farms (Zahm et al., 2008; Paracchini et al., 2015). This kind of evaluation suffers from the difficulty of extending the results to wider territorial areas. Some exceptions are represented by ex-post assessments, on the effects of participation in the agri-environmental measures of the CAP (Pufahl and Weiss, 2009; Chabé-Ferret and Subervie, 2013; Bertoni et al., 2020), on the effect of greening (Bertoni et al., 2021) and of CAP direct payments (Arata and Sckokai, 2016; Coderoni and Esposti, 2018). Such ex-post analysis relies on datasets provided by public administrations (Pufahl and Weiss, 2009, Chabé-Ferret and Subervie, 2013, Bertoni et al, 2020; Bertoni et al, 2021). Particularly, the Farm Accountancy Data Network (FADN)[1] is usually exploited in the assessments of CAP effects, (Mary, 2013; Arata and Sckokai, 2016; Coderoni and Esposti, 2018). However, being conceived to evaluate the economic performance of farms, it reports a limited amount of information on environmental performance, usually limited to the inputs (pesticides and fertilizers) and water consumption (Kelly et al., 2018).

The main bottleneck of such assessment studies is the lack of data having, at the same time, a reasonable detail (at least farm level) and full territorial coverage (Primdahl et al., 2010). Indeed, the availability of indicators measured at a detailed spatial scale represents one of the main challenges in assessing the sustainability of the agricultural sector (Burkhard et al., 2009). A further challenge is represented by the extensibility of the results to a larger scale (Kelly et al., 2018). This condition is guaranteed when, as in our case, available data cover the universe of observations on a given territory. For the above-mentioned reasons, ex-post CAP impact assessments could be usefully complemented by using geo-referenced data with wide spatial coverage, deriving from remote sensing.

In line with the performance-measurement of policy measures, this paper describes a first attempt to assess whether and to what extent the crop-mix change induced by the greening measures (Bertoni et al., 2018; Micheletti et al., 2020; Bertoni et al., 2021) may be associated with a change in soil quality indices.

In particular we aim at testing how different factors, including farmland use type, eligibility and compliance with respect to greening policies, contribute to explaining the dynamic variability in soil properties derived from remote sensing indices. In the first stage, we develop a methodology to combine high resolution remote sensing and administrative agricultural datasets in an efficient manner, to provide dynamics maps of soil properties in a wide agricultural region of the EU without the need for field surveys; secondly, we undertake a preliminary assessment of the evolution of soil properties before and after the implementation of greening policies, and finally we perform a correlation analysis to evaluate the possible influences on the observed changes in soil properties in the context of CAP greening.

1.1. Study area

[1] The FADN is a sample dataset of about 80,000 farms, representing about 5 million EU farms that concentrate 90% of EU agricultural production (Kelly et al., 2018)

The area examined in this study is a large portion (covering about 2,150 km^2) of the flatland of Lombardy region, in Northern Italy. Lombardy is the most populated Italian region with more than 10 million inhabitants, corresponding to 16.4% of the Italian population, concentrated in only 7.9% of the national territory. Over 53% of the area, mainly in the north, is mountainous or hilly, while the southern part of the region is a plain, where more than 72% of the land is managed by the agricultural sector. Here, arable crops – in particular maize and forage crops - represent the main farmland utilization type (89%), while permanent grassland is limited to only 6% of the farmland. Water flood irrigation is widespread. Agriculture in Lombardy is characterized by high-intensity farming systems (Fumagalli et al. 2011). The average value of production per hectare of farmland is 3.9 times that of the EU-28, while the average economic dimension of the farms is 5.7 times. Livestock products, especially milk and pigs, provide two thirds of the agricultural value, with the livestock density (measured as the number of Livestock Standard Units – LSU – per hectare), being 3.7 times that of the EU-28 (Eurostat Farm Structure Survey, 2013). Given the high livestock density, both nitrate leaching in water, and its dispersion in air, are considered serious problems (Perego et al., 2012; Acutis et al., 2014; Paracchini et al., 2015).

2. The greening policy

The greening policy represented one of the main novelties of the 2015-2020 CAP programming period. Greening ensures that the allocation of CAP direct payments to the farmers is bound by their fulfilment of some 'agricultural practices beneficial for the climate and environment'.

The practices are as follows:

a) diversification of arable crops;

b) maintaining existing permanent grassland;

c) having an ecological focus area on the agricultural area.

In Italy, only the first and the third practice were applied at farm level, while the second was implemented at national level, not representing in such a way a real bond for farms. For this reason, we considered in our analysis only 'diversification of arable crops' and 'ecological focus area' practices.

'Diversification of arable crops' mandates that farms having more than 10 (30) hectares of arable land should cultivate at least 2 (3) arable crops, allocating a minimum share of cropland to the less represented crop(s). The third rule establishes that in farms with above 15 hectares of arable land, at least 5% of such surface should be devoted to Ecological Focus Areas (for instance nitrogen-fixing crops, fallow land, landscape features, buffer strips, etc.). Organic farms and farms with a large share of forage crops and/or leguminous crops and/or fallow land and/or flooded crops (rice) were exempted from the compliance with greening rules, regardless of their dimension. For further details, see Regulation (EU) n. 1307/2013, articles 43-47.

It is quite evident that these practices potentially affect farmland uses, particularly in a region like Lombardy, traditionally characterized by the presence of large farms and a widespread maize monoculture. Given such features, some studies have attempted to estimate how greening introduction impacted on farmland allocation choices in Lombardy. Most of these analyses were ex-ante simulations, based on small-scale sample data (e.g. Cortignani et al., 2017). Conversely, Bertoni et al. (2018), Micheletti et al. (2020) and Bertoni et al. (2021) performed a detailed ex-post analysis by observing the actual behaviour of all farmland parcels in the Lombardy region for some years before and after greening implementation. Results of Bertoni et al. (2018) and Micheletti et al. (2020) claim for a change in transition probabilities of the main arable crops. Such changes consist in a decrease of transitions probabilities toward maize and in an increase of those toward nitrogen-fixing crops (soybean, alfalfa), herbages and other cereals. Bertoni et. al. (2021) estimated the net effect of greening on farmland allocation between 2014 and 2015. Their results show a reduction of 10% of maize area in eligible and not initially compliant farms, counterbalanced by increases of other crops (mainly soybean, alfalfa, wheat, barley and fallow land). However, all these estimations focus on the effects of the policy on farmland allocation, which is only the visible outcome of the greening policy, and not on its environmental impact. In this sense, our study aims at testing whether and to what extent level and variations in soil indices may be somehow associated to observable outcomes (land use change) induced by the CAP greening.

3. Datasets and methods

3.1. Remote sensing data

Remote sensing data were acquired for 2014 (pre-greening conditions) and 2017 (post-greening conditions). To map soil properties through spectral indices, soils are required to be bare to exclude the influence of vegetation (Wang et al., 2007). Thus, we selected satellite images from October/ early November, as this time of year marks the period of rotation between summer and winter crops.

For 2014, we acquired Landsat-8 OLI data at 30 m spatial resolution, at the L1T processing level. These data are freely available from USGS and were downloaded at http://earthexplorer.usgs.gov/;

altogether we selected four cloud-free tiles (see Table 1), acquired between 23/10 and 01/11, covering the low-lying areas of Lombardy. Individual tiles were merged together using the mean value for overlapping portions and top-of-atmosphere percent reflectance between 0 and 1 was calculated using the coefficients found in the Landsat tile metadata.

For 2017, we downloaded six cloud-free 100 km by 100 km tiles (see Table 1) from the Sentinel-2A and –B satellites, acquired on 14/10 and 16/10, at the L1C processing level. The tiles were downloaded from the ESA Copernicus open access hub (https://scihub.copernicus.eu/) and were merged together using the same approach described for Landsat before calculating the indices. For consistency with the other bands, we resampled bands 8A, 11 and 12, originally at 20 m spatial resolution, to 10 m resolution. These bands are necessary for calculation of the NMDI. We did not resample the other 20 m or 60 m bands of Sentinel-2, as they were not needed for calculation of other indices. Sentinel-2 digital numbers are provided as scaled reflectance between 0 and 10,000. We transformed this value to percent reflectance between 0 and 1.

Table 1: satellite images used to calculate indices for 2014 and 2017. Tile refers to the tiling system of Landsat 8 (path_row) and Sentinel-2 (UTM Military Grid Reference System).

Satellite	**Tile**	**Date**	**Resolution (m)**
Landsat 8 OLI	193_28	01/11/2014	30
Landsat 8 OLI	193_29	01/11/2014	30
Landsat 8 OLI	194_28	23/10/2014	30
Landsat 8 OLI	194_29	23/10/2014	30
Sentinel-2	32TMQ	14/10/2017	10
Sentinel-2	32TMR	14/10/2017	10
Sentinel-2	32TNQ	14/10/2017	10
Sentinel-2	32TNR	14/10/2017	10
Sentinel-2	32TPQ	16/10/2017	10
Sentinel-2	32TPR	16/10/2017	10

3.2 Administrative data

In our analysis, remote sensing data were combined with georeferenced administrative data coming from the SIARL dataset of Lombardy Region. SIARL is an administrative dataset by which Lombardy Region administration manages farmer requests for CAP payments. For each of about 50,000 farms located in the Region, it contains information about farm structures, crops, livestock, family and hired labour, and CAP payments received. Particularly, for our purposes we gathered data about the use of each of the two millions of farmland parcels of the Lombardy region from 2011 to 2017. These data came from yearly declarations of farmers applying for CAP payments.

Given the occasional contemporary presence of more crops on the same parcel in the same year, following Bertoni et al. (2018), we applied some rules to assign to each georeferenced parcel only one use per year. The number of potential farmland uses was 23. Subsequently, we created a balanced panel 2011-2017, eliminating those parcels not declared in all the observed years. In any case, the resulting balanced panel of farmland parcels represents 95% of the total agricultural area. Finally, we reduced the georeferenced balanced panel of parcels, considering only those parcels which overlap with remote sensing data. The result was a balanced panel 2011-2017 of 153,954 farmland parcels for a total area of 214,968 hectares. Since some farmland uses result in a permanent land cover, leading to distortions in remote sensing indices, and/or are not affected by greening rules at all, we decided to eliminate parcels with those land use types[2]. After cleaning these parcels, the balanced panel 2011-2017 shrinks to 129,166 parcels for 191,645 hectares. The final number of farmland uses included in the model was 17.

Each parcel belonging to the dataset was assigned to one of three groups based on criteria of both eligibility and compliance with the greening policy of the farm to which they belonged. These conditions were verified by making reference to the year 2014, which was the last year before greening introduction. Specifically, we separated parcels into three groups: 1) Group 1 (not eligible). This group includes parcels belonging to small farms and those that are exempted from greening payments because of their characteristics; 2) Group 2 (eligible and compliant). This group includes parcels belonging to those farms that are eligible for greening practices, but were already compliant with these rules in 2014; 3) Group 3 (eligible, not compliant). This group includes parcels pertaining to farms that were eligible for greening payments, but that before the implementation of greening policies did not satisfy greening requirements.

[2] More specifically, we excluded from the dataset parcels with the following uses for at least one year between 2014 and 2017: permanent crops, permanent grassland, flowers, woods and rice.

Classification of farmland parcels into three greening groups resulted in the creation of three sub-samples of respectively 32,155 hectares (Group 1), 74,810 hectares (Group 2), and 84,680 hectares (Group 3). In annex 1 we show the details about the evolution of the farmland use, before and after greening introduction, in each of the three above mentioned groups.

3.3 Calculation of remote sensing indices for each parcel

Four types of indices were calculated based on the merged Landsat 8 and Sentinel-2 data, including the NMDI, SI, BI and NDVI. The NMDI, developed by Wang and Qu (2007), has an inverse relationship with the moisture content of the soil: higher values (> 0.7) represent a moisture content lower than 0.1, values around 0.6 intermediate wetness conditions and < 0.6 wet soil conditions (Wang and Qu, 2007). It is calculated following equation (1)

$$NMDI = \frac{NIR-(SWIR1-SWIR2)}{NIR+(SWIR1+SWIR2)} \quad (1)$$

Where NIR stands for near infrared and SWIR stands for shortwave infrared. The equation proposed by Wang and Qu (2007) is based on the MODIS sensor, where NIR is a band centered at 860 nm, SWIR1 is centered at 1640 nm and SWIR2 at 2130 nm. We selected the closest bands of Landsat 8 (USGS, 2018) and Sentinel-2 (ESA, 2015). For Landsat, these are band 5 (865 nm), band 6 (1608.5 nm) and band 7 (2200 nm). For Sentinel-2, we used band 8A (20 m resolution, resampled to 10 m) which is narrower than band 8 and closer to the original center wavelength, at 865 nm. Bands 11 (1610 nm) and 12 (2190 mn) were used as SWIR1 and SWIR2, respectively.

The three other indices only require a red and NIR band, combined in different ways. For the three indices, NIR (near infrared) corresponds to Landsat 8 OLI band 5 and Sentinel-2 MSI band 8, while the red band corresponds to band 4 in both Landsat 8 OLI and Sentinel-2 MSI mosaics.

The SI and BI (sometimes called SI-1 and SI-3) are both sensitive to the salinity content of the soil, with higher values representing an increase in salinity (Bouaziz et al., 2011), and a range generally between 0-0.30 (Nguyen et al., 2020). The indices were calculated following equations (2) and (3), see Dehni and Lounis (2013):

$$SI = \sqrt{RED \times NIR} \quad (2)$$

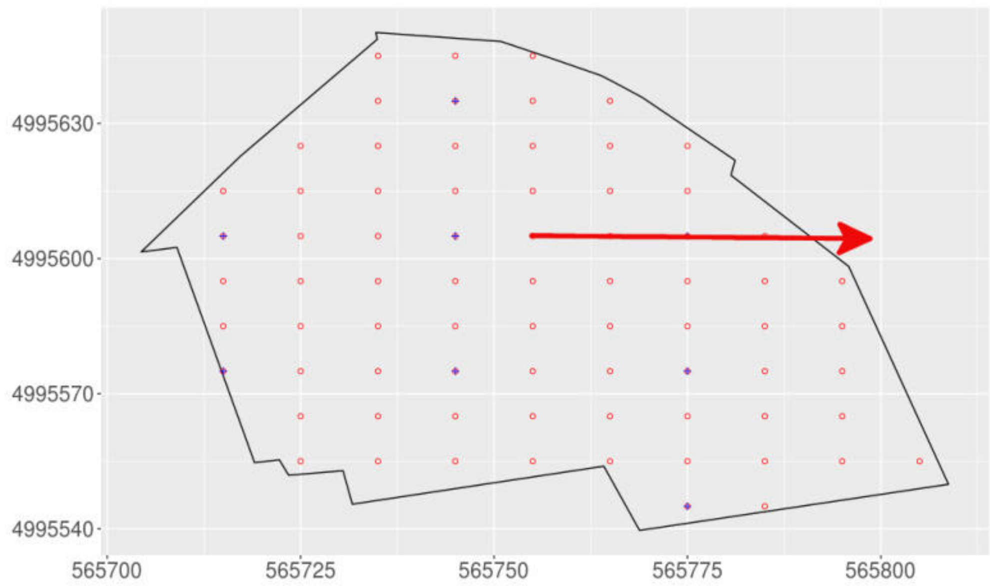
$$BI = \sqrt{RED^2 + NIR^2} \quad (3)$$

The NDVI, while generally employed to retrieve vegetation properties, has also been linked to the organic carbon content of soils. This index generally ranges between -1 and +1, with values < 0.2 identifying bare soils, and is directly related to the organic content (Guo et al., 2017; Gholizadeh et al., 2018). We followed Rouse et al. (1973) to calculate the NDVI according to equation (4).

$$NDVI = \frac{NIR-RED}{NIR+RED} \quad (4)$$

We further extracted a single value of each index for all agricultural parcels. In view of the large number of parcels in the administrative database (153,954) and high resolution of raster data, using conventional GIS software proved too time consuming to perform these calculations; thus, we developed a computationally efficient version of the ray casting algorithm (Hormann and Agathos, 2001) in the C programming language. The ray casting algorithm is used to detect whether a point lies inside a polygon and is based on the concept of ray crossing (see Fig. 1). A point is deemed inside a polygon if a horizontal ray starting from the point in a fixed direction crosses one side of the polygon an odd number of times. Otherwise, the point lies outside the polygon. The center of each raster cell was used as a starting point and each parcel was attributed the average of all raster cells lying inside it for each remote sensing index.

Figure 1: The principles of the ray casting algorithm. Blue dots represent the center of Landsat 8 OLI cells (30 m resolution), while red dots represent the centers of Sentinel-2 cells (10 m resolution). The horizontal ray (red arrow) from one dot inside the polygon in a fixed direction crosses a polygon side an odd number of times.



3.4 Statistical tests on remote sensing indices and their variation

Based on the ray casting algorithm, we calculated for each parcel the value of each index and the difference between its value in 2017 and 2014, that is the last year before greening implementation (Δ_{index}=index$_{2017}$-index$_{2014}$). Recalling that both BI and SI are directly related to the salinity degree of the soil, for these two indexes a positive variation of Δ_{index} means that salinity increased between 2014 and 2017. Conversely, being NMDI inversely correlated with the content of water in the soil, an increase of Δ_{index} results in a reduction of water in the soil, and vice-versa. As for the NDVI, as the index is directly linked to organic matter content when soil is bare, an increase of Δ_{index} means an increase in soil organic matter content over the period 2014-2017.

To evaluate the degree of association of different, competing factors in affecting values or variations in the indices, we performed five tests using stepwise selection for a linear regression based on the Akaike information criterion (AIC) and weighting the observations by parcel size (see Venables and Ripley, 2002). Stepwise selection (or sequential replacement) is a combination of forward and backward selections. It starts with no predictors, then sequentially adds the predictor that most increases the AIC, like in a pure forward selection. After adding each new variable, it removes any variables that no longer provide an improvement in the model fit (like in a pure backward selection). When the procedure reaches an equilibrium, it stops. Depending on the test, in turn we used each index, or Δ_{index}, as the dependent variable. It is worth pointing out that the tests performed aim to detect a statistically significant effect of the independent variables on the soil indices (in absolute or in variations), keeping in mind that those dependent variables may be affected by other, unobserved factors. Particularly, in the five tests we evaluated:

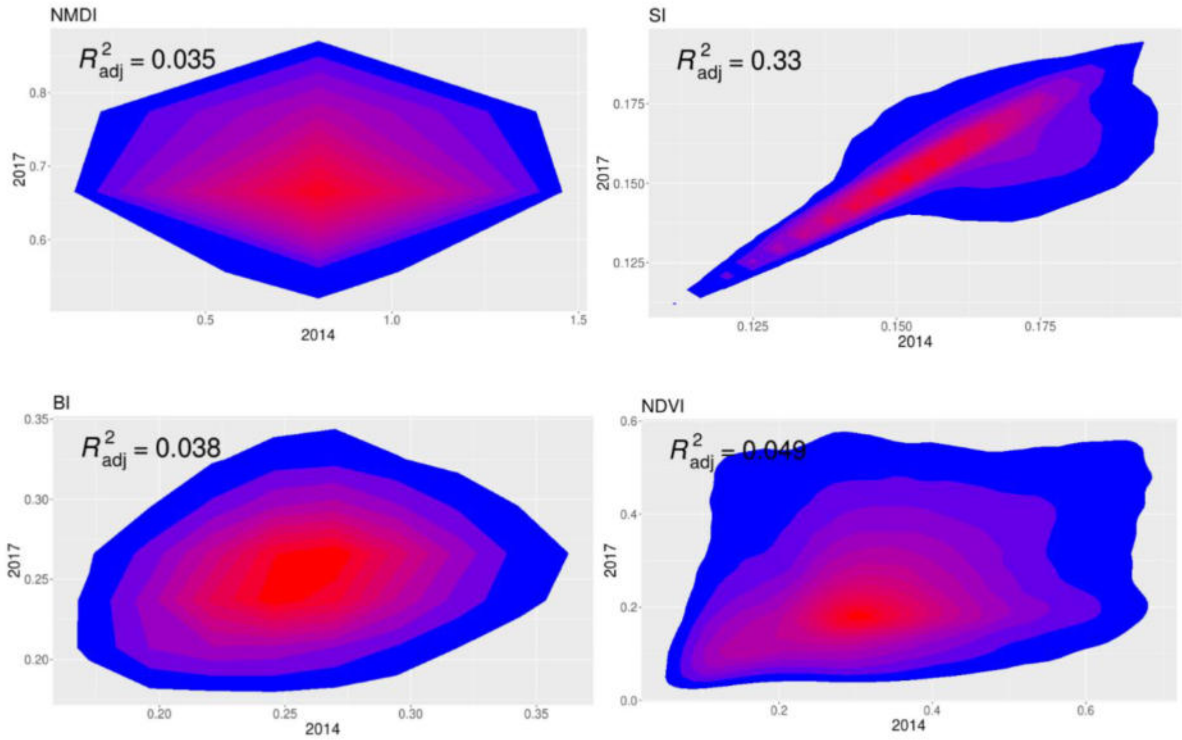
1) Variation of soil indices with respect to farmland use. For each parcel, we determined the farmland use type in the three years post-greening (2015, 2016 and 2017) and summed the number of years for each type of land use as the variable coefficient. Δ_{index} was selected as the dependent variable (see table 2 in the results section). As an example, if the parcel use in 2015 and 2016 was wheat, while in 2017 it was soybean, the model evaluates $\Delta_{index} = 2\alpha_{wheat} + 1\alpha_{soybean}$. Maize farmland use was used as a reference.
2) Variation of soil indices with respect to crop rotation. As in step (1), we identified the farmland use type for every year after 2014 and summed the number of changes in farmland use type from one year to another, which was used as the independent variable in the regression model. Δ_{index} was used as the dependent variable (see table 3 in the results section). In the previous example, the model would evaluate $\Delta_{index} = 1\alpha_{rot}$, while in case of no changes the number of rotations would be 0.
3) Pre-greening soil conditions with respect to eligibility and compliance with greening policies before they came into effect. The aim of this test was to understand whether soil indices were significantly different in the farms/parcels targeted by greening policies (group 3) compared to those which already complied with the policies (group 2) and those which were not eligible (group 1, chosen as reference). Here, the absolute value of each index, calculated in 2014, was used as the dependent variable (see table 4 in the results section).
4) Variation of soil indices with respect to eligibility for and compliance with greening policies before they came into effect. We used the same approach described at point (3) to determine independent variables. In this case Δ_{index} was used as the dependent variable (see table 5 in the results section). The aim of this test was to determine whether farms/parcels that had to change cultivation practices to comply with greening rules actually underwent an improvement in soil quality as seen by remote sensing indicators. Group 3 (eligible, not compliant) was the reference.
5) Variation of soil indices with respect to eligibility for and compliance with greening policies before they came into effect, and with respect to the farmland use and number of rotations. This last model is aimed at testing whether or not the estimated effects in model 4 are affected by the changes in farmland uses and number of rotations induced by the greening policy. If so, it would be possible to state that the differences between the greening groups are attributable to the variation in the crop mix. If not, these variations could largely depend on unobserved factors linked to the group to which each farmland parcel belongs.

4. Results

4.1 Variation in soil indices

We first investigated changes in remote sensing based soil indices between 2014 and 2017, to understand how they evolved over time and which factors can contribute to variations aside from actual changes in soil quality. Density plots in figure 2 show the relationship between the value of each index in 2014 and 2017 for all agricultural parcels considered in the analysis. Among the indices, the SI shows a very high persistence, confirmed by a relatively high adjusted r-squared. Lower relative values of this index in 2014 were followed by low values in 2017, while for higher values (> 0.15) in 2014 there is a higher spread and a tendency towards lower values in 2017. In comparison the BI, which should be linked to the same soil characteristics as the SI, i.e. salinity, has a much larger spread, and so do the NDVI and NMDI. The former shows slightly lower values in 2014 than in 2017 while the latter shows very little persistence, as the value of the index in 2014 and 2017 appear independent from each other. For these indices, factors including meteorological variability and the use of different satellite sensors with slightly different spectral bands might explain a significant amount of variance.

Figure 2: density plots of soil index values in 2014 and 2017 for all parcels considered in the analysis. Red represents a greater density of observations than blue. The value of adjusted R-squared is also reported.



4.2 Regression Analysis

While the variations in soil indices appear shaped by various parameters, we performed subsequent statistical tests to provide insights into the factors more directly related to the implementation of the greening policy. In the stepwise regression analysis, we found that the constant term is negative for all models where Δindex was used as the dependent variable, suggesting an average decrease in the value of all soil indices between 2014 and 2017 (see tables 2, 3, 5). Adjusted r-squared values are generally low in all five predictive models. However, several independent variables included in the models attain high statistical significance. Here, we describe only those values that were significant in stepwise regression at the 99% confidence level.

In the first test, we evaluated the relationship between farmland use type and Δindex (Table 2). The final number of land use types included in the model was highest for the ΔNDVI (14, 12 with $p < 0.01$) and lowest for the ΔBI (8, of which 2 with $p < 0.01$). At the same time, 11 (7) and 9 (8) variables were included in the models for the ΔNMDI and ΔSI, and found significant for their variations at the 99% confidence level, respectively. Variations in BI had a negative correlation with rotation ryegrass + maize for silage and horticulture, but a positive correlation with alfalfa and other temporary grassland. ΔNDVI was negatively correlated with rotation ryegrass + maize for silage, triticale, legume herbages, temporary grassland and fallow land. It was positively correlated with wheat, soybean, grass and mixed herbages, horticulture, ryegrass and alfalfa. Variations in NMDI were positively correlated with wheat, soybean, horticulture and alfalfa. They were negatively correlated with triticale, pulses (highest coefficient), grass herbages and fallow land. Finally, variations in SI were positively correlated with rotation ryegrass + maize for silage, triticale, temporary grassland and fallow land. They were negatively correlated with wheat, soybean, horticulture, other arable crops and alfalfa. Alfalfa and horticulture were significant in predictive models for all indices with concordant effect (with the exception of ΔBI).

In the second test, we looked at the influence of rotation practices (see Table 3). The number of rotations at parcel level was positively correlated with ΔNDVI and ΔNMDI and negatively correlated with ΔSI, with ΔNDVI attaining a slightly higher coefficient. The coefficients suggest a decrease in salinity and an increase in organic matter with increased number of crop rotations, but also decreased soil water content.

In the third and fourth test, we investigated the relationship between soil indices and compliance with greening policies, both before and after the implementation of greening policies. The estimated coefficients indicate the effect of the membership of a farmland parcel to group 1 (not eligible) and to group 2 (eligible and compliant) vs group 3 (eligible and not initially compliant to greening policies). We first checked whether membership in predefined groups had a relationship with the value of soil indices in 2014 (see Table 4). Both group 1 and group 2 had a positive relationship with the SI and a negative correlation both with the NDVI and the NMDI. These findings could point to relatively high salinity in both groups in 2014, but also higher water content, particularly for members of group 1. BI coefficient confirms that the salinity was higher for group 1, at least. For the NDVI, the initial content of organic matter in the soil appears lower in groups 1 and 2, compared to group 3.

The analysis of the variation in soil indices with respect to eligibility and compliance to greening policies (see Table 5) shows that membership in group 1 (not eligible) and group 2 (eligible and compliant) has a negative relationship with variations in the SI, and positive relationships with variation in the BI, NDVI and NMDI. This suggests group membership could play a role by leading to decreased water content and increased organic matter for groups not expected to change their farmland allocation after the implementation of greening policies, while the changes in salinity are less clear.

Finally, in Table 6, we performed a more complete estimation of membership in greening groups, controlling for both number of rotations and farmland uses. This last elaboration permits us to evaluate how much of the variability between greening groups depends on increased crop variability or on other not controlled factors. Estimated coefficients for greening groups do not change sign and level of significance (with the exception of ΔBI for group 1 which lost significance). However, the magnitude of the coefficients is reduced compared to the model in Table 5, particularly for those of group 2.

Table 2: predictive models of changes in soil remote sensing indices by farmland use type. Land use types are the independent variables, Δ_{index} is the dependent variable. Only variables significant at the 90% confidence level or above are included.

Farmland uses	Dependent variables			
	ΔBI	ΔNDVI	ΔNMDI	ΔSI
Maize for silage			0.0009	
Ryegrass + maize for silage	-0.0009***	-0.0057***		0.0006***
Wheat		0.0106***	0.0023***	-0.0009***
Barley	0.0007			
Triticale	0.0011*	-0.0170***	-0.0041***	0.0013***
Soybean		0.0132***	0.0035***	-0.0016***
Pulses		-0.0162**	-0.0110**	
Horticulture	-0.0008*	0.0133***	0.0038***	-0.0016***
Other arable crops		0.0046**	0.0020	-0.0007***
Ryegrass	0.0013*	0.0077***		
Grass herbages		0.0089***	-0.0098***	
Legume herbages		-0.0176***		
Mixed herbages	0.0015**	0.0110***		
Alfalfa	0.0008***	0.0129***	0.0032***	-0.0006***
Other temporary grassland	0.0005**	-0.0049***	-0.0008*	0.0004***
Fallow land		-0.0061***	-0.0040***	0.0004**
Intercept	-0.0090***	-0.0425***	-0.0130***	-0.0034***
Observations	129,166	129,166	129,166	129,166
R-squared	0.0003	0.0091	0.0016	0.0048
Adjusted R-squared	0.0003	0.0090	0.0015	0.0047
Residual Std. Error	0.0629	0.1921	0.1315	0.0222
F Statistic	5.4539***	85.1864***	18.5115***	69.2321***
	(df = 8; 129157)	(df = 14; 129151)	(df = 11; 129154)	(df = 9; 129156)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3: predictive models of changes in soil remote sensing indices by rotation practices. The number of rotations from one year to the other is considered as independent variable, Δ_{index} is the dependent variable.

N. rotations	Dependent variables			
	ΔBI	ΔNDVI	ΔNMDI	ΔSI
N. rotations		0.0101***	0.0025***	-0.0012***
Constant	-0.0086***	-0.0503***	-0.0151***	-0.0021***
Observations	129,166	129,166	129,166	129,166
R-squared	0.0000	0.0014	0.0002	0.0014
Adjusted R-squared	0.0000	0.0014	0.0002	0.0013
Residual Std. Error	0.0629	0.1929	0.1316	0.0222
F Statistic		176.9489*** (df = 1; 129164)	22.5275*** (df = 1; 129164)	175.3862*** (df = 1; 129164)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4: Predictive model of soil indices in 2014 with respect to eligibility and compliance with greening policies. The index value in 2014 is the dependent variable. Group membership represents the independent variable.

Eligibility and compliance to greening	Dependent variables			
	BI	NDVI	NMDI	SI
Not Eligible (gr.1) vs Eligible and not Compliant (gr.3)	0.0013***	-0.0105***	-0.0043***	0.0011***
Eligible and Compliant (gr.2) vs Eligible and not Compliant (gr.3)	-0.00005	-0.0221***	-0.0020**	0.0013***
Constant	0.2660***	0.3373***	0.5977***	0.1626***
Observations	129.166	129.166	129.166	129.166
R-squared	0.0001	0.0034	0.0002	0.0007
Adjusted R-squared	0.0001	0.0034	0.0002	0.0007
Residual Std. Error	0.0564	0.1640	0.1249	0.0225
F Statistic	6.6760*** (df = 2; 129163)	223.3371*** (df = 2; 129163)	11.2833*** (df = 2; 129163)	45.2999*** (df = 2; 129163)

*Note: *p<0.1; **p<0.05; ***p<0.01*

Table 5: Predictive model of changes in soil remote sensing indices by eligibility and compliance with greening policies. Δindex is the dependent variable; group membership is the independent variable.

Eligibility and compliance to greening	Dependent variables			
	ΔBI	ΔNDVI	ΔNMDI	ΔSI
Not Eligible (gr.1) vs Eligible and not Compliant (gr.3)	0.0013***	0.0191***	0.0044***	-0.0012***
Eligible and Compliant (gr.2) vs Eligible and not Compliant (gr.3)	0.0017***	0.0242***	0.0051***	-0.0015***
Constant	-0.0095***	-0.0462***	-0.0137***	-0.0033***
Observations	129.166	129.166	129.166	129.166
R-squared	0.0001	0.0032	0.0003	0.0009
Adjusted R-squared	0.0001	0.0032	0.0003	0.0009
Residual Std. Error	0.0629	0.1927	0.1316	0.0222
F Statistic	9.1570*** (df = 2; 129163)	209.7070*** (df = 2; 129163)	20.7218*** (df = 2; 129163)	59.0731*** (df = 2; 129163)

*Note: *p<0.1; **p<0.05; ***p<0.01*

Table 6: Predictive model of changes in soil remote sensing indices by eligibility and compliance with greening policies, number of rotations and farmland use. Δindex is the dependent variable; group membership, number of rotations and farmland uses are the independent variables.

Eligibility and compliance to greening	Dependent variables			
	ΔBI	ΔNDVI	ΔNMDI	ΔSI
Not Eligible (gr.1) vs Eligible and not Compliant (gr.3)	0.0008	0.0158***	0.0042***	-0.0010***
Eligible and Compliant (gr.2) vs Eligible and not Compliant (gr.3)	0.0013***	0.0169***	0.0035***	-0.0010***
Constant	-0.0097***	-0.0620***	-0.0200***	-0.0016***
Number of rotation controlled	yes	yes	yes	yes
Farmland uses controlled	yes	yes	yes	yes
Observations	129.166	129.166	129.166	129.166
R-squared	0.0004	0.0113	0.0019	0.0058
Adjusted R-squared	0.0003	0.0112	0.0018	0.0057
Residual Std. Error	0.0629	0.1919	0.1315	0.0221
F Statistic	5.4366*** (df = 10; 129155)	86.8755*** (df = 17; 129148)	20.5504*** (df = 12; 129153)	53.4458*** (df = 14; 129151)

*Note: *p<0.1; **p<0.05; ***p<0.01*

5 Discussion

5.1 Assessing the effects of policy changes through remote sensing: advantages and limitations

CAP greening is a relatively new concept, having been introduced with the CAP reform 2015-2020. Consequently in the context of remote sensing most research has only recently approached the issue of assessing compliance with the greening requirements, either by investigating different supervised classification schemes for the identification of land use types at the parcel scale (Sitokostantinou et al., 2018), or by addressing the automatic extraction of satellite data and their integration into a spatiotemporal framework (Rousi et al., 2020). Estimating the effects of the CAP reform however is a more complex issue, and one that has been relatively overlooked from a remote sensing perspective. Previous efforts have been made particularly in the field of soil erosion monitoring. For instance, Borrelli and Panagos (2020) developed an indicator to estimate soil erosion in the EU incorporating data from the MERIS satellite, which could be used to evaluate the effects of policy changes; however, their approach is based on the Corine land cover product (which is updated every 6 years) at 100 m resolution, while our methodology uses higher resolution satellite data (10/30 m) and considers individual farm parcels.

In our study, we combine remote sensing-based spectral indices, geospatial administrative data, a fast algorithm for data processing and a robust statistical approach to provide a first attempt to detect the effects of the CAP reform on soil quality in the Lombardy region. The novelty of the work lies in the combination of these sources to assess policy changes, and particularly in the use of spectral indices from satellite data. These indices have the advantage of simplicity over other methods, making use of models (e.g. Borrelli et al., 2016), and the availability of data from Landsat-8 and Sentinel-2 before and after the implementation of the CAP reform offers a unique possibility to look at the changes over wide areas while also providing a great level of detail.

The use of satellite sources for the assessment of soil quality however also comes with a number of uncertainties. In fact, the estimation of remote sensing indices is related to seasonality and a requirement that limits the availability of data for this approach is the choice of the best period to obtain a homogeneous bare soil. Recommendations by Bartholomeus et al. (2008) suggest that vegetation cover should be lower than 20% to be able to estimate bare soil indices; the value might also be lower for the NDVI, which in this study was used for soil organic carbon and which is sensitive to the vegetation content of pixels observed by the satellite. As we cannot exclude that residual vegetation was present at the time of image acquisition, there is a chance that our approach to assess changes in soil organic carbon was affected. To exclude this possibility, and obtain a more robust indication of changes in this soil variable, other indices or individual bands might be tested, including the reflectance in the visible band of the electromagnetic spectrum or the indices proposed by Bartholomeus et al. (2008).

Another issue which limits data availability from satellites is the presence of cloud cover, which can be rather high in the plains of Lombardy especially during the winter season, as low clouds can persist for several days (Kästner and Kriebel, 2001). Cloud cover particularly influences data availability before the implementation of greening policies, as in 2014 only data from Landsat 8 were available; with the launch of Sentinel-2A in 2015 and its twin satellite Sentinel-2B in 2017, the number of remote sensing images for the post-greening period have greatly increased, and with them the chance to obtain high quality cloud-free data. Thus, future changes in remote sensing indices of soil quality might be investigated over a longer period and used to assess the effects of further changes in the agricultural policy if those are implemented.

A possible limitation of this study is that we did not perform an atmospheric correction on Landsat and Sentinel-2 data before calculating the spectral indices. The effects of this lack of atmospheric correction should nevertheless be limited, as normalized indices show a low sensitivity to atmospheric conditions. After comparing Sentinel-2 and Landsat-8 imagery acquired on the same day and processed with three separate atmospheric schemes and without correction, Rumora et al. (2021) conclude that correlations between index values from the two sensors are always highly statistically significant (> 99%) when no atmospheric correction is applied in spite of the slightly different wavelengths used, and that using a simpler or no atmospheric correction produces better results than using more complicated schemes. Although a greater effect of the atmosphere might be hypothesized for non-normalized indices such as those used to estimate salinity content (SI e BI), the strength of our analysis is that it focuses on the relative variation in indices compared to a reference, and the absolute value of indices is unimportant. To further increase the reliability of our approach, the integration with radar remote sensing, with its ability to provide estimates of soil moisture (Ezzahar et al., 2020), might prove useful and improve the assessment of soil quality estimates in relation to policy changes.

5.2 Remote sensing for the assessment of CAP environmental performance

Among several proposed objectives, our analysis seeks to demonstrate the feasibility and benefits of integrating administrative and remote sensing data into agricultural policy ex-post evaluation processes. Administrative datasets ensure full territorial coverage and a high level of detailed information (down to the parcel level). On the other hand, they contain a limited amount of information, especially on environmental indicators (often limited to land use or participation in voluntary agro-environmental measures). So far, broad-spectrum ex-post evaluations do not directly quantify the environmental effects of policies, but rather changes in agricultural practices (Dupraz and Guyomard, 2019), or in the allocation of farmland that is measurable from administrative datasets. At most, environmental effects are indirectly assessed by applying tabulated coefficients on GHG emissions inputs to the various agricultural practices or uses of agricultural land (Chabé-Ferret and Subervie, 2013; Bertoni et al. 2021).

Following the line of reasoning conducted so far, our study provides some important innovations in the literature of ex-post evaluations of agricultural policies. Firstly, the combination of remote sensing techniques with administrative datasets ensures the almost total coverage of the territory and, at the same time, an extremely detailed level of analysis (farmland parcel level). Secondly, it represents a direct assessment of parameters related to the environmental sustainability of agriculture, and not derived from other parameters. Thirdly, it aims to offer an assessment of environmental performance parameters, linked to the quality of the soils, not investigated until now in previous studies. Finally, our methodology can be replicated over time and space.

The present analysis represents a first attempt to establish a procedure for assessing the effects of agricultural policies using remote sensing techniques. Given its innovativeness, of course it suffers from some limitations and technical difficulties mentioned in paragraph 4.1. (e.g. calibration of indicators based on the degree of land cover and weather conditions). These aspects deserve to be carefully investigated on a second step of improvement of such methodology. The present analysis is therefore characterized above all from a methodological point of view and aspires to indicate a path for a new line of research.

5.3 Assessment of soil indexes dynamics after the introduction of CAP greening

CAP Greening mainly affects the allocation of agricultural land. As previously pointed out, in the area under investigation, greening has resulted in a reallocation of maize and maize for silage areas towards other crops such as soy, alfalfa, other cereals and set-aside (Bertoni et al., 2021). This occurred especially in group 3 (eligible and not compliant farms). For this reason, our first two elaborations have been related to the variations of the soil quality indices in relation to the farmland use (Tab. 2) and to the number of rotations in the reference period (Tab. 3). The coefficients calculated for the individual crops express a variation with respect to corn, which is the crop mainly affected by the introduction of the new policy. In general, the coefficients are very low, as is the R-square, a sign that the conditions of the soils tend to persist over time and are not particularly affected by crop changes, especially in a relatively short time interval such as that analysed. In any case, the coefficients of different crops were significant[3]. With reference to the main crops that have replaced maize, it is observed that soy has a positive effect on the organic substance content (NDVI) and contributes to the reduction of salinity (SI), on the contrary the NMDI coefficient goes in the direction of a reduction of the content of water in the soil. The trend of wheat is similar. Alfalfa would cause an increase in organic matter and a reduction in water content, while the results on salinity are contrasting between the two indices. The number of rotations over the period analysed is positively correlated with the organic matter content and negatively with the salinity and water content.

We then tested the changes in the indices based on the group to which the farmland parcels belong, in terms of eligibility and compliance with greening. The regression in Tab. 5 shows the coefficients of the two groups that have not been affected by greening (group 1 - not eligible farms and group 2 - eligible and compliant farms) vs the reference group (group - 3 eligible and not compliant farms), that has been affected by the introduction of the new policy. Regression results show that group 3 had better outcomes for the NMDI indicator (soil water content) and worse for NDVI (organic matter content). The salinity variation appears smaller than in the other groups if we consider BI, but the opposite when we observe the SI trend.

Finally, in Tab. 6 we repeated this previous regression by groups, controlling at the same time for farmland use and the number of rotations. The sign of the coefficients does not change, pointing to a time persistence of the dynamics of such indicators. Evidently, these are mainly due to specific factors

[3] A positive coefficient indicates: for BI and SI indicates an increase in salinity, for NDVI an increase in the content of organic matter, for NMDI a reduction in the water content in soils.

of the groups analyzed for which we do not have available control variables at the level of detail necessary for our analysis. This is also confirmed by the regression in Table 4, which highlights different starting conditions between the various groups. The control variables that would have been useful to refine our analysis undoubtedly include the cultivation and irrigation practices adopted, for which there is no georeferenced information in the territory considered, and soil quality, that are mapped to a scale not usable for our detail of analysis. The presence of this kind of information would have certainly improved the quality of our analysis, like the possibility of conducting the analysis over a longer period.

In any case, it is interesting to note that by controlling for farmland uses and number of crops, the coefficient magnitude of the greening groups decreases. This applies, in particular, to the soil organic matter content (NDVI) and the salinity index (SI), the latter in relation to group 2. Both of these indicators show a negative performance in group 3 farms, which however improved when controlling for crop mix change associated with the adaptation to greening.

In any case, results shown should be considered as an outcome of a preliminary and innovative research study. The aim of such a tool of analysis is to combine available big data (from administrative and remote sensing sources) in the attempt to lay the foundations for an ex-post assessment of CAP greening on soil quality. Keeping this in mind, its efficacy and accuracy can and should be improved in different ways. The first one has been already mentioned and relates to additional data and information to consolidate the results. The second one pertains to improvements on the calibration of the soil quality indicators. In particular, the indicator of organic matter content (NDVI) presents the most critical issues. Our choice of excluding perennial crops, rice and stable meadows, as well as that of calculating the indicators in the period with the greatest probability of having bare soil, goes in the direction of a refinement of the analysis. However, we cannot exclude confounding effects due to the presence of crop residues in the field (eg corn stalks). Therefore, such aspects should be improved in order to make such combined methodology more reliable for ex-post assessment of environmental effects of agricultural policy.

Conclusions

In this study, we assessed the dynamics of agricultural land soil quality indices in the Lombardy region of Italy, over the period subsequent to the introduction of CAP greening in 2015. Soil quality indices considered in this study are the Salinity index (SI) and brightness index (BI), used to investigate the salinity content of the soil; Normalized difference vegetation index (NDVI) used to estimate soil organic carbon, normalized difference drought index (NMDI), used to estimate soil moisture. The indices were obtained from remote sensing imagery, specifically Landsat 8 OLI for the period before the introduction of greening policies, i.e. 2014, and Sentinel-2A for the post-greening period, i.e. 2017, and combined with an administrative database of all agricultural parcels of the region; based on these two datasets, we performed a regression analysis to assess the impact of different factors, including farmland use type, eligibility and compliance with respect to greening policies, on the dynamic variability in soil properties in the region.

Our preliminary results indicate a high persistence of the soil quality indicators before and after the introduction of CAP greening but also significant correlations (99% confidence level) between variations in the indices and membership in specific groups pertaining to farmland use, eligibility and compliance with greening policies. In particular, greening group membership appears to lead to decreased water content and increased organic matter for groups not expected to change their farmland allocation after the implementation of greening policies. We identified some uncertainties in relation to the choice of the NDVI, which might particularly be impacted by residuals of vegetation in the parcel; these issues need to be addressed in detail by conducting further research. Nevertheless, the study is mainly methodological and by combining administrative and remote sensing data with a high level of detail it shows a potential tool to be used, with further improvements, for ex-post assessment of CAP policy instruments, with special focus on the assessment of soil quality changes over the long term.

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Annex 1 – Farmland uses 2014-2017 in the greening groups

Group 1 – Not eligible farms

Farmland use	*2014 (before greening)*		*Average 2015-2017 (after greening)*		*Difference*
	Area (hectares) (a)	*Area (%) (b)*	*Area (hectares) (c)*	*Area (%) (d)*	*Area (%) (e) = (d) - (b)*
Maize	8.146	25,3%	7.215	22,4%	-2,9%
Maize for silage	1.056	3,3%	1.265	3,9%	0,7%
Rotation ryegrass + maize for silage	639	2,0%	705	2,2%	0,2%
Wheat	3.580	11,1%	4.331	13,5%	2,3%
Barley	664	2,1%	825	2,6%	0,5%
Triticale	388	1,2%	441	1,4%	0,2%
Soybean	1.771	5,5%	1.692	5,3%	-0,2%
Pulses	48	0,1%	37	0,1%	0,0%
Horticulture	978	3,0%	1.126	3,5%	0,5%
Other arable crops	682	2,1%	553	1,7%	-0,4%
Ryegrass	34	0,1%	377	1,2%	1,1%
Grass herbages	518	1,6%	663	2,1%	0,5%
Legume herbages	6	0,0%	45	0,1%	0,1%
Mixed herbages	353	1,1%	477	1,5%	0,4%
Alfalfa	6.717	20,9%	6.145	19,1%	-1,8%
Other temporary grassland	4.995	15,5%	4.830	15,0%	-0,5%
Fallow land	533	1,7%	615	1,9%	0,3%
Non-eligible surfaces	1.048	3,3%	813	2,5%	-0,7%
Total Balanced Farmland	32.155	100,0%	32.155	100,0%	0,0%

Source: own elaboration on SIARL data

Group 2 – Eligible and compliant farms

Farmland use	*2014 (before greening)*		*Average 2015-2017 (after greening)*		*Difference*
	Area (hectares) (a)	*Area (%) (b)*	*Area (hectares) (c)*	*Area (%) (d)*	*Area (%) (e) = (d) - (b)*
Maize	21.740	29,1%	17.998	24,1%	-5,0%
Maize for silage	7.446	10,0%	8.205	11,0%	1,0%
Rotation ryegrass + maize for silage	4.172	5,6%	4.738	6,3%	0,8%
Wheat	8.964	12,0%	10.923	14,6%	2,6%
Barley	1.590	2,1%	2.010	2,7%	0,6%
Triticale	1.352	1,8%	1.014	1,4%	-0,5%
Soybean	6.237	8,3%	6.271	8,4%	0,0%
Pulses	53	0,1%	172	0,2%	0,2%
Horticulture	1.699	2,3%	1.998	2,7%	0,4%
Other arable crops	1.801	2,4%	1.377	1,8%	-0,6%
Ryegrass	146	0,2%	793	1,1%	0,9%
Grass herbages	2.317	3,1%	1.173	1,6%	-1,5%
Legume herbages	9	0,0%	87	0,1%	0,1%
Mixed herbages	435	0,6%	542	0,7%	0,1%
Alfalfa	11.950	16,0%	12.859	17,2%	1,2%
Other temporary grassland	3.711	5,0%	3.558	4,8%	-0,2%
Fallow land	401	0,5%	372	0,5%	0,0%
Non-eligible surfaces	789	1,1%	718	1,0%	-0,1%
Total Balanced Farmland	74.810	100,0%	74.810	100,0%	0,0%

Source: own elaboration on SIARL data

Group 3 – Eligible and not compliant farms

Farmland use	*2014 (before greening)*		*Average 2015-2017 (after greening)*		*Difference*
	Area (hectares)	*Area (%)*	*Area (hectares)*	*Area (%)*	*Area (%)*
	(a)	*(b)*	*(c)*	*(d)*	*(e) = (d) - (b)*
Maize	38.097	45,0%	29.241	34,5%	-10,5%
Maize for silage	13.403	15,8%	11.838	14,0%	-1,8%
Rotation ryegrass + maize for silage	6.376	7,5%	8.415	9,9%	2,4%
Wheat	7.832	9,2%	10.217	12,1%	2,8%
Barley	1.956	2,3%	3.025	3,6%	1,3%
Triticale	2.398	2,8%	1.971	2,3%	-0,5%
Soybean	1.405	1,7%	4.458	5,3%	3,6%
Pulses	31	0,0%	126	0,1%	0,1%
Horticulture	3.264	3,9%	3.423	4,0%	0,2%
Other arable crops	1.093	1,3%	984	1,2%	-0,1%
Ryegrass	103	0,1%	543	0,6%	0,5%
Grass herbages	694	0,8%	896	1,1%	0,2%
Legume herbages	3	0,0%	115	0,1%	0,1%
Mixed herbages	346	0,4%	326	0,4%	0,0%
Alfalfa	1.781	2,1%	3.482	4,1%	2,0%
Other temporary grassland	4.549	5,4%	4.239	5,0%	-0,4%
Fallow land	97	0,1%	872	1,0%	0,9%
Non-eligible surfaces	1.251	1,5%	508	0,6%	-0,9%
Total Balanced Farmland	84.680	100,0%	84.680	100,0%	0,0%

Source: own elaboration on SIARL data

The authors declare that there is no conflict of interest all ethical practices have been followed in relation to the development, writing, and publication of the article.