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A new soil quality index based on morpho-pedological indicators as a site-specific web service applied to olive groves in the Province of Jaen (South Spain)

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ABSTRACT

Soil quality has become a fundamental concept in soil science and agriculture, but it can be difficult to apply its theoretical and experimental approaches to poorly surveyed zones where precision techniques are far from being applied. In this paper, we propose a new technique that enables little-used qualitative morpho-pedological data to be managed and integrated into a single Field Soil Quality Index (FSQI). Nonlinear Principal Component Analysis (NLPCA), a technique able to handle categorical data, is applied here to deal with morpho-pedological indicators. When categorical values are transformed, they can be properly analyzed and interpreted. This procedure requires less expert knowledge, so it can help soil quality assessments by non-experts. We applied the FSQI protocol to soils in the most important olive-growing area in the world, Jaen Province (Southern Spain), which has serious problems with soil degradation and erosion. First, a soil database for the study area was compiled, including 18 morphological attributes for 131 surface horizons belonging to eight Land Use Types. Secondly, the NLPCA provides optimal scalings and attribute weights that transform and integrate morphological indicators into a simple weighted additive index (FSQI). Thirdly, the scaling functions and weights found were applied to the same attributes of an evaluation set comparing two soil management types (conventional *vs.* organic) in olive groves. The FSQI means for the first (conventional) were significantly lower than in the organic groves (0.278 *vs.* 0.463, $P < .05$), which supports the validity of the index. A site-specific FSQI web service has been created to assist in decision-making in the study area, whose methodology can be generalized to other zones and crops.

1. Introduction

Soil quality is the capacity of soils to support ecosystems functions (Larson and Pierce, 1991). Soil quality can be assessed from a set of parameters, the soil quality indicators, which accurately summarize soil functions. Any negative impact affecting soil quality indicators would be related, through these functions, with a loss of the economic or ecological value of the ecosystems. Agriculture is probably the global activity that most affects soil quality, mainly causing the destruction of the structure and loss of soil organic matter (Lal, 1998). Knowledge of soil quality is valuable for decision making process in many aspects of agriculture, such as assessing soil for precision agriculture (Vitharana et al., 2008) and consolidating land in fragmented parcels (Gajendra and Gopal, 2005). Awareness of soil quality can be determinant to ensuring the success of new or reconverted production areas.

As in other fields of environmental sciences, in soil science efforts have been made to make quantitative assessments from heterogeneous datasets (Harden, 1982), which are either qualitative or measured using scales difficult to compare. This is the case of soil quality assessment (Seybold et al., 1998), where soil quality indices, integrating the most relevant soil indicators of each system into a single numerical measurement, have proven to be a suitable way to deal with soil quality (Velasquez et al., 2007; Bastida et al., 2008). Prior to their integration in an index, these indicators must be normalized by means of mathematical and logical functions (scoring functions) to relate the physical value of the indicator with a standardized soil quality scale. This may be the key step in soil quality index development (Andrews et al., 2002). Scoring functions may be more or less complicated (linear, nonlinear, etc.), but all have several adjustable parameters which must be set heuristically for different places and conditions, based on

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previous knowledge of the soil (Andrews et al., 2004).

Field morphological soil properties are among the most important pedological properties for genesis and classification. They can be found easily and economically, are included in virtually all soil databases, and can be readily applied by growers. However, as they are non-numerical, their quantitative use in soil quality creates significant difficulties (MacEwan and Fiztpatrick, 1996). Thus there are few antecedents for the calculation of soil quality indexes on the basis of pedo-morphological indicators, which were established only through knowledge-based decision rules (Onweremadu et al., 2008; Pulido-Moncada et al., 2014). However, numerical techniques can make categorical variables provided by users manageable. Nonlinear Principal Component Analysis NLPCA (Gifi, 1990) enables an object to be fitted into a multidimensional space given by principal components, which are linear combinations of a set of attributes with which the system can be characterized. This is the same as classical or linear principal component analysis (PCA), except that non-numerical (ordinal or nominal) variables can be included in the initial set of attributes and transformed into a numerical scale by optimal scalings. The method optimizes the correlations between the transformed variables and the principal components, which in essence means that the correlational structure among the variables is represented as clearly as possible, for the particular dataset analyzed. NLPCA is highly efficient in systems based on qualitative information, such as pedometrics (Calero et al., 2005, 2008; Sánchez-Marañón et al., 2011).

Olive groves are one of the main crops in southern Spain, where they strongly influence the landscape and culture. Furthermore, olive groves are vital to its economy, particularly in Jaen Province, which accounts for more than 21% of world production. This explains the high impact of this crop on soil quality (Gómez et al., 2009), and the growing interest of European land managers to adopt strategies (*i.e.*, the "greening" policy) to deal with soil degradation, mainly soil erosion (COM (2012) 46 final; RD (2014) 1078). So given the critical levels of soil degradation, it is urgent to advance in the regional impact of agricultural practices on soil quality beyond just the plot or the farm. Nevertheless, there are very few studies dealing with soil quality indexes in olive groves and those are based on analytical indicators (Gómez et al., 2009; García-Ruiz et al., 2012).

The aim of this study was to develop and validate a new soil quality index (FSQI) based on field morphological indicators acquired from soil surveys, and apply it to the soils of the world's largest olive-growing area. Lack of prior knowledge requires easy access to our index by growers using a web-based tool. Web-based decision support systems are emerging as effective tools for reaching a wide range of crops, including olive cultivation (Orellana et al., 2011). However, most of them require a certain amount of expertise for their effective usage. Our tool is intuitive and can serve as a low cost assessment solution for present and potential land management.

2. Material and methods

2.1. Site and crop description

Olive groves (*Olea europaea* L.) occupy over 6600 km^2 in the Jaen Province (South of Spain), the 49% of its total area. They are located mainly on level or gently sloping lands and over carbonated materials (marls, limestones and dolostones), and are strongly limited in altitude by frost (approx. 1200 m above sea level). Despite the predominance of olive trees, other crops, forestry and natural areas are also present, but limited mainly to steep or very steep slopes in mountainous reliefs and at altitudes > 1000–1200 m. The climate is Mediterranean, with summer droughts, a mean annual temperature ranging from 7 °C to 18 °C and a mean annual precipitation of around 400–570 mm (xeric soil moisture regimen). The potential vegetation is dominated by an ilex xeromorphic forest (*Quercus* sp.) to 1800–1900 m, and black pine (*Pinus nigra* subsp. *salzmanii* (Dunal) Franco) at higher altitudes.

A tendency to the intensification of olive groves in the Jaen Province by increasing fertilizers, pesticides, tree density, mechanical harvesting and irrigation, occurred in the last decades. Intensification has favored important processes of soil degradation as the loss of organic matter and accelerated erosion. In view of this situation, since 2003 successive reforms of the Common Agricultural Policy (CAP) has encouraged the farmer to adopt sustainable soil management. Currently, CAP 2014–2020 implements the Good Agricultural and Environmental Conditions (GAEC), some of them can actively promote soil quality, e.g. the GAEC 4 forces the farmer to maintain a minimum ground cover by grass strips in lanes (RD (2014) 1078). Nevertheless, the majority of soil management systems still remove the plant cover by tillage, herbicides or both. Only about a 20% of the olive groves in the Province show a temporary or permanent plant cover (MAGRAMA, 2015).

2.2. Soil data and Land Use Types (LUTs)

We compiled a soil database, explicitly designed for this work, for the olive grove region in the Province of Jaen. This was one of the most complete collections of morpho-pedological data on the study area. A total of seven 1:100,000 soil cartography sheets (Aguilar et al., 1993, 1995, 1997; Delgado et al., 1997a, 1997b, 1997c; Sierra et al., 2003) were used along with other soil studies (de Haro, 1992; Aranda, 1998; Martín-García et al., 2000; Calero et al., 2008, 2009). All of these information sources were to be observed with minimum quality criteria and georeferenced. The soil database provided a total of 131 soil profiles and the morphological and analytical properties commonly handled in pedological works. In this case, 18 field soil morphological indicators (FSMI) and 23 analytical properties were collected. Of the soil profiles, only the surface horizons (Ah and Ap), with a mean thickness of 18 cm, were used to develop the soil quality index. FSMIs were described according to the Schoeneberger et al. (1998) and FAO (2006) field guides, employing the Munsell soil color chart (Munsell Color Company, 1990) to determine color. Eight Land Use Types (LUTs) were defined in the study area soil database. LUT characterization was based on the FAO (2006) Land Use Classification Scheme, including some modifiers for crop type, human influence and vegetation class.

LUTs were described as follows: (1) Little-Disturbed Forest (LDF): small scattered and relic patches throughout the study area with the presence of holm oak (*Quercus ilex* subsp. *ballota* (Desf.) Samp.) forest, often also including other semi-deciduous and deciduous oak species (*Quercus faginea* Lam.; *Quercus pyrenaica* Will.), (2) Mediterranean Xeromorphic Woodland (MXW): holm oak, with an open community structure, more or less altered by human influence, and tending to *dehesa* (traditional forest management, subjected to extensive traditional grazing and scant firewood extraction by selective cutting), (3) Pine Plantation Forestry (PPF): areas subjected to low-intensity forestry use, mainly *Pinus* subsp. (*P. halepensis* Miller, *P. salzmanii* (Dunal) Franco, *P. pinaster* Aiton, *P. radiate* D. Don), in some cases semi-naturalized, (4) Mediterranean Xeromorphic Scrub (MXS): successional stages commonly occupying fire-disrupted MXW, including evergreen scrub such as *Quercus coccifera* L., *Rhamnus* sp., *Retama sphaerocarpa* L., etc., (5) Alpha Grass communities (AG): composed mainly of alpha grass (*Stipa Tenacissima* L.) and/or other tall and medium height Mediterranean perennial grasses with similar ecological status (*Lygeum spartum* L.), which form high-density prairies, (6) Pastures and degraded grassland (PDG), including both the earliest successional stages (short grasses and dwarf-scrubs) and those traditionally used for grazing sheep and goats, (7) Olive groves (OG), and (8) frequent, but scattered Herbaceous Annual Cultures (HC), mainly wheat and barley, and to a lesser extent, corn and cotton. From a pedological view, the soil database includes information about 11 WRB-soil groups (FAO, 2015), which summarize virtually all the soil typologies present in the study area. These include from Arenosols and Gleysols (frequencies of 1%) to Calcisols, Regosols and Leptosols (frequencies of 31, 21 and 15%, respectively).

2.3. Nonlinear Principal Component Analysis with Optimal Scaling (NLPCA)

In Calero et al. (2008), the Categorical Principal Component Analysis (CatPCA[1]) NLPCA algorithm (Gifi, 1990; Meulman and Heisser, 1999) was employed to create a numerical pedological index (PDI) from morphological field soil properties. This procedure was at least as efficient as the methods used to date (*i.e.* Harden, 1982), with the advantage of requiring little expert soil knowledge.

The optimal scaling process was defined as nonlinear transformation of the categorical variables by assigning them quantitative values optimizing the variance accounted for by the whole model (Meulman and Heisser, 1999). The only restriction applied to the transformation was monotonicity, which makes it possible to distinguish between FSMIs measured on an ordinal scale (having an intrinsic categorical order *i.e.*, stickiness: from not sticky to very sticky) from nominal variables not having this restriction. The hue (moist and dry), structure type and texture class were considered to be of the latter type. CatPCA interpretation is similar to the classic or linear principal component analysis (PCA): the vector coordinates of the FSMIs in each component are the square of their component loadings. All the statistical analysis was performed with IBM SPSS 24 (2016).

2.4. Checking the NLPCA solution by bootstrapping

Because the NLPCA was carried out on one particular data set (the Jaen database), the robustness of the solution was examined by the balanced bootstrap option in CatPCA. First, we check the bias of component loadings by comparing the centroid of bootstrap clouds with the component loading of original parent sample. Component loadings are unbiased if these point are close to each other. Second, the sizes of 90% confidence intervals (CIs) for the bootstrap centroids are used to look at the stability of the solution. The solution will be stable if slight changes in the data, such as those produced on the different bootstrap samples, lead to only slight changes in the results (Linting et al., 2007).

2.5. Soil quality indexing with optimal scaling: Field Soil Quality Index (FSQI)

We followed a five-step procedure to calculate and validate the soil quality index. The mathematical details for CatPCA and index development are omitted but can be reproduced by applying the method described by Calero et al. (2008).

Step 1 – Scaling: The first step was the numerical quantification of FSMIs using CatPCA. No previous selection of morphological indicators was made for a minimum dataset, since the categorical nature of FSMIs prevents proper *a priori* application of the statistical tests used for this aim (*i.e.* Kruskall-Wallis test in Andrews and Carroll, 2001). Moreover, since we were also interested in scaling all the morphological indicators for weighting, the minimum dataset approach was not appropriate here. Thus all FSMIs were entered in the CatPCA. CatPCA provided optimal scaling for the categories of every variable, depending on whether the analysis specified for each FSMI was nominal or ordinal. At this point, FSMIs can be accurately correlated with the other numerical indicators by using the Pearson's correlation coefficient.

Step 2 – Selecting the soil quality PC: Once the model has been calculated, the components found can be interpreted in terms of soil quality, as in classical PCA (Shukla et al., 2006). To label and select the principal component most associated with the soil quality, relationships between the LUTs and components were assessed both, graphically (biplots) and statistically, by mean of the Kruskal-Wallis χ^2 test. We choose a non-parametric method because it did not require assumption of normality and homoscedasticity, avoiding any need to transform the data.

Step 3 – Scoring: For a normalized score s_{ij} ranging from 0.1 to 1 for each horizon i and indicator j, the numerical quantifications (optimal scalings) were rescaled with homothetic transformations (Velasquez et al., 2007). According to the relative signs of the loadings in the soil quality component, we used either the *more is better* function, if soil quality increases with component scores:

$$s_{ij} = 0.1 + \left(\frac{q_{ij}-y_{jmin}}{y_{jmax}-y_{jmin}}\right) \times 0.9 \tag{1}$$

or the *less is better*, if soil quality decreases with the component scores:

$$s_{ij} = 1.1-\left(0.1 + \left(\frac{q_{ij}-y_{jmin}}{y_{jmax}-y_{jmin}}\right) \times 0.9\right) \tag{2}$$

where q_{ij} is the optimal scaling for the ith horizon and the jth indicator, and y_{jmin} and y_{jmax} are the minimum and maximum category quantification for the jth indicator. As the scoring was done over the maximum and minimum soil quality levels, s_{ij} should be taken as the percentage of soil quality concerning the reference values, that is, a soil functioning at full potential in the studied area (Seybold et al., 1998).

Step 4 – Indexing: Integration of normalized scores into a weighted index. This step includes the selection of the weights to be used in the index. Several strategies have been employed (Andrews et al., 2004; Sharma et al., 2005). Here, an approach similar to Velasquez et al. (2007) was followed. The jth-FSMI weight w_j ($j = 1, \ldots, m$) in the index is the vector coordinate of this indicator in the soil quality component, but we used the bootstrap averages of vector coordinates as weights instead of those based on the sample observations. Finally, the FSQI was calculated for soil database horizons ($i = 1, \ldots, n$) as a *weighted additive index* of the FSMI weighting factors w_j and the normalized scores s_{ij} obtained in the previous step:

$$\mathrm{FSQI}_i = \sum_{j=1}^{m} s_{ij} w_j \tag{3}$$

rescaling again to one. As a last step, the statistical significance between FSQI values for the different LUTs was assessed with the non-parametric Mann-Whitney U test.

2.6. FSQI evaluation

Once the FSQI was calculated, it was tested in olive groves in the Atanor valley, at a site previously well studied by our research group (Aranda et al., 2011, 2014; Calero et al., 2013) which was not included in the original database. This evaluation set was compiled to determine how well the index discriminates between two types of soil management in olive groves (Step 5), while avoiding overfitting the model. The groves are located in the southeast of Jaen province in the Sierra Magina Natural Park (from 37°41′ to 37°50′N latitude and 3°20′ to 3°37′W longitude). Physical conditions are similar to those in the rest of the province, although the climate is slightly drier and colder than the provincial average (470 mm, 17.3 °C) and the slopes are steeper (from 23 to 32%). Conventional olive groves (COG) coexist with one of the oldest organic olive groves (OOG) in Spain (30 years old, certified by the CAAE, the certification institution for organic production implementing EU regulations 2092/91 and 1806/99). We selected an organic orchard to our index evaluation despite the low representativeness of these systems in Jaen olive groves (less than 2%, according to MAPAMA, 2016) because we know accurately its long history of

[1] Statistical Package for Social Sciences Data Theory Scaling System Group (DTSS), Categorical Principal Component Analysis, IBM@ SPSS@ Statistics Version 24, Armonk, New York, USA.

plant cover. Thus, the organic orchard from the Atanor valley is a very suitable example of continuous sustainable soil management over the last decades, in a variable context in which soil use have been changing following the intensification trends of the modern oliviculture and the successive CAP guidelines. In COG, a non-tillage system with extensive application of herbicides maintains a bare, weed-free soil, all year-round. OOG are characterized by no mineral fertilization or pesticides, no-tilled soils and animal manure that it is incorporated about every four years. In OOG, The plant cover, composed of native weeds, remains all year-round, although is controlled by mechanical mowing (shallow cultivator) along the spring with the aim to reduce water stress and probability of fire. Ten A horizons from each of the two olive soil management classes (COG and OOG, N = 20) were sampled and the morphological properties estimated. FSMIs were described the same way as in the Jaen database. Then the categories found in each horizon were transformed using the CatPCA optimal scalings, to arrive at the normalized scores. Finally, the normalized scores were integrated in the FSQI using the same weighting factors. Statistical differences between the FSQI means for both treatments were determined by the Student's-*t* test ($P < .05$).

3. Results

3.1. CatPCA model and optimal scalings

A model with three principal components with eigenvalues higher than one was selected, taking into account the interpretability of components and the variance-accounted-for. Component loadings and variance explained by components and individual variables are shown in Table 1. The mean bias for component loadings, estimated according to Van Ginkel et al. (2011), was close to cero and similar to the reported by these authors (−0.00). Moreover, a diagnostics of the stability of component loadings can be checked in Table 2. In general, the model showed an acceptable stability, because the mean size of the 90% CIs for component loadings along dimensions was relatively small (< 0.4),

Table 2
Sizes of the 90% confidence intervals for bootstrap component loadings.

Variable	90% Confidence interval (CI) size*			
	PC1	PC2	PC3	Average
Moist hue	0.190	0.255	0.132	0.192
Moist value	0.138	0.295	0.148	0.194
Moist chroma	0.410	0.306	0.149	0.288
Dry Hue	0.195	0.260	0.142	0.199
Dry value	0.150	0.357	0.155	0.221
Dry chroma	0.237	0.218	0.131	0.195
Structure type	0.281	0.528	0.225	0.345
Structure size	0.680	0.761	0.376	0.606
Structure grade	0.423	0.363	0.332	0.373
Dry consistence	0.300	0.268	0.297	0.288
Moist consistence	0.393	0.414	0.378	0.395
Plasticity	0.314	0.312	0.266	0.297
Stickiness	0.300	0.204	0.260	0.255
Pore abundance	0.488	0.557	0.528	0.524
Pore size	0.316	0.545	0.219	0.360
Root abundance	0.245	0.309	0.180	0.245
Root size	0.545	0.763	0.338	0.549
Texture class	0.471	0.653	0.388	0.504
Average	0.338	0.409	0.258	**0.335**

* CI size = |upper CI limit − lower CI limit|.

Table 1
Categorical Principal Component Analysis (CatPCA) of field morphological soil indicators: component loadings and variance explained by components and variables for the parent and the bootstrapped samples.

Principal Component	PC1		PC2		PC3		From the Parent sample	
	Parent sample	Bootstrap average	Parent sample	Bootstrap average	Parent sample	Bootstrap average	*VAF_j*	*$PVAF_j$*
Moist hue (n)	−0.724	**−0.745**	0.491	**0.471**	−0.233	**−0.213**	0.819	4.551
Moist value (o)	0.851	**0.845**	0.057	**0.054**	−0.362	**−0.343**	0.859	4.771
Moist chroma (o)	−0.134	**−0.121**	0.527	**0.523**	−0.633	**−0.610**	0.697	3.873
Dry Hue (n)	−0.722	**−0.742**	0.480	**0.460**	−0.223	**−0.205**	0.801	4.450
Dry value (o)	0.817	**0.815**	0.012	**0.015**	−0.413	**−0.393**	0.839	4.659
Dry chroma (o)	−0.444	**−0.433**	0.641	**0.628**	−0.491	**−0.478**	0.849	4.714
Structure type (n)	0.661	**0.663**	0.161	**0.164**	−0.114	**−0.096**	0.476	2.645
Structure size (o)	−0.206	**−0.145**	0.225	**0.190**	−0.106	**−0.062**	0.105	0.581
Structure grade (o)	−0.103	**−0.053**	0.471	**0.502**	0.530	**0.493**	0.513	2.852
Dry consistence (o)	0.275	**0.280**	0.682	**0.664**	0.356	**0.356**	0.668	3.708
Moist consistence (o)	0.212	**0.208**	0.482	**0.465**	−0.209	**−0.080**	0.321	1.786
Plasticity (o)	0.418	**0.414**	0.528	**0.523**	0.425	**0.381**	0.633	3.519
Stickiness (o)	0.225	**0.241**	0.678	**0.657**	0.552	**0.503**	0.814	4.524
Pore abundance (o)	−0.156	**−0.206**	−0.194	**−0.168**	0.419	**0.334**	0.238	1.322
Pore size (o)	0.294	**0.280**	−0.149	**−0.092**	−0.206	**−0.211**	0.151	0.838
Root abundance (o)	−0.693	**−0.672**	−0.219	**−0.216**	0.346	**0.339**	0.648	3.599
Root size (o)	−0.323	**−0.290**	0.174	**0.195**	−0.088	**−0.143**	0.142	0.789
Texture class (n)	−0.527	**−0.489**	−0.458	**−0.469**	−0.198	**−0.189**	0.527	2.925
***VAF_s* (eigenvalue)**	4.460	**4.397**	3.245	**3.123**	2.393	**2.074**	10.099 (**9.595**[†])[a]	
***$PVAF_s$* (percent)**	24.779	**24.430**	18.030	**17.350**	13.297	**11.522**	56.106 (**53.303**[†])[b]	
#	80.159***	**86.46*****	10.139[ns]	**11.44**[ns]	16.595*	**16.37***		

(n) = nominal variable; (o) = ordinal variable.
VAF_j = Variance accounted for by the jth-indicator. $PVAF_j$ = Percentage of variance accounted for by the jth-indicator = ($VAF_j \times 100$)/18 (18 is the number of indicators).
VAF_s = Variance accounted for by the sth-component. $PVAF_s$ = Percentage of variance accounted for by the sth-component = ($VAF_s \times 100$)/3 (3 is the number of components).
**Significant at $P < .01$.
[a] VAF = Σ VAF_j.
[b] PVAF = Σ $PVAF_j$.
\# Mean PC-score differences between Land Use Types: χ^2 for Kruskall-Wallis test.
* Significant at $P < .05$.
*** Significant at $P < 0.001$
[ns] not significant.
[†] (In brackets) Eigenvalue and percentage of variance accounted for by the bootstrapped samples.

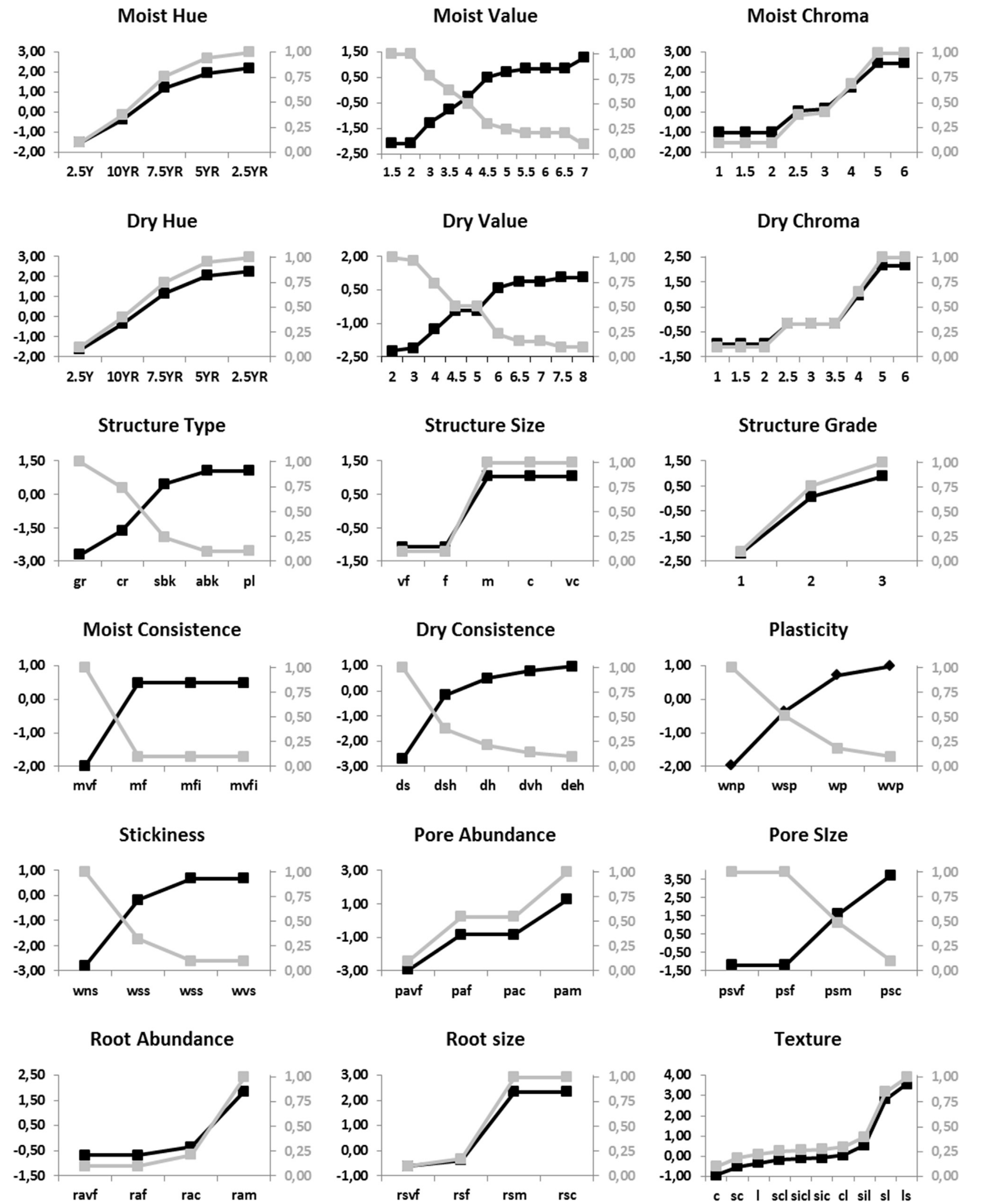

Fig. 1. Optimal scalings (black line, left axis) and normalized optimal scores (grey line, right axis) of field soil morphological indicators. For category label abbreviations see Table A.1 (Appendix A).

in the order of those given by Timmerman et al. (2007) for the same bootstrap method (Procrustean rotation).

The three components explained 56% of system variance. The first explained 25%, the second 18% and the third 13%. This is only a slightly lower total percentage of variance explained than the linear or classic PCAs of analytical soil quality indicators for olive grove soils studied by Gómez et al. (2009), but higher than the morphological indicators by Velasquez et al. (2007). On the other hand, the amounts of variance explained by individual variables fluctuated between 4.8% for moist value and 0.6% for structure size. Color indicators (values), which were considered by MacEwan and Fiztpatrick (1996) to be rather sensitive to change in soil use, explained the most variance. Values were also the indicators that showed the smallest biases and one of the largest stabilities (shorter CI sizes) of all variables (Table 2). Furthermore, the explanatory power of consistence indicators (stickiness, plasticity, dry consistence) is also high.

The optimal scalings given by the model are shown in Fig. 1. It was possible to observe three types of ordinal variable scaling leading to varying degrees of nonlinearity: from gentle nonlinear trends (e.g., dry and moist hues) to strongly nonlinear (e.g., structure size). Highly nonlinear functions were characterized by sudden leaps in category quantification. As an extreme example of this, the moist consistence indicator showed a quantified value of -1.981 for very friable, while there was no difference among the rest of the categories (0.491). Because a monotonically increasing restriction between categories was imposed on the ordinal variables, this has to be interpreted as the centroids for the categories friable, firm and very firm, representing the cloud of object points (horizons) so labeled in the *p*-component space, yield the same value after their projection onto the vector representing this indicator (Linting and Van der Kooij, 2012). It could also be said that the very friable soils are more discernible, in terms of moist consistence, than those with other moist consistence categories.

The nominal attributes structure type, hue (moist and dry) and texture class did not have any *a priori* ordination of their categories when entered in the CatPCA. Their ordering must be interpreted according to the optimal scalings shown in Fig. 1. Hues order followed a logical gradient from the yellow (2.5Y) to red cards (progressively redder: 10YR, 7.5YR, 5YR and 2.5YR). The response was almost linear from 2.5Y to 5YR, but then decreased to 2.5YR, suggesting that this difference is poorly perceived by who describes the color. It might be explained by the strong dependence of red hues on daylight conditions in field color determination (Sánchez-Marañón et al., 2011). The structure-type ordering given by the method goes from granular and crumbly to angular blocky and laminar, with little response to subangular blocky, angular blocky and platy. This indicates stronger discriminating power for biogenic structures (mainly granular structure) than any of the other types. Finally, the texture classes were loosely ordered on a complex gradient going from heavy (clayey, sandy clayey) to light textures (sandy loam and loamy sand), but the response was important only for the latter, so they are probably more relevant in soil quality across the study zone.

Table 1 also enables the principal components to be interpreted. The first component is positively correlated with moist and dry value (component loadings of 0.851 and 0.817, respectively) and structure type (loadings of 0.661), and negatively with moist and dry hues (loadings of −0.724 and −0.722, respectively) and root abundance (loadings of −0.693). Thus as their value increases, implying both loss of organic matter and increase in carbonates in the surface horizon, root abundance decreases. The latter can be inferred from the correlation study, where some analytical variables were included (Table 3). Moist value was significantly correlated positively with carbonates ($r = 0.676$, $P < .001$), and inversely with organic carbon ($r = -0.709$, $P < .001$) and root abundance ($r = 0.673$, $P < .01$). The structure–type order had low scores on PC1 for the granular and crumbly classes and high for platy, which is coherent with a loss of organic matter and soil quality from tillage (the platy structure is characteristic of compacted soils). The order of hues from 2.5Y to 2.5YR shows a rational trend toward redder colors because 2.5Y (yellow) is a frequent hue in deeply eroded profiles such as Ck horizons and C horizons over marls. This component showed a close relationship with the soil quality, which decreased with increasing component scores (fewer roots, lighter, tendency to platy structure, etc.). The second component was positively correlated with stickiness (loading of 0.678), dry consistence (loading of 0.682) and dry chroma (loading of 0.641) and

Table 3
Some significant correlations between transformed field soil morphological indicators and analytical properties in the Jaen database.

x	*y*	Equation	*r*	
Moist value	Organic carbon	$y = -1.2175x + 7.4817$	−0.709	***
	Carbonates	$y = 12.202x - 16.372$	0.676	***
Texture class	Exchangeable calcium	$y = -6.0914x + 29.372$	−0.608	***
	pH	$y = -0.9917x + 7.7453$	−0.515	***
Root abundance	Organic carbon	$y = 0.2393x - 0.5963$	0.543	***
	Moist value	$y = -0.6658x + 0.0046$	−0.673	***
	Structure type	$y = -0.4854x - 0.029$	−0.476	**
Plasticity	Stickiness	$y = 0.6504x + 0.0125$	0.650	***
	Texture class	$y = -0.4539x - 0.0334$	−0.496	***

Significance: $^{*}P < .05$. $^{**}P < .01$. $^{***}P < .001$.

negatively with texture class, despite not having a particularly high load on this component (−0.458). From these loadings and the order of the texture classes in Fig. 1, it may be deduced that an increase in texture generally implies a decrease in those properties related with the clay content, as the stickiness, consistence and chroma. This component may be related to an increase in fine-soil content and probably is not easily related to the soil quality influenced by the user, that is, the dynamic soil quality. The third component was negatively correlated with the moist chroma (load of −0.633) and positively with the structure grade (load of 0.530) and stickiness (load of 0.552). Chroma and structure grade might be influenced by both pedogenesis and soil management, so it could be related to a certain extent with the dynamic soil quality, but much more ambiguously than PC1.

The centroids-components loadings (vector) biplots, when including LUT as a supplementary variable with multiple nominal scaling level, are shown in Fig. 2. The low angles among the vectors of dry and moist values and structure type, and the centroids for the crop units, HC and OG, reveal close interrelationships between these indicators and crops. The angles and lengths of the vectors on one specific axis expressed the correlation of each indicator with the corresponding component. Thus, dry and moist values and structure type are not only closely related with HC and OG, but also with PC1. Less-altered natural and semi-natural LUTs are better ordered following other soil indicators, which seem more related with pedogenesis, as dry and moist hues, structure grade or texture (Calero et al., 2008). Moreover, projecting centroids on axes allows identifying the component that better discriminates between LUTs. Clearly, centroid coordinates on PC1 are more homogeneously distributed along the axis and show less overlap between them. The Kruskal-Wallis test supported this interpretation, because it was most significant for PC1 ($P < .001$, Table 1). Since the main interest of the FSQI is to evaluate the quality of crops (specifically olive groves), PC1 was selected as the soil quality component, because is simultaneously related with HC, OG, dry and moist values and structure type.

3.2. Scoring and FSQI

Fig. 1 shows the scoring of the optimal scalings (Step 3). The numerical values of the optimal scalings were normalized according Eqs. (1) and (2) from 0.1 (poorest soil quality) to 1 (best soil quality), depending on the relative signs of the loadings of each indicator in PC1. The normalized scores and the square of bootstrapped component loadings (vector coordinates) were employed for the FSQI (Step 4, Eq. (3)). As the index integrates normalized scores, a value of 1 (100%) should be interpreted as the maximum soil quality regarding the reference values from the Jaen database. Mean FSQI values for horizons in each LUT applied to the 131 sites of the Jaen soil database are shown in Table 4.

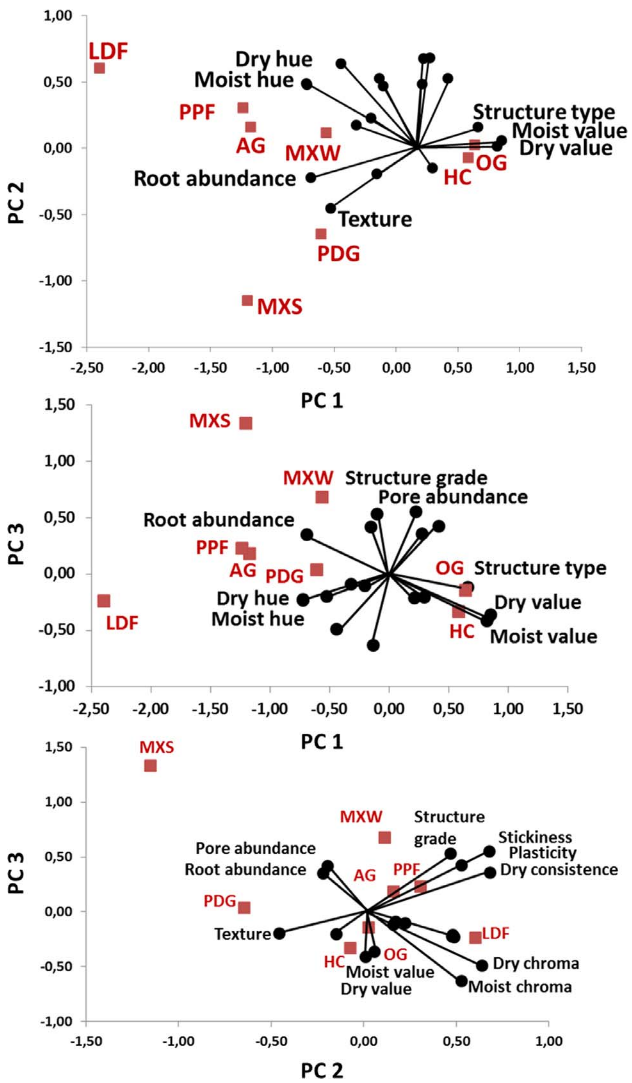

Fig. 2. Biplots of LUT category centroids (in red) and component loadings (in black) from CatPCA. LDF = Little-disturbed forest; AG = Alpha grasses; PPF = Pine plantation forestry; MXW = Mediterranean xeromorphic woodland; MXS = Mediterranean xeromorphic scrubland; PDG = Pastures and degraded grassland; HC = herbaceous cultures; OG = Olive groves. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4
FSQI values (means and standard deviations SD) for land use types.

	N	*Mean*	*SD*
LDF	5	0.839	0.098
AG	5	0.680	0.094
PPF	6	0.670	0.088
MXW	16	0.615	0.100
MXS	5	0.524	0.125
PDG	9	0.500	0.085
HC	14	0.290	0.078
OG	71	0.287	0.092

LDF = Little-disturbed forest; AG = Alpha grasses; PPF = Pine plantation forestry; MXW = Mediterranean xeromorphic woodland; MXS = Mediterranean xeromorphic scrubland; PDG = Pastures and degraded grassland; HC = herbaceous cultures; OG = Olive groves.

It may be seen that the index enables discrimination of LUTs, which were ordered from most to least human disturbance and plant successional stage. This arrangement can therefore be understood based on the soil quality. The statistical significance was tested by the Mann-Whitney *U* test, comparing LUTs two by two (Table 5). Four groups, from highest to lowest soil quality, can thus be defined. The first group is composed only of LDF with evergreen (Holm oak *Quercus ilex ballota*) and deciduous (Portuguese oak *Quercus faginea*) climax forests, with a mean FSQI significantly higher than all the other LUTs ($P < .05$). The second set includes woody areas with pines (PPF) and holm oaks (MXW), the latter moderately altered with an open structure (dehesa) and the alpha grass meadows (AG). The third group was composed of "stage communities" of tall (MXS) and dwarf (PDG) xeromorphic scrub, but MXS was not significantly different from the second group ($P = .075$ and .082 with MXW and PPF, respectively). Therefore, the MXS units can be assigned to an intermediate soil quality between woodland areas and scrub landscapes. Finally, a fourth and clearly differentiated group is composed of agricultural lands ($P < .001$), which includes olive groves (OG) and annual cultures (HC) with the lowest FSQI means (below 0.300).

3.3. FSQI evaluation

The last step was evaluation of the index with samples not previously used in its development. New field morphological data were taken to validate the FSQI (data are shown in Table A.1, Appendix A) by finding out whether it could distinguish between soil management in olive groves (conventional COG and organic OOG). All the steps enumerated above were applied to these data, including optimal scaling and scoring of horizon categories based on plots from Fig. 1. The resulting FSQIs for COG, with a mean value of 0.278 and a standard deviation of 0.161, and OOG, with a mean value of 0.463 and a standard deviation of 0.148, are shown in the Box-and-whiskers plot in Fig. 3 (Student's *t* significant, $P = .016$). The mean FSQI for the ten conventional A horizons sampled was similar to that of olive groves (0.287) from the Jaen database. However, the mean OOG FSQI increased to 0.473, a score close to MXS (0.524) scrubland and PDG (0.500) in the database.

3.4. FSQI web service

Finally, we have made FSQI computation available for users. Anyone in the study area interested in calculating this index can go to the URL http://fsqi.ujaen.es and complete the form (Fig. 4, left) in any web browser. When applied, the method consists of a series of values characterizing the soil being analyzed (Fig. 4, right). These morpho-pedological values are entered in a simple web form. The values are mapped into the corresponding scores which will be, once the form is submitted, weighted and linearly combined to compute the final quality index. The index is returned to the user on a web page showing this value in terms of a quality percentage for easy interpretation (Fig. 5).

The data is sent to our servers where the index is computed remotely and returned to the user. This service has been developed with standard web technologies (HTML, CSS3, Javascript), so no special requirements are expected from its users apart from a modern web browser. On the server side, we have open-source architecture (Linux + Apache + PHP + SQLite). The script used to compute the index is written in PHP language and any submission is stored in a SQLite database for future analytics. The scores are coded as values in the HTML form. The script receives the data from the form and calculates the linear combination of scores and factors. This value is normalized and the final index is presented to the user as a percentage. The full architecture is shown in Fig. 6.

Now we are developing a more elaborated decision support system (Aronson et al., 2005) to allow the user to enter the data from their soils and get the index on mobile devices, as the current system does, but also to maintain records of the different measurements with geospatial coordinates, so the qualities can be drawn on a map. The app developed will be intuitive and will guide the user on the process of entering the needed information, to ensure precise data taking. According to the

Table 5
FSQI differences in Land Use Types (*U* of Mann-Whitney's-test).

	MXW	PPF	MXS	AG	PDG	HC	OG
LDF	5.0 (−2.891)**	2.0 (−2.379)*	0.0 (−2.619)**	2.0 (−2.200)*	0.0 (−3.007)**	0.0 (−3.242)***	0.0 (−3.719)***
MXW		31.0 (−1.253) n.s	18.0 (−1.817) n.s.	23.0 (−1.404) n.s	25.0 (−2.661)**	0.0 (−4.656)***	5.0 (−6.169)***
PPF			5.0 (−1.826) n.s	15.0 (0.000) n.s	5.0 (−2.595)**	0.0 (−3.464)***	1.0 (−4.029)***
MXS				2.0 (−2.193)*	20.5 (−0.267) n.s	1.0 (−3.148)***	17.0 (−3.363)***
AG					3.5 (−2.539)**	0.0 (−3.240)***	0.0 (−3.719)***
PDG						4.0 (−3.718)***	33.5 (−4.355)***
HC							496.0 (−0.012) n.s

LDF = Little-disturbed forest; AG = Alpha grasses; PPF = Pine plantation forestry; MXW = Mediterranean xeromorphic woodland; MXS = Mediterranean xeromorphic scrubland; PDG = Pastures and degraded grassland; HC = herbaceous cultures; OG = Olive groves.
Z values (in brackets).
n.s = not significant.
* Significant at P < .05.
** Significant at P < .01.
*** Significant at P < .001.

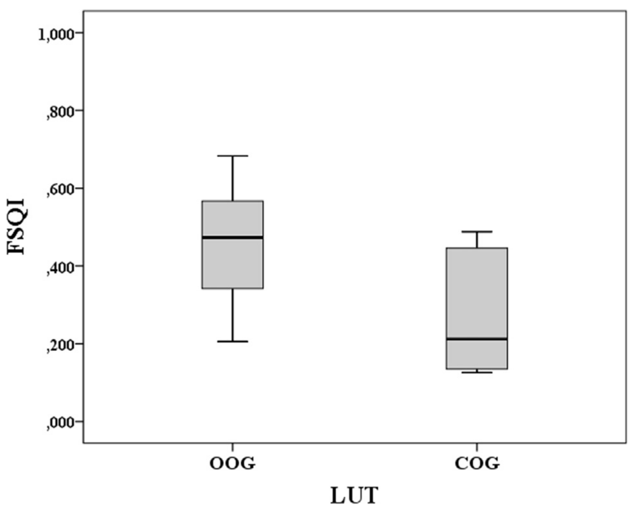

Fig. 3. Box-and-whiskers plot of Field Soil Quality Index (FSQI) for Organic olive groves (OOG) and Conventional olive groves (COG) in the evaluation set (Atanor valley). LUT = Land Use Type.

characteristics of the soil and a knowledge base at the backend, the system will help the user to understand the index and will suggest different interventions to improve soil conditions. The collected data from different users will be suitable for analysis and data mining as an additional value from this cloud-based architecture.

4. Discussion

The results highlight the relationship between the morpho-pedological attributes and soil quality goals, as discussed by other authors (MacEwan and Fiztpatrick, 1996). Thus, except for the hue, the FSMIs explaining most of the variance in the soil quality component are the dynamic, time-dependent attributes: value, root abundance and structure (MacEwan and Fiztpatrick, 1996). The dynamic nature of these indicators is correlated with the soil organic carbon in the surface horizons (Table 3), which studies on soil quality indexing of olive groves consider the main pedological indicator (Gómez et al., 2009; Álvarez et al., 2007). Hue and some other properties related to soil quality (e.g. texture class or plasticity) could also be considered inherent indicators. These could be dependent on the soil parent material (e.g., marls and limestone colluvium in the Atanor valley) and probably influenced the wide dispersion of FSQI values for COG horizons in the evaluation set (Fig. 3), but the index was sensitive to management practices. In general, because olive groves are concentrated over Calcisols and Regosols (> 50%), it is expected that certain characteristics of soil quality indicators are related to soil typology rather than to soil management. Applying an analytical SQI, Marzaioli et al. (2010) found a LUTs distribution similar to ours, in soils of Southern Italy very different (Mollic-Vitric Andosols). Nevertheless, the effect of parent material and pedogenesis should be considered in regions with other patterns of crop distribution.

To date, there have been few soil quality studies dealing with single morphological properties. As morpho-pedological attributes are included in any soil survey database from regional to national resource inventories, this could facilitate their use in soil quality assessment at this scale. This procedure could thus improve national soil quality monitoring programs, such as those described by Sparling and Schipper (2004), which are based exclusively on analytical indicators. This would seem to be the most suitable way for growers to assess soil quality in their groves when little knowledge of the soil is available, even more when our results show that an adequate treatment of the morpho-pedological data can explain similar percentages of the system variability that the analytical ones. Some authors have suggested score cards for untrained farmers (Romig et al., 1995), but this type of data would be more difficult to interpret and merge with scientific knowledge than pedological data (Calero et al., 2005; Delgado et al., 2009). Farmers and land managers should still receive some training in soil science (soil color card use, etc.) before they can use the index proposed here effectively. Such courses could be economical and easily taught (compared to physical and chemical soil measures). Morphological indices could complement other complex measures of soil quality that are completely beyond the reach of olive grove farmers, such as the enzymatic activities carried out by García-Ruiz et al. (2012).

The most critical indexing procedure may be the scoring step. Because of their flexibility, nonlinear functions seem to be the best choice for use with different soils and conditions, but require more profound expert knowledge due to the parameters that must be adjusted (Andrews et al., 2002, 2004). For example, in their olive grove soil quality ("soil degradation") index, Gómez et al. (2009) used nonlinear algorithms with at least five parameters and logic statements as scoring functions, but not all properties studied have clear reference values for scoring functions in olive groves (e.g. bulk density). In this case, the authors resorted to general interpretation of indicator tables (USDA, 1999, e.g., for setting the parameters for the bulk density scoring function mentioned). On the other hand, Marzaioli et al. (2010) used a simpler linear algorithm but needed to set the reference values for some indicators (e.g., pH) after a thorough review of previous studies (none of which involved olive groves).

In our study, these expert knowledge-based procedures were replaced by a more automated method, optimal scaling functions, which were transformed into true scoring functions by using the categorical principal component most closely related to the soil quality. The latter was defined in terms of its capacity to discriminate among LUTs. Shukla et al. (2006) used a similar procedure to identify the appropriate soil

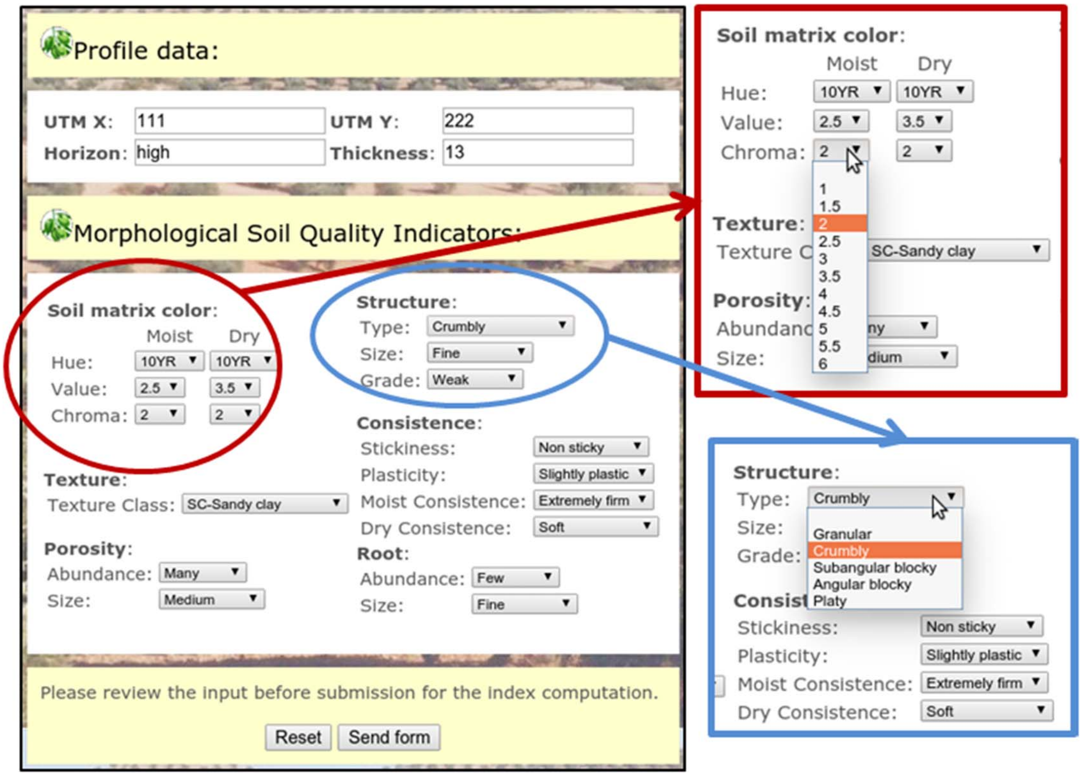

Fig. 4. Screen capture of the web form (left). Some possible color and structure values are also shown (right).

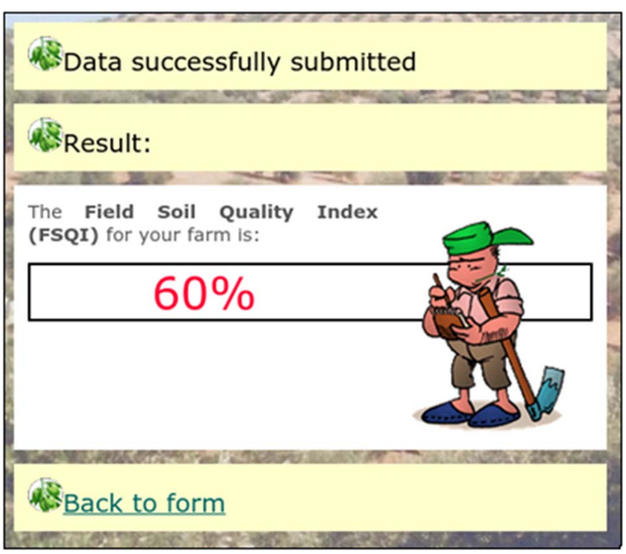

Fig. 5. Web page showing a result of FSQI calculation.

quality indicators from PCA and analysis of variance of the different treatments, but only included analytical indicators. Moreover, many indices use the PCs from PCA not only for assessing indicators, but also for weighting them (Andrews et al., 2002; Sharma et al., 2005), where the goodness depends on the variance explained by the model. Our procedure is based on premises which are not very different from the usual indexing techniques, with the additional advantage of avoiding much of the subjectivity involved in conventional scoring.

An important result of this work is that it supports soil quality aggradation through the organic management of olive groves with a long history of plant cover in the evaluation area. These results have already been reported by other authors (Álvarez et al., 2007; Gómez et al.; 2009; García-Ruiz et al., 2012; Marzaioli et al., 2010). As with analytical indicators, some time of suitable management (*i.e.* plant cover) is probably needed to give significant results for the FSQI. In the present study it can be estimated from FSMIs, giving a single useful value for the evaluation set: 18% (from a FSQI value of 0.28 in COG to 0.46 in OOG). This increase in soil quality by the organic farming applied in the Atanor valley has also been found in several previous studies (Aranda et al., 2011, 2014; Calero et al., 2013). Despite organic farming are considered the best practice regarding environmental sustainability

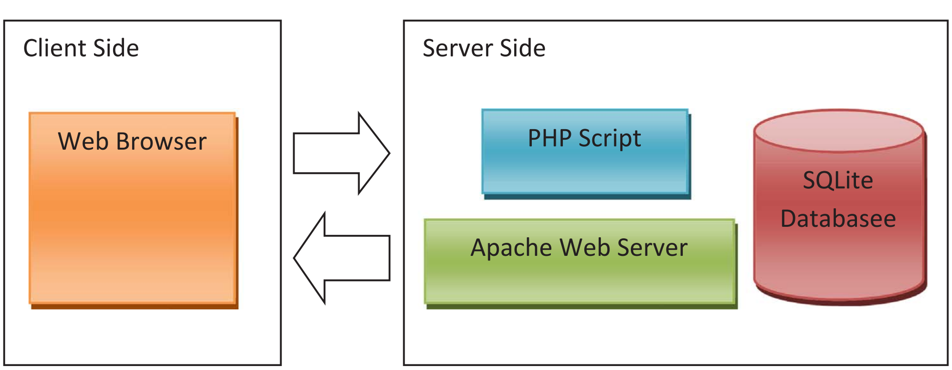

Fig. 6. FSQI web service architecture.

(Parra-López et al., 2008), some non-organic systems, as integrate production or protected designation of origin, implement nowadays a suitable plant cover and other sustainable soil management practices (Carmona-Torres et al., 2014), so they should also show increases in the FSQI. The index thus demonstrates its agroenvironmental applicability in the geographical area where it was defined. Of course, like any indexing procedure, proper extrapolation depends on the identification and specification of site-dependent factors in the study area (Bastida et al., 2008), but the suitability of the procedure allows it to be rapidly exported and tested in other areas or scales.

5. Conclusions

The methodology described in this study for developing and calculating the Field Soil Quality Index (FSQI) is based on an easily accessible NLPCA algorithm (CatPCA) and some simple statistical tests, which require little previous knowledge of the soils in the study zone. The index yielded consistent ecological results: classification of land use types (LUTs) by the extent of human alteration they have undergone (from little disturbed forest to cultivation). Moreover, it was properly evaluated in an agro-environmental context of interest (olive groves in southern Spain), finding significant amelioration of soil quality from organic management. The applicability of this methodology to soil quality assessment must be emphasized, especially the advance in automation of the scoring functions, which helps the standardization of soil quality indicators. However, the main advantage of the FSQI may be that it is derived from user-friendly data. This enables this indexing procedure to be applied in poorly characterized countries or crops, in a way that might be useful to growers and land managers. This type of numerical and quantitative approach to soil quality could be highly useful for modeling and prediction in future physical, agronomical or socio-economic scenarios.

Acknowledgements

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Appendix A

See Table A.1.

Table A.1
Morpho-pedological data for evaluation (Atanor valley).

	Texture class	Color		Structure	Consistence				Roots		Pores	
		Dry	Moist		Dry	Moist	Stickiness	Plasticity	Abundance	Size	Abundance	Size
OOG-1	cl	7.5YR 4/4	7.5YR 3/3	sbk2m	dsh	mf	wss	wnp	rac	rsfn	pac	psfn
OOG-2	cl	10YR 5/4	10YR 4/4	sbk2m	dh	mf	wss	wsp	ram	rsfn	pac	psfn
OOG-3	cl	10YR 4/4	10YR 3/6	cr2f	dsh	mf	wns	wnp	ram	rsfn	pac	psfn
OOG-4	cl	10YR 5/4	10YR 4/4	cr3f	dsh	mvf	wss	wnp	rac	rsvfn	paf	psvfn
OOG-5	l	10YR 6/4	10YR 4/4	cr2m	ds	mvf	wns	wnp	ram	rsvfn	pac	psfn
OOG-6	cl	2.5Y6.5/5	2.5Y4.5/5	cr2c	dsh	mvf	wss	wsp	raf	rsfn	pavf	psvfn
OOG-7	cl	10YR 6/4	10YR 4/5	cr2m	dh	mf	wss	wnp	raf	rsfn	paf	psfn
OOG-8	l	2.5YR 6/3	2.5YR 4/3	cr2m	dh	mf	wns	wnp	raf	rsfn	paf	psvfn
OOG-9	l	2.5Y6.5/3	2.5Y 4.5/3	sbk2m	dh	mf	wss	wsp	raf	rsfn	paf	psvfn
OOG-10	cl	10YR 6/4	10YR 4/4	gr2m	dh	mf	wss	wsp	rac	rsfn	pac	psm
COG-1	cl	10YR 7/3	10YR 5/3	abk2m	dh	mf	wss	wnp	ravf	rsfn	pavf	psvfn
COG-2	cl	7.5YR 6/6	7.5YR 4/6	sbk2m	dh	mf	wss	wsp	ravf	rsvfn	paf	psvfn
COG-3	sic	7.5YR 5/6	7.5YR 4/4	abk2m	dh	mf	wss	wp	ravf	rsfn	pavf	psvfn
COG-4	c	2.5Y 8/1	2.5Y 7/2	sbk2f	ds	mvf	wss	wp	ravf	rsvfn	paf	psvfn
COG-5	scl	2.5Y 8/1	2.5Y 7/1	sbk1f	ds	mvf	wss	wp	n.d	n.d	pavf	psvfn
COG-6	cl	2.5Y 8/1	2.5Y 7/2	sbk1m	dh	mf	wss	wsp	n.d	n.d	paf	Psfn
COG-7	cl	7.5YR 6/4	7.5YR 4/6	abk1c	dh	mf	wss	wsp	raf	rsfn	pac	Psfn
COG-8	cl	2.5Y 8/1	2.5Y 7/2	abk2m	dsh	mf	ws	wsp	ravf	rsvfn	paf	Psfn
COG-9	l	2.5Y 8/1	2.5Y 7/2	sbk1m	dh	mf	wss	wsp	n.d	n.d	pavf	psvfn
COG-10	c	7.5YR 6/4	7.5YR 4/6	abk2m	dh	mf	ws	wsp	n.d	n.d	paf	psvfn

Texture class: c: clay; sc: sandy clay; l: loam; scl: sandy clay loam; sicl: silty clay loam; sic: silty clay; cl: clay loam; sil: silty loam; sl: sandy loam; ls: loamy sand. *Structure type*: gr: granular; cr: crumbly; sbk, subangular blocky; abk, angular blocky; pl: platy. *Structure grade*: 1: weak; 2: moderate; 3: strong. *Structure size*: vf: very fine; f: fine; m: medium; c: coarse; vc: very coarse. *Dry consistence*: ds: soft; dsh: slightly hard; dh: hard; dvh: very hard; deh: extremely hard. *Moist consistence*: mvf: very friable; mf: friable; mfi: firm; mvfi: very firm. *Stickiness*: wns, non-sticky; wss, slightly sticky; ws, sticky; wvs: very sticky. *Plasticity*: wnp, non-plastic; wsp, slightly plastic; wp, plastic; wvp: very plastic. *Root abundance*: ravf: very few; raf: few; rac: common; ram: many. *Root size*: rsvf: very fine; rsfn: fine; rsm: medium; rsc: coarse. *Pore abundance*: pavf: very few; paf: few; pac: common; pam: many. *Pore size*: psvf: very fine; psfn: fine; psm: medium; psc: coarse. n.d.: not detected.

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