Promoting Small-Scale Biofuel Production: A Qualitative GIS-OWA Methodology for Land Suitability Analysis of Winter Rapeseed

Mauro Viccaro, Mario Cozzi, Antonella Vastola, and Severino Romano

Abstract Biofuels could be a possible solution to promote agricultural development in rural areas by increasing farm income. Different studies suggest that all problems linked to large-scale biofuel production can be overcome by promoting small-scale production, particularly of rapeseed straight vegetable oil (SVO) used as self-supply agricultural biofuel, specially if the rapeseed is cultivated in crop rotation systems with minimum tillage practices. However, an ex-ante analysis would be very important to explore the feasibility of rapeseed production, via the evaluation of land use suitability.

As land planning issues are complex problems with multiple decision makers and criteria, we propose a spatial multi-criteria analysis model for supporting decision makers in the site selection process for winter rapeseed production. The methodology applied is the Ordered Weighted Averaging (OWA) extended by means of fuzzy linguistic quantifiers. The results have shown as the proposed methodology is more flexible compared to the other MCA methods, in particular for the possibility to make the choice in qualitative rather than quantitative terms, enabling the decision-maker to explore different decision strategies or scenarios, thus facilitating a better understanding of alternative land use suitability models.

Keywords Biofuel · SVO · Land suitability · GIS · Ordered Weighted Averaging · Linguistic quantifiers

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This research was carried out in the framework of the project 'Smart Basilicata' (Contract n. 6386 – 3, 20 July 2016).
Smart Basilicata was approved by the Italian Ministry of Education, University and Research (Notice MIUR n.84/Ric 2012, PON 2007–2013 of 2 March 2012) and was funded with the Cohesion Fund 2007–2013 of the Basilicata Regional authority.

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J. Berbel et al. (eds.), *Multicriteria Analysis in Agriculture*, Multiple Criteria Decision Making, https://doi.org/10.1007/978-3-319-76929-5_6

1 Introduction

Agricultural sector plays an important role in the rural economy, and it is considered one of the most important elements to take into account in the rural development processes (Sánchez-Zamora et al. 2014). However, farmers face different shocks, mainly related to the climate change, global market instability and political decisions that frequently make them vulnerable (Eakin 2005). In several rural regions, like Basilicata (in Southern Italy), marginal farmland areas are being increasingly abandoned due to their low productivity and as a result of the reforms of the EU Common Agricultural Policy (Romano and Cozzi 2008). Different studies suggest that farm diversification could be a viable solution to reduce risk management and increase farm income (Meert et al. 2005; Barbieri and Mahoney 2009; Gautam and Andersen 2016).

In this scenario, the development of bioenergy–as a new business model integrated with environmental and social dimensions of a region–is a valuable tool with positive impacts both in socio-economic and environmental terms. In particular, biofuels are not only the main alternative for fossil fuels to reduce global greenhouse gas emissions, but they can provide local and regional benefits such as energy security, rural development, positive impacts on regional gross domestic product, and mitigation of local pollutant emissions (Franke et al. 2012).

All problems linked to large-scale biofuel production (land grabbing, land-use change, competition with the main agricultural products) can be overcome by promoting small-scale production of rapeseed straight vegetable oil (SVO) used as self-supply agricultural biofuel (Baquero et al. 2010). Rapeseed can be cultivated in crop rotation generating many economic and environmental benefits, *primarly* the non-competition between fuel and food production (Zegada-Lizarazu and Monti 2011).

However, given the economic relevance of investment related to SVO production (Baquero et al. 2011), an ex-ante analysis would be very important to explore the feasibility of rapeseed cultivation in a given area, via the evaluation of land use suitability (Cozzi et al. 2015). Land evaluation is the process of predicting the potential use of land on the basis of its attributes (Rossiter 1996), and in particular it is considered the basic tool for the consideration of agriculture in rural development plans (Hafif et al. 2013).

Several studies suggest that crop selection based on land suitability analysis, using a Multi-Criteria Analysis (MCA) and Geographical Information Systems (GIS) approach, is the most efficient low-cost method to determine the optimal cropping system as a function of biophysical variables. Pirbalouti (2009), Grassano et al. (2011) and Kamkar et al. (2014) use the weighted linear combination method (WLC) to evaluate land use suitability for rapeseed cultivation. However, there are some major limitations associated with the use of conventional MCA procedures (as well as WLC method) in a decision process, especially in situations that involve a high number of assessment criteria (Malczewski 2004). The main difficulty is to combine the criterion maps in a way that the results reflect decisions-makers' preferences. In these circumstances, the key issues of decision-making might be specified in terms of some linguistic quantifiers such as, for example, *"most criteria should be satisfied"* or *"at* *least 80% of criteria should be satisfied"*, etc. (Malczewski 2006; Mokarram and Hojati 2017; Romano et al. 2013). This necessitates extending the conventional MCA procedure so as to include situations that involve *qualitative* statements in the form of fuzzy linguistic quantifiers (Yager 1996).

This work is aimed to propose a *qualitative* GIS-OWA methodology for land use suitability analysis in order to identify the target investment areas for the cultivation of rapeseed to be use as self-supply agricultural biofuel at regional scale. The *qualitative* GIS-OWA enables the decision-maker to explore different decision strategies or scenarios, thus facilitating a better understanding of alternative land use suitability models (Malczewski 2006; Mokarram and Hojati 2017; Romano et al. 2013).

The Case Study is introduced in Sect. 2, and data and methods are presented in Sect. 3. Section 4 provides the results deriving from a set of alternative land use suitability maps, and the paper ends with a discussion section containing final remarks.

2 Case Study Area

The study area was carried out in Basilicata region, a rural region of Southern Italy (Fig. 1). The study area, typically Mediterranean, is located between latitude 39°54' N and 41°12' N and longitude 15°21' E and 16°51' E. The approximate surface area of the region is 9995 km^2 with a population of 570,365 inhabitants (ISTAT 2017), a mostly rural territory with the population being concentrated by the two thirds in the few large urban towns.

In geomorphological terms, the region is characterised by mountainous and hilly areas of the Apennine range (in the NW-SE direction), limited by the limestone base of the Murge hills and the Bradano depression in the north-east and by the Ionian coastal plains in the east.

In terms of climate there are differences specifically due to the complex orography of the region and its geographical position. The elevation varies between the sea level and 2200 m so, while a large portion of the territory shows typically Mediterranean features (Ionian coast, Bradano depression and Murge hills), the areas above 800 m asl are characterized by a temperate-cool climate with quite dry summers. Average annual precipitation ranges from 529 till about 2000 mm, concentrated in the South-Western area of the region, as the Apennine range intercepts most of the Atlantic weather perturbations into the Mediterranean. The most rainy months are November and December, the driest are July and August, when severe droughts are frequent. The temperature is characterised by wide variations, with very hot summers and very cold winters. The coldest month is usually January (with an average temperature between −4 and 7 °C).

How it's possible to observe in Fig. 1, agricultural land covers about 67% of the regional surface area. According with the last agricultural census (ISTAT 2010), the utilised agricultural area (UAA) is equal to 519,127 ha (52% of the total regional area), mostly dedicate to cereal cultivation on non-irrigated arable land (158,851 ha), followed by olive groves (31,351 ha), vegetable and orchards on permanently

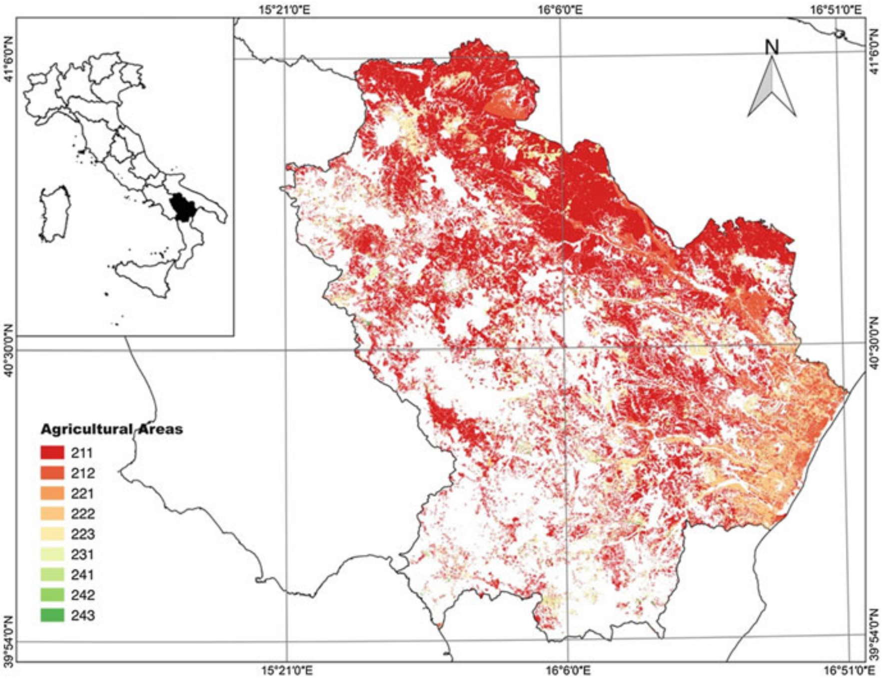


Fig. 1 Location and agricultural land use map of the study area (CLC code: 211 = Non-irrigated arable land; 212 = Permanently irrigated land; 221 = Vineyards; 222 = Fruit trees and berry plantations; 223 = Olive groves; 231 = Pastures; 241 = Annual crops associated with permanent crops; 242 = Complex cultivation; 243 = Land principally occupied by agriculture, with significant areas of natural vegetation)

irrigated land (about 16,000 ha), and vineyards (5361 ha). In this context, there exist good conditions to cultivate rapeseed in crop rotation with cereals on non-irrigated arable land. During the last decade, in Basilicata there was a reduction of land for the production of rapeseed, from 2700 ha (in 2000) to 343 ha (in 2010) (ISTAT 2010); but in the near future, rapeseed cultivation for straight vegetable oil (SVO) production could be a sustainable solution to diversify farm income, especially now that the traditional cultivations (e.g. durum wheat cultivation) in Basilicata region show a high risk management for farmers (Vastola et al. 2017).

3 Materials and Methods

3.1 Qualitative GIS-OWA Methodology

Since 2006, when Malczewski proposed, for the first time, the OWA approach with linguistic quantifiers in GIS environment, the method was widely used in different fields of study. Among others, Romano et al. (2013) and Mokarram and Hojati

(2017) have used it for land evaluation in agriculture showing its flexibility and easyness in land use analysis.

There are three main input components of GIS-OWA: (i) criterion maps (with associated standardization procedures); (ii) criterion weights (with associated procedures for defining preferences regarding the relative importance of criteria); and (iii) order weights (with associated ORness degree of the OWA operator) (Malczewski and Liu 2014).

The extension of conventional GIS-OWA approach with linguistic quantifiers–as in the case of others GIS-based approaches for land use suitability analysis–can be considered as a combination of purely MCA methods and Artificial Intelligence (AI) techniques (Malczewski 2004). After criterion map selection, we use *fuzzy logic* techniques, as standardization procedure of criterion maps (see Sect. 3.1.1), and AHP method, to calculate the relative criterion weights (see Sect. 3.1.2), classified as AI technique and MCA method respectively. At last, we use the OWA operator (MCA method) to aggregate the criterion maps after calculating the order weights through the linguistic quantifiers (AI technique) (see Sect. 3.1.3).

3.1.1 Criterion Maps

In order to assess the land suitability in agriculture for any crop type, all possible suitability criteria and their characteristics should be collected (Mendas and Delali 2012).

In our study, the criterion maps used in the analysis are related to the agro-ecological needs of rapeseed; topographic characteristics such as slope were not included, as the analysis was carried out only in non-irrigated arable land, where rapeseed can be cultivated in crop rotation systems.

The agro-ecological factors (climatic and soil factors) were selected from those proposed by Grassano et al. (2011), after an experts' panel evaluation. For each single factor under investigation was generated a geo-referenced *raster* layer (100 × 100 m cell size), by using Gauss Boaga East, on datum Monte Mario–Roma 1940 as geographic reference system.

Regarding climatic factors, we used the Crop-specific Thermal Index (CTI), but we modified the formula to calculate Seasonal Rainfall Deficit (SRD).

CTI was calculated on the basis of thermal requirements of rapeseed as average of the Monthly Thermal Indices (MTI) calculated for each month of the crop cycle (Eq. 1).

$$MTI = (x - B)(x - L)\left[(B + L - 2T)(x - T) + (T - B)(T - L)\right] / (T - B)^2 (T - L)^2 \tag{1}$$

where x = average monthly temperature of the site; B = base temperature (0 °C); L = heat stress temperature (30 °C); T = optimum temperature (18 °C).

SRD can be assimilated to the irrigation water requirement (IWR), i.e. the amount of water that has to be applied in addition to rainfall to meet crop water requirements. It is calculated by difference between crop evapotranspiration (ET_c)

and that part of rainfall which is effectively used by plants (Pe) (Brower and Heibloem 1986).

The ET_c is calculated by multiplying the reference crop evapotranspiration (ET_0) by a crop coefficient (K_c) (Allen et al. 1998). In the study, the monthly ET_c was calculated using raster images representing the monthly ET_0, and the K_c values of each growth stage were derived from FAO paper n. 56 (Allen et al. 1998).

Effective rainfall (Pe) was calculated by the formula proposed by the Soil Conservation Service of the United States Department of Agriculture (Martin and Gilley 1993), adjusted for units converted from inches to mm:

$$Pe = fc\,(1.253 \times P^{0.824} - 2.935) \times 10^{0.001ET_c}$$

where *fc* is the correction factor depending on the soil available moisture; for the present work it is assumed to equal 1 (standard soil condition); *P* is the total monthly rainfall. In this way SRD values for rapeseed were calculated for the critical period of plant life cycle, from March to May.

Concerning the soil factors, we considered soil physical and chemical characteristics, such as texture, percentage of gravel, pH, soil depth, total carbonate content, and drainage. As suggested by the experts' panel, we did not take into account salinity due to the great adaptability of rapeseed and to the negligible influence of this factor on regional agriculture. Moreover, the map of the organic matter content was replaced with the map of land use capability.

As CTI is the only factor that ranges between 0 and 1, with 0 unsuitable and 1 suitable, the next stage involved the use of *fuzzy logic* technique (Zadeh 1965): given a fuzzy set (membership functions) is possible to standardize criterion maps defining the suitability degree within a range from 0 to 1. The fuzzy functions were chosen on the basis of the type of processed data and the uncertainty associated with it (Caniani et al. 2011, 2016; Eastman 2012) from those proposed by Cozzi et al. (2014), after an experts' panel evaluation. Criterion maps and fuzzy functions used in the analysis are shown in Table 1.

3.1.2 Criterion Weights

Because not all criteria affecting land suitability have equal levels of significance, the Analytical Hierarchy Process (AHP) method (Akıncı et al. 2013; Saaty 1977) was used for defining preferences regarding the relative importance of criteria and calculating the criterion weights necessary for the OWA aggregation procedure.

The AHP approach is one of the most widely known and used multi-criteria analysis approaches in GIS environment (especially for raster data models), allowing users to determine the weights associated with suitability maps. After the suitability maps (criteria) are set on a hierarchical structure, the weights can be derived by taking the principal eigenvector of a square reciprocal matrix of pairwise comparisons between the criteria (Eastman 2012). The comparisons concern the relative

Table 1 Criterion maps and related fuzzy function for land use suitability of rapeseed

Fuzzy function	Criterion maps	Criterion value	Fuzzy value
Null[a]	Crop-specific Thermal Index	–	–
Decreasing sigmoidal	Seasonal Rainfall Deficit (mm)	0	1
		50	0
User defined	Carbonates (% $CaCO_3$)	<0.5	1
		0.5–1	1
		1–5	1
		5–10	1
		10–25	1
		25–40	0.93
		>40	0.84
	Soil depth (cm)	<25	0.58
		25–50	0.70
		50–100	0.90
		100–150	1
		>150	1
	Gravel (%)	0	1
		1–5	0.90
		5–15	0.85
		15–35	0.65
		35–70	0.50
		>70	0.20
	Land use capability	Without limitations	1
		Moderate limitations	0.95
		Severe limitations	0.90
		Very severe limitations	0.80
		Accurate management	0.70
		Forestry and pasture use	0.50
		Very strong limitations	0.45
	Soil reaction (pH)	<4.5	0.75
		4.5–5.5	0.85
		5.6–6.5	0.92
		6.6–7.3	1
		7.4–7.8	0.95
		7.9–8.4	0.95
		8.5–9.0	0.90
	Soil texture	Coarse	0.65
		Moderately coarse	0.88
		Medium	0.88
		Moderately fine	0.95
		Fine	0.91
	Drainage	Rapid	0.70
		Good	0.93
		Mediocre	0.80
		Slow	0.70
		Very slow	0.50
		Prevented	0.30

[a]CTI (Crop-specific Thermal Index) range between 0 and 1 so it's no necessary standardize it

Table 2 Criterion weights resulting from the AHP approach (CR = 0.03)

Criterion map (j)	Criterion weights (u_j)
Carbonates	0.0192
Soil depth	0.0788
Soil reaction	0.0192
Soil texture	0.0378
Seasonal Rainfall Deficit	0.2865
Gravel	0.0378
Drainage	0.1554
Land Use Capability	0.0788
Crop-specific Thermal Index	0.2865

importance of the two criteria involved in determining suitability for the stated objective and it is made by using the preference scale suggested by Saaty.

Since performing pairwise comparisons of criteria in the AHP method a certain level of inconsistency may occur, Saaty proposes also a procedure to calculate an index of consistency, known as a consistency ratio (CR), indicating that, in case the CR of a matrix is above 0.10, the matrix of pairwise comparisons should be revaluated (Akıncı et al. 2013).

In our study, the criterion weights resulting from the AHP approach, calculated according to the estimation of the criterion influence on the rapeseed cultivation suitability, are shows in Table 2.

3.1.3 Order Weights

The order weights are relevant for the GIS-OWA combination procedures (Malczewski 2004). From different sets of order weights a wide range of OWA operators may be generated, including the most common map combination procedures: the weighted linear combination (WLC) and Boolean overlay operations, like the intersection (AND) and union (OR). In the conventional OWA approach, the OWA operators are defined by two parameters: the measures of trade-off and ORness (Yager 1996; Malczewski 2006). The trade-off is a compensation measure (substitutability criterion) ranging between 0 and 1, so that 0 indicates the lack of compromise between criteria, whereas 1 indicates a full compromise. The measure of ORness indicates the degree to which an OWA operator is similar to the logical connective OR in terms of its combinations behaviour. In this case as well the degree of OR required goes from 0 (*risk-averse*, operator MIN, AND) to 1 (*risk-taking*, operator MAX, OR).

However, in a complex spatial decision situation decisions-makers might be expected to find difficulties (or even impossible, notably for the problems that involve a number of criteria) to formulate accurate numerical information in relation to the OWA parameters.

In these situations, the key issue of decision-making might be specified in *qualitative* terms through the use of fuzzy linguistic quantifiers. A linguistic

Table 3 Regular increasing monotone quantifiers and their proprieties

Quantifier (Q)	α	GIS combination procedures	Position in the decision-strategy space (see Fig. 2)
All	$\alpha \rightarrow \infty$	OWA (AND, MIN)	1
Almost all	$\alpha = 10$	OWA	–
Most	$\alpha = 2$	OWA	–
Half (identity)	$\alpha = 1$	OWA (WLC)	2
A few	$\alpha = 0.5$	OWA	–
At least a few	$\alpha = 0.1$	OWA	–
At least one	$\alpha \rightarrow 0$	OWA (OR, MAX)	3

Source: Malczewsky (2006)

quantifier, used for computer–human interaction, enables decision makers to formulate OWA procedure in a simple way (Romano et al. 2013). Malczewsky (2006) proposes a set of linguistic quantifiers known as Regular Increasing Monotone (RIM) (Table 3), so that, given a set of standardized criterion map ($j = 1, 2, \ldots, n$) and criterion weight, the qualitative GIS-OWA for each i-th location (cell) is defined as follows:

$$OWA_i = \sum_{j=1}^{n} v_j z_{ij}$$

with the order weight

$$v_j = \left(\sum\nolimits_{k=1}^{j} u_k\right)^{\alpha} - \left(\sum\nolimits_{k=1}^{j-1} u_k\right)^{\alpha}, \text{ such that } v_j \in [0, 1], \quad \sum\nolimits_{j=1}^{n} v_j = 1$$

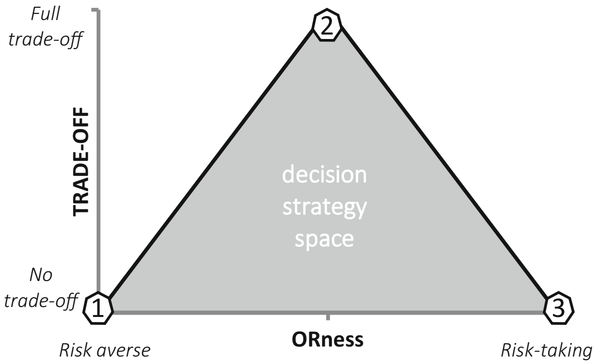
where $z_{i1} \geq z_{i2} \geq \ldots \geq z_{in}$ is the sequence obtained by reordering the standardized criterion values $a_{i1}, a_{i2}, \ldots, a_{in}$, u_j is the criterion weight reordered according to the value of z_{ij} and α is the parameter associated with RIM.

By specifying an appropriate linguistic quantifier, in the continuum that goes from the quantifier "*All*" (position 1) to the quantifier "*At least one*" (position 3), it's possible to generate a wide range of decision-making strategies (alternative models of land use suitability) with different degrees of ORness and trade-off (Fig. 2).

It's important to point out that in land use analysis, the linguistic quantifier to be adopted changes case by case. In the case of land use suitability analysis for agricultural crops, Romano et al. (2013) argue that the success of crop depends on the species finding the best climatic and edaphic conditions; it is evident that higher is the number of criteria considered, more reliable is the result.

In our case study, the linguistic quantifiers that best express this concept and that have contributed to the calculation of order weights are: "all criteria should be satisfied" ("*All*" quantifier, AND operator) and "almost all" ("*Almost all*" quantifier). All considered quantifiers are associated with a low ORness (low risk) and low trade-off (low compromise) degree. However, in order to evaluate the differences with the approach used by Pirbalouti (2009), Grassano et al. (2011) and Kamkar et al. (2014) in rapeseed land use analysis, we have chosen also the quantifier "*Half*" representing the WLC operator.

Fig. 2 Space of decision-making strategy in MCA and position of the main OWA operators (see Table 3)



4 Results and Discussions

Different scenarios representing suitability map of rapeseed cultivation, obtained with the multi-criteria analysis model, are described in Fig. 3.

The maps obtained with the "*All*" and "*Almost All*" quantifiers (All and Almost all quantifier scenario) look quite similar, showing some variability across the region with suitability values ranging between a minimum value of 0.32 and 0.33 and a maximum value of 0.68 and 0.70, for All and Almost all quantifier scenario respectively. About 75% of analysed arable lands (over the first quartile) shows suitability values higher than 0.50, despite the wide range (see box-plots). Most of the areas with higher values are mainly concentrated in the North-East, in the flat part of the region. The factor that has mainly influenced this distribution is the CTI. In fact, while other factors generally show a high suitability value, the CTI shows a mean value around 0.55, due to the presence of the Apennine ridge extending from North-West to South-East, where the mean annual temperatures are lower and not useful for heat requirements for rapeseed production.

Conversely, the map derived from the "*Half*" quantifier (WLC operator, Half quantifier scenario) shows a restricted range of suitability values (between 0.66 and 0.88). However, the resulting scenario is more optimistic: 50% of investigated area record suitability values range between 0.79 and 0.88. In this case, there is not the same variability across the region as described before. In the WLC approach, characterized by an ORness degree of 0.5 and full trade-off (position 2 in the decision strategy space, see Fig. 2), the low values of the CTI criterion (its relevance in the analysis, see Table 2) are compensated by the high values of the all other criteria.

To facilitate the reading of the results obtained using the OWA method, the non-irrigated arable lands have been classified into suitability classes for rapeseed cultivation using Chen-Hwang method (Chen and Hwang 1992). This method is a well-established tool to convert cardinal values to quality attributes, as it provides the mathematical representation of a linguistic term. Chen and Hwang identify 8 scales of linguistic terms. By the use of scale 4, four suitability classes were obtained (null, low, medium, high) (Table 4).

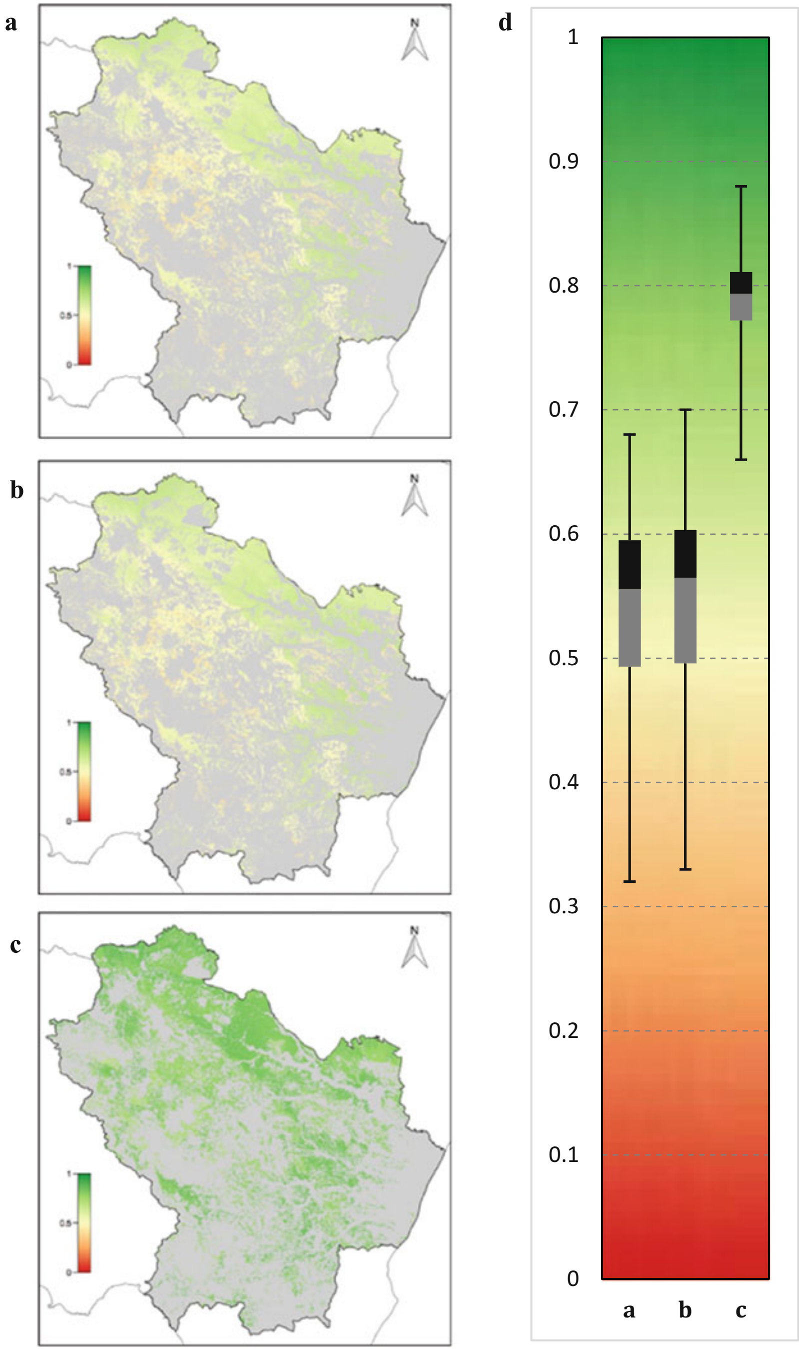


Fig. 3 Land suitability maps [(**a**) All quantifier scenario, (**b**) Almost all quantifier scenario, (**c**) Half quantifier scenario] for rapeseed cultivation and distribution of suitability values [(**d**) box-plot] for different scenarios

Table 4 Suitability classes of non-irrigated arable lands for rapeseed cultivation in different scenarios (ha)

Description	Range	All quantifier scenario	Almost all quantifier scenario	Half quantifier scenario (WLC operator)
		Surface (ha)		
Null	0–0.17	0	0	0
Low	0.17–0.5	33,259	25,048	0
Medium	0.5–0.83	125,592	133,803	145,652
High	0.83–1	0	0	13,199

According to the results in Table 4, no arable land shows non-suitability (null class) in all scenarios. With a non and low risk (non and low trade-off) associated to the "*All*" and "*Almost all*" quantifiers respectively, All and Almost all quantifier scenarios present low and medium classes; no high class has been recorded. With an average risk and full trade-off (WLC operator), arable lands show only medium and high suitability.

However, considering the surface, all scenarios have the highest area in the medium class (79%, 84% and 92% of arable land in All, Almost all and Half quantifier scenario respectively). Such result could explain the reduction of the area dedicated to the cultivation of rapeseed that has occurred over the years: farmers may have preferred to cultivate more profitable crops. If so, the results obtained with the WLC operator could be misleading. Accepting a higher risk associated with MCA analysis, investments in rapeseed SVO production could be not cost-effectiveness also in those areas that, in the half scenario, result to have a high suitability.

5 Conclusions

In agriculture, small-scale production of rapeseed SVO used as self-supply agricultural biofuel represents an opportunity to diversify farm income and achieve independence from fossil fuels.

However, given the economic relevance of investment related to SVO production, it is important to acquire instruments for agricultural planning to address investments towards areas that are more suitable for the crop's growing. Therefore, the aim of the present study was to propose a qualitative GIS-OWA methodology, applied to Basilicata region (in Southern Italy), helpful to produce land use suitability maps for rapeseed cultivation. The qualitative OWA procedure, through the use of linguistic quantifiers, enables to translate, in a simple way, the decision-maker's preferences in MCA combination procedures.

In order to produce land suitability maps, firstly the criterion maps were standardized by the use of fuzzy functions and then the relative criterion weights were calculated using the AHP method. Lastly, in order to aggregate the criteria with

OWA operators, the most suitable linguistic quantifiers were chosen. Since the success of rapeseed production depends on the specie finding the best climatic and edaphic conditions, it is evident that higher is the number of criteria considered, more reliable is the result. In our case study, the linguistic quantifiers that better express this concept and that have contributed to the calculation of order weights are "*All*" and "*Almost all*" quantifiers. The WLC operator was also applied in order to make a comparison with the most used approach in land use suitability analysis for rapeseed cultivation. Results showed that, in Basilicata region, the highest area has medium suitability values in all scenarios and this may explain the contraction of the surface dedicated to rapeseed cultivation over the years. The rest of the area in All and Almost all quantifier scenarios shows low suitability. Areas with a high level of suitability are recorded only in WLC scenario. This scenario is certainly more optimistic but unrealistic: the WLC operator corresponding to "Half quantifier, i.e. "half criteria should be satisfied". This expression is in disagreement with the aim of the analysis and the preferences of the decision maker for which all criteria or almost all must be met. Therefore, in a context of high-risk investments in agriculture, the WLC operator could be not appropriate in land use suitability analysis.

The proposed methodology is more flexible compared to the WLC methods, in particular for the possibility to make the choice in qualitative rather than quantitative terms, enabling the decision-maker to explore different decision strategies or scenarios, thus facilitating a better understanding of alternative land use suitability models.

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