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Modelling and mapping Soil Organic Carbon in annual cropland under different farm management systems in the Apulia region of Southern Italy

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ABSTRACT

Soil Organic Carbon (SOC) plays a crucial role in many soil functions and ecosystem services. Monitoring its spatial and temporal changes is essential for planning strategies to minimize soil degradation and loss and maintain its quality. Conservation Agriculture (CA) can make a significant contribution to increasing SOC. This article reports on the spatially modeled SOC concentration in the topsoil (0–0.3 m) of the Annual Cropland (ACL) under Conventional Management (CM) and CA in the Apulia region in Italy. To assess the spatial and temporal dynamics of SOC at the regional scale, the "Scorpan-SSPFe" (soil spatial prediction function with spatially autocorrelated errors) approach to predictive modeling and mapping of soil, based on the Geographically Weighted Regression (GWR) model was performed. The method was implemented using a Geographic Information System (GIS) and Google Earth Engine (GEE) environment to calculate the percentage distribution for each SOC level, altitude, and slope class and their combination. 80 environmental variables and 250 soil samples were analyzed to map the SOC in ACL. The SOC values showed an average of 16.68 and 17.73 g/kg for CM and CA respectively. Adequate map accuracy was obtained by GWR, which showed an R^2 of 0.71 for CA and R^2 of 0.52 for CM The Root Mean Squared Error (RMSE) predictions obtained were better in CA (3.96 g/kg) than CM (5.65 g/kg) with a percentage RMSE difference of 30 %. Predicted SOC obtained by GWR ranged from 4.06 to 35.60 g/kg for CA and from 5.00 to 29.99 g/kg for CM. The proposed method was shown to be promising in predicting SOC in a region of the Mediterranean area and can be used to assess the effect of land use changes, such as the application of CA, on SOC in the whole basin.

1. Introduction

The Food and Agriculture Organization of the United Nations (FAO) defines soil organic matter (SOM) as "any material produced originally by living organisms (plant or animal) that is returned to the soil and goes through the decomposition process" (Bot and Benites, 2005). SOM is considered as the main element for maintaining fertility in soils and it has prominent implications on the biological, physical, chemical, and hydrological properties of the soil. It is crucial for stabilizing the soil structure and enhancing particle aggregation, releasing and retaining plant nutrients, increasing water-holding capacity and promoting microbial activity (Lefèvre et al., 2017; Youcai, 2018; Farooq and Pisante, 2019). SOM is conventionally agreed to contain 58 % Soil Organic Carbon (SOC) Nelson and Sommers (1996), but a critical review by Pribyl (2010) reported that the carbon content of SOC can range between ~ 50–60 % depending on various factors (e.g., soil type, clay content, and analytical methods). SOC is important for its contributions to food production and to climate change mitigation and adaptation. In addition, a high SOC content provides nutrients to plants and improves water availability, both of which enhance soil fertility and improve crop productivity (Panakoulia et al., 2017; Ramesh et al., 2019). With an optimal SOC level (2 % or more), the water filtration capacity of soils supports the supply of clean water (Ramesh et al., 2019). Through accelerated SOC mineralization during tillage operations, soils can be a substantial source of Greenhouse Gas (GHG) emissions into the atmosphere. SOC storage is also an important ecosystem function as it is directly linked to increased C input into the soil through root and microbial biomass, increased decomposition of plant biomass, and plant productivity (Wiesmeier et al., 2019). In addition, since 2006, the Intergovernmental Panel on Climate Change has reported that SOC stocks are stabilized or reach a steady state of equilibrium only after 20 years or more with different management practices (IPCC, 2006). It is

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also argued that for soils containing large amounts of clay and SOC, a 20-year fixed time horizon is too short to establish SOC equilibrium by following any land use or land cover change. One of the most important cost-effective options for mitigating climate change is SOC sequestration which can also increase soil fertility and other ecosystem services. At the Conference of the Parties (COP21) to the United Nations Framework Convention on Climate Change (UNFCC) in Paris, stakeholders voluntarily committed to promoting agricultural practices that increase soil carbon (Chambers et al., 2016). Although the overall impact of climate change on SOC stocks is variable according to the region and soil type, rising temperatures and increased frequency of extreme events are likely to lead to increased SOC losses.

Recently, the influence of management practices and land-use changes on the dynamics of SOC has gained scientific attention, as changes in land use, landcover, and management practices can have a significant impact on global carbon pools and fluxes (Wijesekara et al., 2017). Land-use changes could lead to temporal and spatial changes in soil quality and productivity by altering the structure and functioning of ecosystems and biogeochemical cycles (Braimoh and Vlek, 2004). For example, continuous and intensive tillage practices, together with Conventional Management (CM), have led to a loss of SOC and consequently to a deterioration of biological, physical, chemical, and hydrological soil properties (Srinivasarao et al., 2013). In contrast, Conservation Agriculture (CA) which includes suitable biomass management has been reported to increase the proportion of SOC and its fractions, thereby reducing the risk of soil degradation and improving soil quality (Awale et al., 2013; Pisante et al., 2015).

The Rural Development Policies (RDPs) established through the Common Agricultural Policy (CAP) of the EU aim to promote agricultural sustainability. However, SOC and SOM monitoring and evaluation is not clearly addressed: this makes it difficult for policymakers to reward land management practices that can enhance these two parameters which are, however, essential for soil health. This is why establishing effective tools for the current assessment and future monitoring of SOC is essential to implement both managements and specifically-targeted policies that contrast soil degradation.

The areas most affected by SOC loss are those in the Mediterranean area, which are affected by drought, such as Greece, Spain, and southern Italy, in which climate change is already having a visible impact on crops and soils (Ronco et al., 2017). The region Apulia, located in the southeast of Italy, can be considered to be representative of these areas. Most of the Apulia lands are used for agriculture (e.g., cereals, forage crops, and table grapes (Zdruli, 2014). Yet, the region suffers from hydro-climatic hazards as well as decreasing precipitation. The rise in temperatures and the resulting drought caused by the increasingly evident effects of climate change pose an additional threat to Apulian soils, which are already suffering from the loss of SOC (Ronco et al., 2017; UNFCC, 2021).

Advancements in Remote Sensing (RS) technologies provide a great opportunity to facilitate the monitoring of SOC content of large areas with affordable cost. The RS imagery acts as an environmental predictor for modelling SOC in Digital Soil Mapping (DSM) models.

The relationships between soil properties and covariates are used to predict SOC and create maps (Casa et al., 2013). The high temporal frequency and high spatial resolution of remote imagery offer an unprecedented possibility to study and monitor space–time dynamics of SOC change if used in combination with (long-term) monitoring stations (Chabrillat et al., 2019). SOC mapping has been greatly benefited by DSM.

Among the many techniques commonly used in DSM, Geographically Weighted Regression (GWR) stands out (Mishra et al., 2010; Zhang et al., 2011; Kumar et al., 2012; Wang et al., 2012; Song et al., 2016; Zeng et al., 2016). This technique has a potential in soil science because, unlike classical (global) regression models, GWR has coefficients that are specific to each location rather than global estimates (Fotheringham et al., 2003). This technique can lead to better performance if the analyzed attribute has a local variance. In addition, using geostatistical tools and multivariate analyses is possible to evaluate the spatial variability of SOC, in relation with altimetry, sloping, exposition of each landscape unit, using geostatistical tools and multivariate analyses (Buss et al., 2019). Despite that, the performance of whole-area calibrated models versus locally calibrated models (e.g., GWR) in mapping SOC over large extents have seldom been explored in detail, particularly with respect to the type of model being employed.

In this study, we attempted to develop a framework for predicting carbon for soil mapping for ACL at a regional scale; a Geographic Information System (GIS) and Google Earth Engine (GEE) approach were used to map SOC through the use of environmental covariates from open-source datasets to monitor SOC at regional scale highlighting the difference between CM and CA in ACL of Apulia region by GWR. In addition, the percentage distribution of SOC for each quantile, altitude, and slope class and their combination was calculated. The predicted maps of the validation set of our model was also compared with those predicted maps by de Brogniez et al. (2015) for the same ACL.

2. Materials and methods

2.1. Study area

Apulia region (South of Italy) is about 400 km long and surrounded mainly by the Adriatic and Ionian seas (Fig. 1). The geographic extent is 41°03′46″N 16°22′50″E, and covers about 19,541 km^2 with 4029,053 inhabitants. The study area is bounded by Molise along the Saccione and Fortore rivers (northwest), and is separated from Basilicata and Campania by the Apennine Mountains (west and southwest). The Apulia region is characterized by low mountains located in the Sub-Appennino Dauno and the Gargano promontory, respectively in the east and north of the province of Foggia (FG), by the Murgia plateau, which covers an area of 4000 km^2 in the provinces of Barletta-Andria-Trani (BAT) and Bari (BA), and by the Tavoliere plain, the second largest plain in Italy, which covers 3000 km^2 in the central and southern part of the province of Foggia. Most of the region is characterized by small plains with moderate hills, located within the provinces of Brindisi (BR), Taranto (TA) and Lecce (LE). From a geo-lithological point of view, there are mainly limestones, clays and dolomites alternating along the region, and aeolian deposits along the Arco Ionico-Tarantino in the province of Taranto (Di Nunno and Granata, 2020). The region has a semi-arid Mediterranean climate with warm, dry summers and mild, rainy winters. In most of the area the annual rainfall is between 450 and 550 mm. The lowest rainfall values, about 400 mm, are observed in the area of Tavoliere in the province of Foggia, while the highest values, with more than 900 mm/year, are recorded in the area of Gargano in the north of the same province (Ladisa et al., 2012). Most of the territory (81.4 %) is used for agriculture, while forest and semi-natural areas cover about 13.3 % of the region. Water bodies cover about 1.2 % of the territory, including natural lakes and artificial dams. Apulia is a region where agriculture has a relevant role in the economic context of the territory; in fact, this region is second in Italy for the production of oil, wine, oats and vegetables. The production of durum wheat in Tavoliere, figs in the area of Bari and tobacco in the area of Lecce is very important. (Serio et al., 2018).

2.2. Soil sampling and analysis

The ACL's mapping (772,654 ha) was made following Petito et al. (2022), while the boundaries under CA are provided by AGEA (Italian Agriculture Payments Agency) and the total interested area corresponds to 25,506 ha. For model calibration, n = 240 soil samples were taken. The soil CA samples (Fig. 2) were selected through a grid of n = 117 points. The n = 58 samples were chosen according to a sample scheme proposed by Brus and Heuvelink (2007) to minimize the Mean Squared Shortest Distance (MSSD) by k-means, which used the spatial

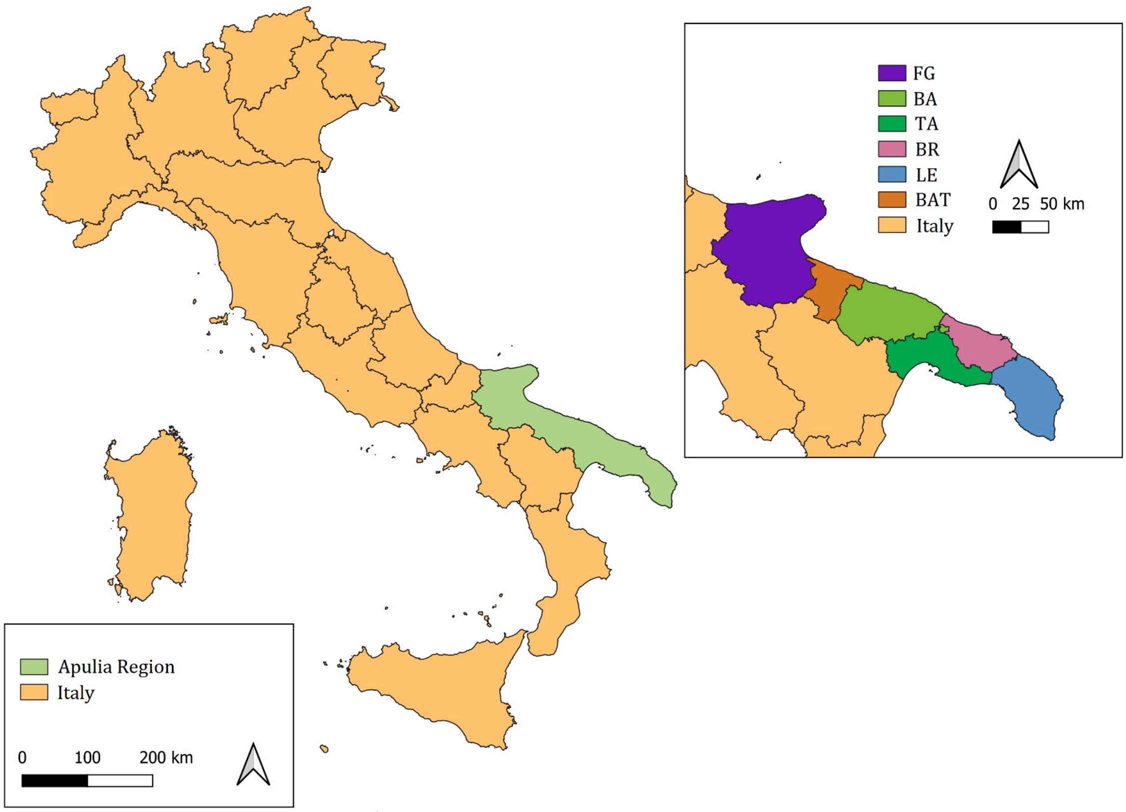

Fig. 1. Study area and relative provinces. (FG = Foggia; BAT = Barletta-Andria-Trani; BA = Bari; TA = Taranto; BR = Brindisi; LE = Lecce).

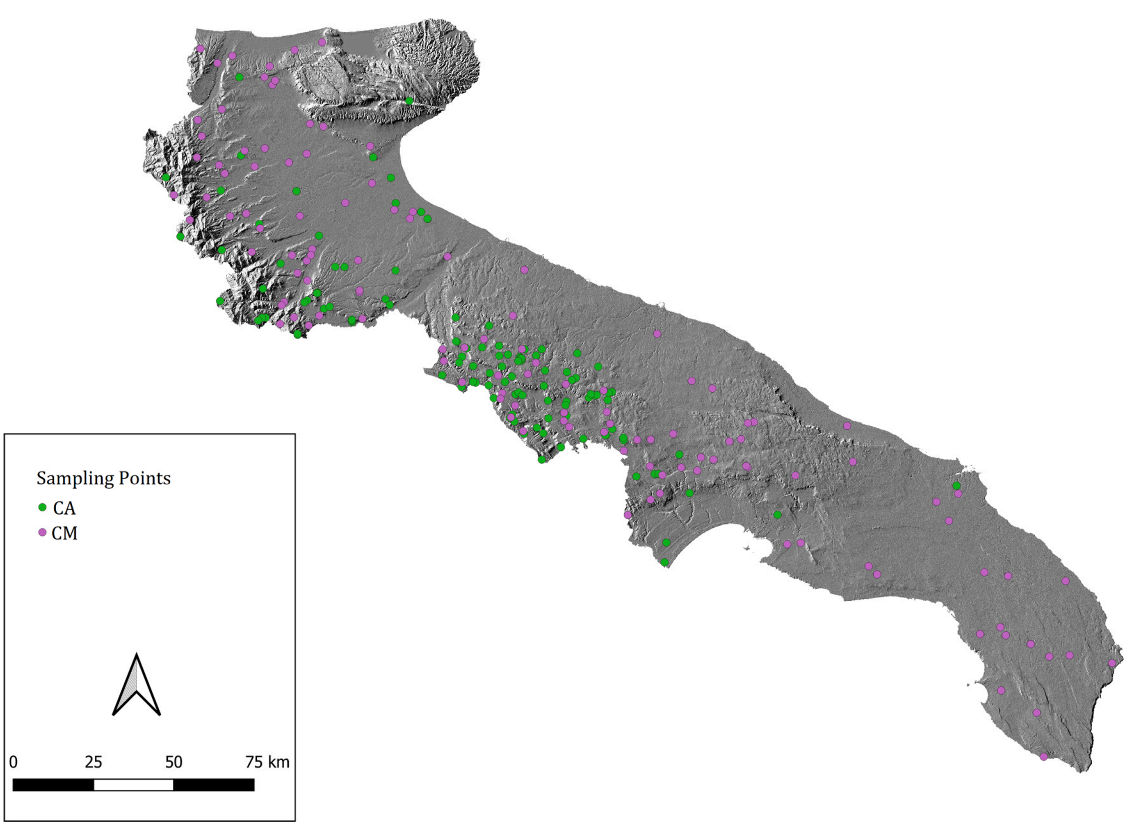

Fig. 2. Sampling points in the Apulia region for Conventional Management (CM) and Conservation Agriculture (CA) in 2021. Hill shade calculated using NASA DEM 30 m (available at: https://lpdaac.usgs.gov/products/nasadem_hgtv001, accessed on 1 April 2022).

coordinates of the centers of the cells of a discretization grid, used as variables in k-means clustering of the grid cells. The centroids of the clusters are used as sampling points. The other n = 59 samples were chosen randomly (Brus, 2018). For CM samples (Fig. 2) were selected based on grid of n = 123 points, n = 36 according to a regular grid and n = 37 chosen randomly, and the remaining n = 50 ACL points from LUCAS survey (Gallego and Bamps, 2008; Tóth et al., 2013). The coordinates of each sampling site were determined with a GPS model SP20 handheld GNSS (Spectra Geospatial). A composite topsoil samples (0 – 30 cm), based on five soil samples around and at the center of each ACL point, were used to create the soil sampling dataset used in this study. The four subsamples were at a distance of 2 m from the central hole, in direction of each cardinal points. We removed vegetation residues, grass and litter, if any, in order to sample only the topsoil. The five subsamples were bulked to create a 500 g sample and put in a labelled plastic bag. For SOC determination, the method reported in (Walkley and Black, 1934) was followed.

2.3. Environmental covariates

The environmental covariates applied in this paper are coherent with concepts and methodologies for DSM that were formalized in an in-depth review by McBratney et al. (2003). Scorpan-SSPFe (soil spatial prediction function with spatially autocorrelated errors) approach for predictive modelling (and mapping) of soil was introduced, which in itself is rooted in earlier works, by Jenny (1941) and Russian soil scientist Dokuchaev (Florinsky, 2012). Scorpan-SSPFe may be a mnemonic for factors for prediction of soil attributes: soil, climate, organisms, relief, parent materials, age, and spatial position, and it is enunciated by the equation:

$$S = f(s, c, o, r, p, a, n) + e \tag{1}$$

where S represents the soil attributes or classes that can be predicted from *s*, the soil, other or previously measured soil attributes, *c* represents climate, *o* are the organisms (including land cover and natural vegetation), *r* is the topography, *p* is the parent material, *a* is the age or time, *n* is the spatial location and finally *e*, are the spatially related residues.

Long-handed, the equation states that the soil type or attribute at an unvisited site (*S*) are often predicted from a numerical function or model (*f*) given the factors just described plus the locally varying, spatial dependent residuals. The *f*(Q) part of the formulation is that the deterministic component or in other words, the empirical quantitative function linking S to the Scorpan-SSPFe factors (Lagacherie and McBratney, 2006). The Scorpan-SSPFe factors or environmental covariates are digitally available: Landsat data, other remote sensing images, radiometric data, geological survey maps, legacy soil maps and data, can be used as relatively simple method to estimate soil change and can have important applications in predicting soil carbon rate under future climate change scenarios (Gray and Bishop, 2016; Schillaci et al., 2021a; Yigini and Panagos, 2016). The Scorpan-SSPFe model (McBratney et al., 2003) assumes that existing information on soil classes and properties can aid in prediction and DSM in areas where spatial information of soils is missing or unavailable at the required scale. Using the "Scorpan-SSPFe " model, the predicted map of Soil Organic Carbon can be projected into the future. This approach is also called spatiotemporal substitution (Pickett, 1989; Blois et al., 2013), where the model is used to project SOC into the future by changing climate and land use covariates. Spatiotemporal substitution has been successfully applied to map temporal changes in SOC in the United States, Australia, and Brazil (Waring et al., 2014; Bonfatti et al., 2016; Adhikari et al., 2017). In the work reported in this paper, environmental covariates that represent only *c*, *o*, *r*, *p* and, *n* factors in the Scorpan-SSPFe method were used.

2.3.1. Climate (c)

Climatic covariates are presented in Table S1. Climatic data were obtained from ERA5-Land high-resolution reanalysis datasets with spatial resolution of 0.1° × 0.1° latitude-longitude referred to geographic coordinate system WGS84 (EPSG:4326), which has resolution of 9 kilometers. ERA5-Land datasets were downloaded from the Copernicus Climate Change Service Climate Date Store (C3S). On GEE, 22 climate covariates were downloaded and processed with a data set from January 1, 1981, to December 31, 2021.

2.3.2. Organism (o)

A total of 36 covariates were used in this study using images from Landsat 8 Tier 1. All GEE-accessible images were acquired at an original spatial resolution of 30 m. SOC plays a relevant role on the growth status of crops, and remote sensing data can record the apparent spectral characteristics of crops that can be useful to explain the variation in the SOC content of soils. These indexes were created and downloaded from GEE for the satellite images available between January 1, 2016 to December 31, 2021. Vegetational indices calculated are present in Table S2.

2.3.3. Topography (r), Parent material (p) and, Position (n)

In this study, 13 topographic variables (Table S3) were derived from the Digital Elevation Model (DEM), distributed at a spatial resolution of 30 m provided by NASA (https://lpdaac.usgs.gov/products/nasadem_hgtv001, accessed on 1 April 2022). The calculation of these variables was possible using the algorithm Slope, Aspect and Curvature provided by System for Automated Geoscientific Analyses (SAGA) and related to terrain morphometry and, also the Topographic Wetness Index (TWI) which was calculated using the specific SAGA algorithm, both algorithms are directly integrated in QGIS.

The nine classes for the parent material (Table S4) were obtained from the lithological map of the Apulia region, available online on the website http://www.sit.puglia.it/ (Di Santo et al., 2009). These categorical variables were transformed in dummy variables applying "fastDummies" library in R environment. Dummy variables are useful for incorporating categorical variables into statistical models. In this method, each observation is represented by a vector of 0 s and 1 s, with a 1 in the position corresponding to the category that the observation belongs to. In this study, Parental material has nine classes (Table S4), nine new binary variables are created, each representing one of the classes. Spatial position (*n*) was related to latitude and longitude associated to each sample point.

2.3.4. Mathematical function and model evaluation (f)

The model was tested using GWR which is an extension of the traditional linear regression (Brunsdon et al., 2010). In DSM, GWR can be used to model the relationships between soil properties (such as texture, organic matter content, pH, etc.) and environmental variables (e.g., elevation, slope, and rainfall). In traditional linear regression, it is assumed that the model coefficients are constant across the study area, but this is not necessarily true in many situations. Therefore, in the GWR, the regression coefficients are specific to a location rather than global estimates. The GWR methods can be represented as:

$$y(x,y) = \beta_0(x,y) + \sum_{i=1}^{k} \beta_i(x,y)x_i + \boldsymbol{\varepsilon}_i(x,y) \tag{2}$$

in which y(*x, y*) is the predicted SOC in the i-th site, (*x,y*) are the coordinates for the i site, k is the number of covariates, β_i is regression coefficient, x_i is the covariate at the site i and ε_i represents the error term.

GWR needs bandwidth to work, which is the distance band used for each local regression equation. The bandwidth is able to control the degree of smoothing and it is a key affecting the regression results. It is used to control the extent of the spatial influence of each data point. The bandwidth determines the spatial extent over which data points are considered neighbours and influence the regression estimates. Akaike Information Criterion corrected (AICc) was used to choose the best bandwidth in this study. The adaptive kernel size, used for the estimation, depends on the location of the samples or the location of the test point. The weight of each point can be calculated using the Gaussian function. GWR was carried out in R environment using 'GWmodel' library (Lu et al., 2015). GWR model were validated using coefficients of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE):

$$\mathrm{RMSE} = \sqrt{\frac{\left(\sum_{i=1}^{n}[D(x_i)] - D*(x_i)\right]^2}{n}} \tag{3}$$

$$MAE = \frac{\sum_{i=1}^{n}|D(x_i)| - D*(x_i)]}{\mathrm{n}} \tag{4}$$

$$MAPE = \frac{100\%}{N} \quad \sum_{i=1}^{n}\left|\frac{(D(x_i) - D*(x_i))}{D(x_i)}\right| \tag{5}$$

where *D* (x_i) is the measurement of SOC, D^* (x_i) is the predicted SOC, and n is the number of validation sites, respectively.

2.4. Data processing

Covariates that have a different spatial resolution were resampled at the same resolution of Landsat-8 satellite (30 m), using the Nearest Neighbor algorithm in QGIS. Covariates affected by multicollinearity were filtered using the function "findCorrelation" developed by Caret library, in R environment (Behrens et al., 2010; Ferhatoglu and Miller, 2022; Chen et al., 2022). This function allows the removing of covariates that are highly correlated among them (the selected cutoff was $r > 0.75$), selecting the covariate that is mostly related with SOC. Then, a model for SOC was constructed by stepwise multiple regression using Bidirectional Elimination approach and Akaike Information Criterion (AIC) as a selection criterion. The stepwise multiple regression was also performed in R environment, adopting "MASS" library. Finally, using the covariates selected by the stepwise multiple regression, the GWR was performed, using the R library "spgwr".

2.5. Distribution of SOC in the Apulia region

To obtain optimal understanding of the distribution of SOC in the Apulia region, altitudes and slopes were calculated using Digital Terrain Model (DTM) in GEE following the methods introduced by Petito et al. (2022). Altimetry was classified into three categories based on the altitude above sea level: plain ($0 \leq$ altitude ≤ 300 m a.s.l.), hilly ($300 <$ altitude < 800 m a.s.l.), and mountain (altitude ≤ 800 m a.s.l.). The slope was categorized by dividing the slope range into three quantiles: low slope (under 1.8 %), medium slope (1.8–3.7 %), and high slope (over 3.3 %). SOC was also categorized using five quantiles: low < 14.21, medium-low 14.21–16.44, medium 16.44–18.14, medium-high 18.14–20.68, and high > 20.68. In addition, the three categories were combined to obtain 45 classes for both scenarios.

3. Results and discussion

3.1. Descriptive statistics of SOC and SOC variation by CM and CA

To effectively test the hypothesis of this study, the sample size took into account the area and location, and further verified by land use continuity in the power analysis to reduce laboratory costs and maximize the accuracy of the assessment as already reported in other papers (Aïchi et al., 2009; Saurette et al., 2022; Schillaci et al., 2021b).

The statistical summary of the SOC values is reported in Table 1 and derived from 122 observations for CM and 117 observations for CA. SOC values for CM are ranging from 5.10 g/kg to 51.89 g/kg with an average of 16.68 g/kg, and for CA the values are between 5.75 g/kg and 58.70 g/kg with an average of 17.73 g/kg. The statistical distribution of the values of sampled SOC for the CM is positively skewed with a value of 1.06 and a Kurtosis value of 3.72. For the CA the Skewness is 0.70, while the Kurtosis value is 2.68. The Skewness and Kurtosis scores, in both cases, indicated not-normal distribution in the datasets.

Table 1
Descriptive statistics of Soil Organic Carbon (SOC) for CM and CA.

	n.	Min. (g/kg)	Max. (g/kg)	Mean (g/kg)	Skew. (g/kg)	Kurt. (g/kg)
CM	123	5.10	51.89	16.68	1.06	3.72
CA	117	5.75	58.70	17.73	2.68	0.70

CM: Conventional Management; CA: Conservation Agriculture; n: number of soil samples; Min: minimum; Max. = maximum; Skew: skewness; Kurt: kurtosis.

Within a given area and a short period of time, change from SOC is driven mainly by the development of agricultural practices (Blanco-Canqui et al., 2011). In this work, there was a 6.30 % increase in SOC in the points sampled under CA in comparison with CM. The adoption of CA system in the last four years increased the quantity of SOC as demonstrated by other works (Bhattacharyya et al., 2015; Hok et al., 2015; Parihar et al., 2018). In these studies, the changes in the concentration of SOC content of soils were positively influenced by CA compared to the CM system. The CA: (a) reduced the SOC mineralization rate due to low residue-SOC mixing and accentuated mulching, which reduced exposure to soil microbial attacks, decreased soil surface temperature and aeration, and increased aggregate stability (Duiker and Lal, 2000; Al-Kaisi et al., 2005; Bronick and Lal, 2005); (b) decreased subsoil C movement due to the burial of residues and SOC-rich topsoil layers; and (c) increased SOC stratification as a result of a change in soil physical properties that hinder rooting depth and promote surface accumulation (Qin et al., 2004; Martínez et al., 2008). Although some studies have shown that no-tillage practices and their association with the retention of crop residues in the field can increase SOC concentrations (Lal, 2004; Poeplau and Don, 2015), the effects of conservation practices may not be detectable in the first years after their adoption (Acuña and Villamil, 2014; Blanco-Canqui et al., 2014).

3.2. Environmental covariates and estimation of the SOC for GWR

The Pearson correlation coefficients, between SOC and its environmental covariables for the two management systems, are shown in

Table 2
Pearson correlations between SOC and covariates for CA.

	Covariates	*r*	*p*
SOC ~	NDVI[a] minimum	-0.44	0.00
	Exposure	-0.04	0.70
	Blue Wide Cloudless min	0.30	0.00
	GRVI[b] minimum	-0.38	0.00
	GARI[c] minimum	-0.04	0.69
	Latitude	-0.03	0.76
	Total Precipitation mean	0.00	1.00
	Altimetry	0.41	0.00
	Skin Temperature mean	-0.10	0.31
	EVI[d] maximum	-0.21	0.03
	ID_1[e]	-0.69	0.00
	ID_2[f]	0.04	0.70
	ID_7[g]	-0.42	0.00

SOC: Soil Organic Carbon; CA: Conservation Agriculture;
a: Normalized Difference Vegetation Index;
b: Green-Red Vegetation Index;
c: Green Atmospherically Vegetation Index;
d: Enhanced Vegetation Index;
e: Unit with a predominantly limestone or dolomitic component;
f: Unit with a prevalent arenite component;
g: Unit with a predominantly silty-sandy and / or arenitic component.

Table 2 for CA and Table 3 for CM. In CA the correlations between SOC and Altimetry, Exposition, Latitude, Total Precipitation, Skin Temperature mean, Unit with a predominantly limestone or dolomitic component (ID1), Unit with a prevalent arenite component (ID2), Unit with a predominantly silty-sandy and / or arenitic component (ID7), NDVI min, BW min, GRVI min, GARI min and EVI max were strong. Unlike the CA system, CM had a strong correlation with Total Precipitation and Unit with a predominantly limestone or dolomitic component (ID1).

Results derived from the two system managements indicate that the correlated environmental variables for SOC could be very different due to different approaches based on different soil conditions in Apulia region. GWR produced the highest value of determination coefficient for CA (0.71), higher than GWR for CM (0.52). The GWR provided reasonable results (Table 4), the RMSE for CA was 3.96 g/kg while the RMSE for CM was 5.65 g/kg, CA WAS 30 % lower compared to CM. A similar trend was observed for MAE and MAPE. The prediction error followed the R^2, and the GWR models generally showed lower RMSE and MAE. The results are in agreement with those of several authors (Mishra et al., 2010; Zhang et al., 2011; Song et al., 2016) and these authors suggest that GWR has better performance in predicting SOC at regional scale. A regional study by Mishra et al. (2010) showed that GWR is the best estimation approach compared to other models (e.g., Regression Kriging, Kumar et al., 2012). GWR also has no restrictions on the number of covariates. As long as the selected environmental factors are well-correlated with the dependent variable, GWR can perform better than other models (Wang et al., 2013; Costa et al., 2018).

3.3. Spatial distribution of SOC in ACL of Apulia Region

Maps of predicted SOC for CM and CA, as obtained by GWR, method are shown in Fig. 3.

The SOC ranged from 4.06 to 35.60 g/kg for CA and from 5.00 to 29.99 g/kg for CM. The SOC spatial distribution in the ACL of Apulia Region varied considerably across the study area. Overall, the spatial distribution pattern of SOC for CM (Fig. 4) showed a decrease in exposure in the southwest, with the highest values in the northeast-exposed mountainous areas in the Murgia plateau in the middle part of the Apulia region. The lowest values were found in the Tavoliere and the Daunian Sub-Apennines in the northwest.

As for the soils under CA system (Fig. 5), in the mountain area, the highest SOC values were obtained in the province of Bari and province of Barletta-Andria-Trani (Murgia plateau) with a north-east exposure. In province of Foggia, in particular in the Daunian Sub Apennines, lower values of SOC were obtained. In the south part of the Apulia region (Salento, province of Lecce) there are no areas under CA, while the values of SOC in the center of this area represent the values for the CM system (~ 18,14 – 20,68 g/kg, Fig. 4).

GWR is suitable for mapping the spatial distribution of soil properties because of its ability to incorporate an unlimited number of predictive variables (Wang et al., 2013). In the reported study, it was observed how, within a given area and within a short period of time for CA, the change of SOC compared to CM was primarily determined by the evolution of agricultural practices. In a study conducted by Bleuler et al. (2017), different measures of SOC sequestration were compared in ACL of the Apulia region (Foggia province). Based on the CA principles, the permanent soil cover represents a pillar for increasing biological activities for SOC stability and storage. From a practical point of view, SOC is highly dependent on land use patterns and applied agricultural practices, such as the addition of exogenous organic matter, tillage, and fertilization (Dignac et al., 2017). These practices significantly affect soil properties, including soil microbial biomass and activity (Tu et al., 2006), soil physical structure, and consequently the spatial and temporal distribution of SOC (Dignac et al., 2017).

Table 3
Pearson correlations between SOC and covariates for CM.

	Covariates	*r*	*p*
SOC ~	Evaporation from Vegetation	0.24	0.01
	Total Precipitation mean	-0.10	0.31
	Curvature Flow	-0.18	0.07
	RVI[a] mean	0.17	0.10
	GARI[b] maximum	0.01	0.94
	ID_1[c]	0.37	0.00

SOC: Soil Organic Carbon; CM: Conventional Management.
a: Ratio Vegetation Index;
b: Green Atmospherically Vegetation Index;
c: Unit with a predominantly limestone or dolomitic component.

Table 4
Performance of the geographically weighted regression (GWR) for CM and CA in ACL of Apulia region.

	R^2	RMSE (g/kg)	MAPE (%)	MAE (g/kg)
CM	0.52	3.96	28.54	4.12
CA	0.71	5.65	20.16	3.06

CM: Conventional Management; CA: Conservation Agriculture; RMSE: root mean square error; ME: mean error; MAPE: mean absolute percentage error; MAE: mean absolute error.

3.3.1. Comparison with existing SOC map based on spatiotemporal resolution

One of the existing and available maps of SOC for Europe is provided by the Joint Research Centre (JRC) / European Soil Data Centre (ESDAC). The data are downloadable from the website (https://esdac.jrc.ec.europa.eu/content/topsoil-soil-organic-carbon-lucas-eu25) through the dataset "Topsoil Organic Carbon for EU25", originated from LUCAS 2009 data, and it is possible to clip it for the ACL of Apulia region (Fig. 6) using QGIS. The maps were created using LUCAS 2009 sample sets with a spatial resolution of 500 m (de Brogniez et al., 2015).

Sampling conducted in 2021 allowed the creation of a map with a spatial resolution of 30 m and validate the data for the same year. With this updated map of SOC, the area can be planned in more detail to monitor agricultural policies (e.g., land degradation), helping farmers to better implement agricultural practices for carbon management and carbon credit sales.

Moreover, following Farina et al. (2017) for the Apulia region, the accuracy of predictions could be improved by a more detailed dataset on farm management and yields obtained through local surveys or remote sensing. New data from CA systems were used to show the improvement in SOC loss reduction in Mediterranean area when no-till system is applied. This allowed the development of a map for Apulia region, providing detailed information for the SOC and for the two soil management systems examined. In this study, we showed that mapping SOC in Apulia region was feasible by using information based on management practices adopted for ACL and by using Remote Sensing covariates.

3.3.2. Altitude and slope classes combination

The percentage of the SOC distribution in the total ACL of Apulia region, were calculated categorizing using five quantiles/SOC levels (Table 5). The percentage distribution, based on the five quantiles, showed the highest and lowest percentage values in the medium SOC and low SOC classes (34.82 % and 10.37 %, respectively). Dividing the total ACL in the two management systems with CA and CM, the percentage distribution of the areas varied. In CA, the highest distribution percentage corresponded to the high SOC (32.57 %), while the lowest value was found in the low SOC (10.37 %). In CM, the highest distribution percentages were found in the medium SOC (36.06 %), while the lowest were found in the low SOC (9.54 %). The impact of land use changes through the application of CA could allow farmers to apply proven agricultural methods to improve the SOC (Pisante et al., 2015). This path should be increasingly accompanied by specific funding (i.e., Common Agricultural Policy) to support farmers and agronomic

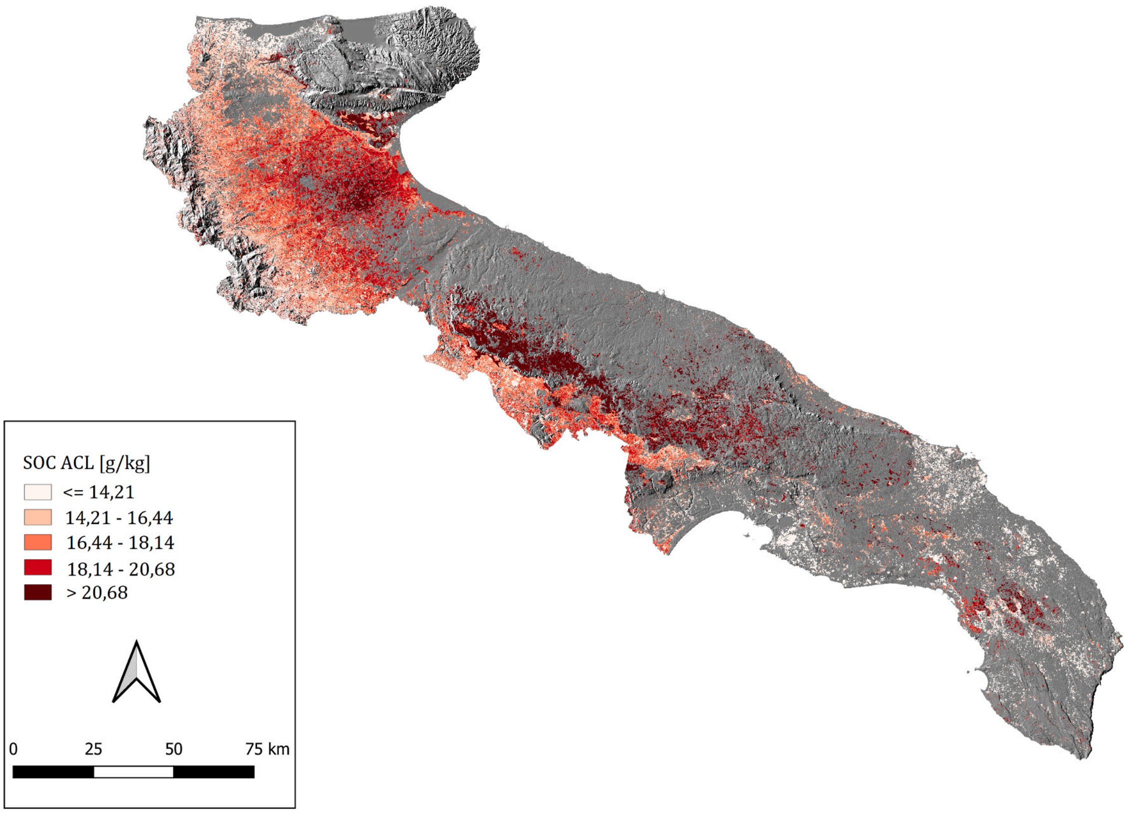

Fig. 3. Map of predicted SOC for Annual Cropland (ACL) in Apulia region obtained by GWR. Hill shade calculated using NASA DEM 30 m (available at https://lpdaac.usgs.gov/products/nasadem_hgtv001, accessed on 1 April 2022).

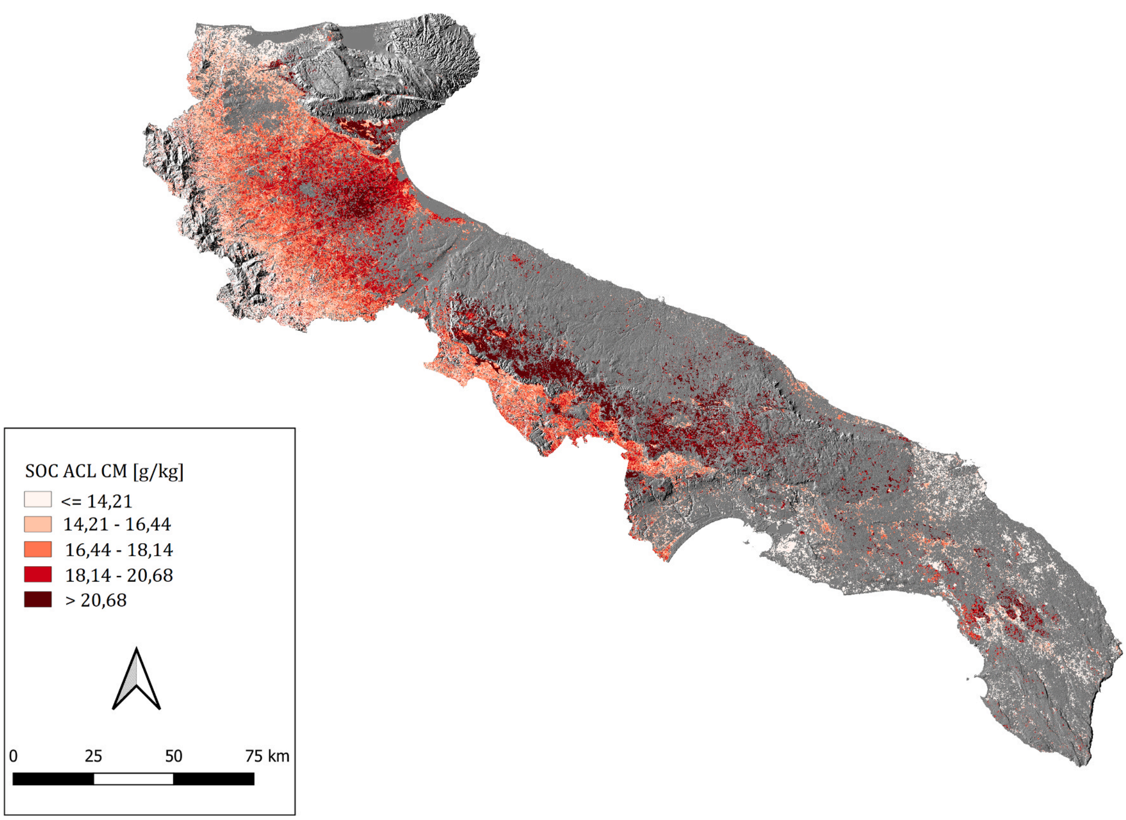

Fig. 4. Map of predicted SOC for CM in Apulia region obtained by GWR. Hill shade calculated using NASA DEM 30 m (available at: https://lpdaac.usgs.gov/products/nasadem_hgtv001, accessed on 1 April 2022).

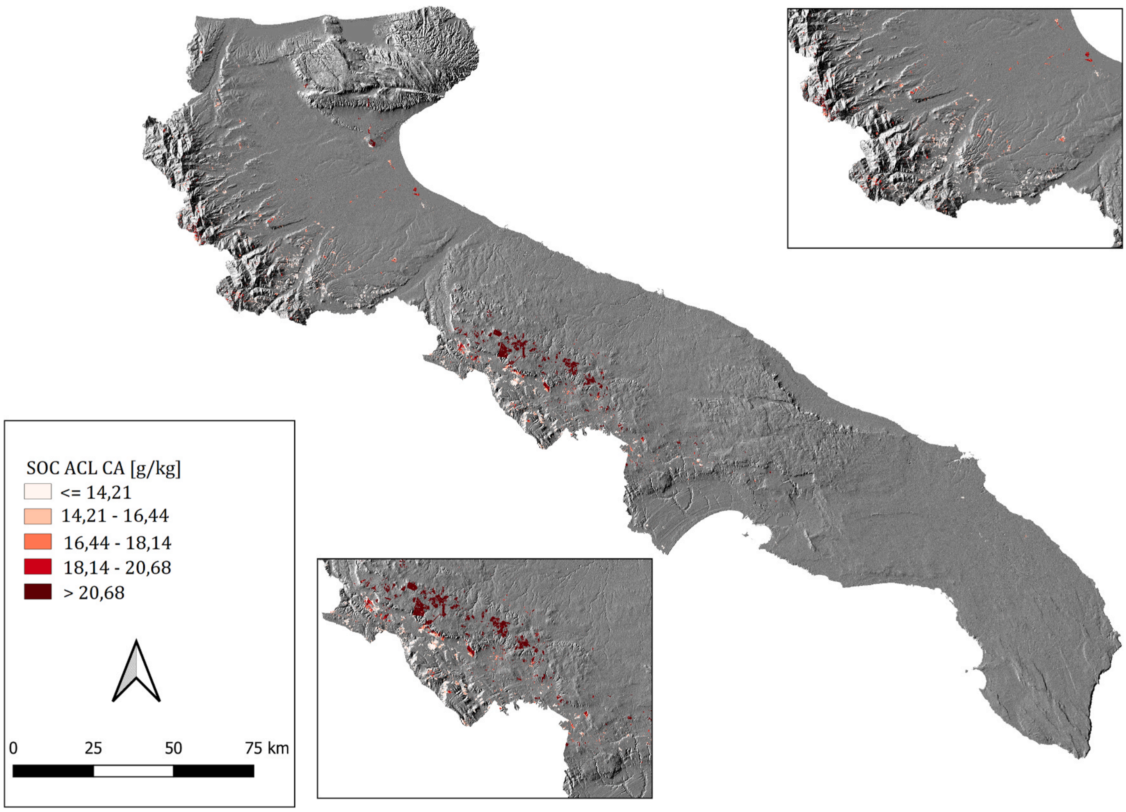

Fig. 5. Map of predicted SOC for CA in Apulia region obtained by GWR. Hill shade calculated using NASA DEM 30 m (available at: https://lpdaac.usgs.gov/products/nasadem_hgtv001, accessed on 1 April 2022).

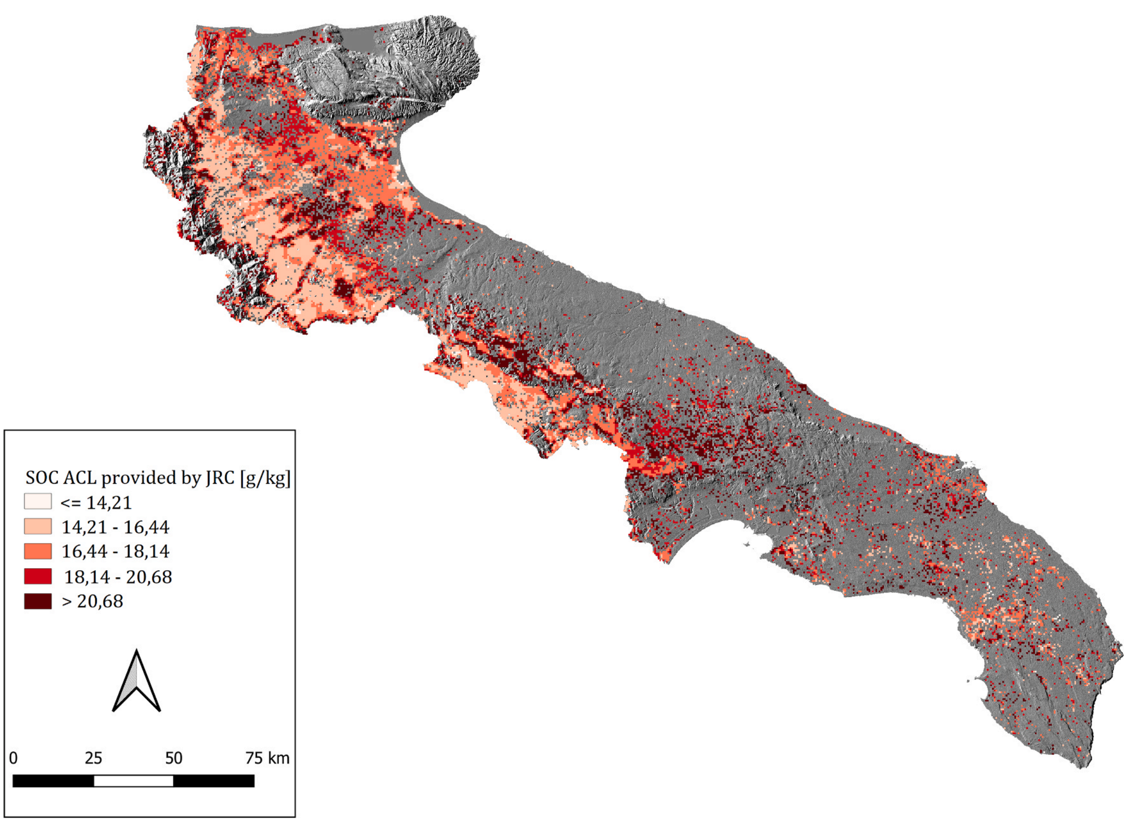

Fig. 6. Map of SOC for ACL in Apulia region provided by dataset from LUCAS 2009 by JRC. Hill shade calculated using NASA DEM 30 m (available at: https://lpdaac.usgs.gov/products/nasadem_hgtv001, accessed on 1 April 2022).

Table 5
Percentage of the SOC distribution areas in the total CM and CA annual cropland of Apulia region.

Level	SOC (g/kg)	Total (%)	CA (%)	CM (%)
Low	≤12.35	10.37	21.12	9.54
Medium-Low	12.35 – 15.93	23.28	21.87	23.07
Medium	15.93 – 19.01	34.82	13.46	36.06
Medium-High	19.01 – 22.71	20.86	10.98	21.23
High	22.71≥	10.67	32.57	10.09
sum		100	100	100

SOC: Soil Organic Carbon; CM: Conventional Management; CA: Conservation Agriculture.

advisors to help to inform themselves better (Llewellyn and Ouzman, 2019).

In addition, the altimetric and slope classes and their combination were calculated (Table S5, S6, and S7). The percentage distribution of SOC by altimetric class showed a similar trend for all quantiles in plain areas, except for the high SOC values found in hilly areas. As for the percentage distribution of SOC in ACL within the altimetric class, the highest value was present in the medium SOC + plain (25.95 %), while the lowest values were found in mountainous areas (Table S6).

The percentage of SOC based on slopes was variable for all quantiles (Table S6). Low SOC and medium-low SOC had similar slope distribution percentage as well as medium SOC and medium-high SOC. While for high rates of SOC, the medium and high slope exhibited higher distribution percentage (39.23 % and 36.24 %, respectively) than the low slope (24.53 %). For the distribution of SOC in the ACLs within the slope classes, the highest and lowest percentages were recorded in the medium SOC + medium slope (13.32 %) and in the high SOC + low slope (2.62 %), respectively (Table S7). Combining SOC levels, altitude and slope classes, the highest percentage of distribution of SOC was on medium SOC + plain + medium slope (10.42 %), while the lowest percentage values in all combinations were found in mountainous areas. In this study area, topography plays a particularly important role because the region combines slopes and intensive tillage, and redistribution of sediments affects the dynamics of SOC mainly by burying rich sediments. The recent paper by Petito et al. (2022) showed that the highest slope and elevation values were found in the mountainous regions with steep orography, especially in the western part where mountains predominate (Daunian Sub Appenine, province of Foggia, and Murgia plateau in province of Bari and Barletta-Andria-Trani). The lowest values were distributed along the Adriatic and Ionian coasts. The heterogeneity in ACL is largely controlled by the topography, which influences the distribution of water, energy and sediments, and thus the dynamics of the SOC (Stevens et al., 2014). The contribution of the CA system can reduce the rate of soil loss. Volk et al. (2010) estimated that soil loss with conventional tillage is 5.4 tons/ha/year which is more than double the soil loss under conservation tillage at 2.2 tons/ha/year. A recent work in the same area of this study, by Petito et al. (2022), CA reduced soil loss rate compared to CM in all classes, from 10.1 % in hill class to 14.1 % for hill + low slope class. Therefore, the monitoring of SOC in this area is essential so that the loss of soil fertility can be reduced.

The observation of the distribution of SOC, based on the quantile division for the ACLs of the Apulia region, is important. The data reported in this paper can improve our understanding of SOC in the Apulia region and help better manage SOC stocks to achieve conservation goals. Based on the percent distribution of mapped ACLs, the higher values of SOC were more distributed in CA than in CM, highlighting the primary role of CA in increasing the amounts of SOC in ACLs (Kassam et al., 2014; Lal, 2015; Valkama et al., 2020).

4. Conclusion

This study is one of the first attempts to predict the accumulation of SOC and its trend in ACLs during the transition phase, after the adoption of sustainable soil management systems at regional scale in Southern Italy, using a GWR approach in a GIS and GEE environment. The methodology can be applied to other regional estimates on ACL when the relevant data are available. Another unique feature the study is that the point database represented actual soil management systems at single field level and thus reflected the management of the farm with a high degree of accuracy. Spatial predictions made it possible to identify when changing from a CM to a CA system would improve soil conditions by increasing SOC in the soil. The GWR model was shown to accurately predict the dynamics of SOC during the first period of adoption of the CA system. SOC predictions showed an average of 16.68 and 17.73 g/kg? for CM and CA respectively while GWR model was able to reach a high R^2 for CA (0.71) and good R^2 for CM (0.52). The RMSE scores for the prediction were smaller in CA (3.96 g/kg) than in CM (5.65 g/kg) with a percentage RMSE difference of 30 %. Predicted SOC obtained by GWR ranged from 4.06 to 35.60 g/kg for CA and from 5.00 to 29.99 g/kg for CM. One of the limiting factors of DSM in the study was the need for a larger sample set to test the GWR model to obtain more accurate SOC predictions and maps. Therefore, working with a larger sample set will be crucial when mapping SOC content in the region. Sampling is necessary but costly procedure in terms of money and time. Such information could be a useful tool for policy makers to assess the impact of agricultural policies on SOC trends, but also for future planning that could take into account issues such as climate change, land management and changes in land use, and reduction of CO_2 emissions in the Mediterranean area.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Michele Pisante reports financial support was provided by Puglia Region. Michele Pisante reports a relationship with Puglia Region that includes: funding grants.

Data Availability

Data will be made available on request.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.still.2023.105916.

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