Original Research Article

Assessment and comparison of soil quality using principal components analysis (PCA)& expert opinion(EO) methods in different Rice-based cropping systems in *Alfisol*

Abstract

The present study was undertaken to assess and compare soil quality using principal components analysis (PCA) and expert opinion (EO) methods in different rice-based cropping systems in *Alfisol*. In both the PCA and EO methods rice cultivation in rotation with legumes (chickpea and field pea) sustained significantly better soil quality than that of RW and RF cropping systems and established a good relationship between soil quality index (SQI) and defined soil functions. The study confirmed that the integration of legumes into the rice-based cropping systems will ensure the maintenance of soil quality and environmental stability under intensive cultivation. However, the PCA method was found comparatively better for soil quality assessment in the North Hill region.

Keywords: soil quality, PCA, EO, Rice-based cropping

Introduction

Soil quality indicates its functionality, which indicates what soil can do for plant, human and animal health. Soil quality influences basic soil functions including medium for plant growth, regulator of water supplies, recycler of raw materials, and habitat for soil organisms (Karlen *et al.* 1997 and Vasu *et al.* 2016). The attribute of high soil quality is to keep up high profitability without evident soil or ecological debasement (Govaerts *et al.* 2006). Acton and Gregorich (1995) figure the actual interpretation of soil quality is "the suitability of soil to support crop growth without causing soil degradation or other damage to the environment." Soil quality is specified through the interaction of specific quantifiable biological, chemical, and physical qualities of soil.

Various soil quality assessment methods have been created like soil quality index ways (Qi *et al.*2009; Marzaioli *et al.*2010a; 2006; Mohanty *et al.*2007; Masto *et* *al.* 2008 and Sharma *et al.* 2008), soil quality test unit and card design (Ditzler and Tugel 2002), multiple variable indicator kriging methods (Nazzareno and Michele 2004), the active changes of soil quality exemplars (Larson and Pierce 1994), visual soil assessment (Mueller *et al.*2009; Shepherd 2000, 2009 and Ball *et al.*2007) and geo statistical methods (Sun *et al.* 2003). However, at present the minimum data set (MDS) based soil quality index (SQI) method is most widely applicable because of its easy-to-use and quantitative flexibility (Andrews *et al.* 2002 and Qi *et al.* 2009). The soil quality index provides a single score/index and a minimum set of indicators to easily monitor soil health. Considering the above facts regarding the assessment of the soil quality, the present study was undertaken as "Assessment and comparison of soil quality using PCA & EO methods in different Rice-based cropping systems in *Alfisol*"

Materials and methods

1. Soil Quality Assessment

The development of the soil quality index involves three basic steps: (1) Indicator selection as minimum data set (MDS); (2) changing indicator scores; and (3) combining the indicator scores into the soil quality index. For the assessment of soil quality, two different approaches were used 1. Principle components analysis 2.Expert opinion (EO).

1.1 Indicator Selection by PCA

The selection of indicators as a minimum data set (MDS) is carried out using two methods *viz.* principal component analysis (PCA) and Expert opinion (EP). Principal components (PCs) for an information set are defined as linear combinations of the variables that account for max variance within the set by describing vectors of closest fit the n observations in p-dimensional space, subject to being orthogonal to at least one another (Dunteman 1989). While there are many documented strategies for using PCA to pick a subset from an oversized data set, the one described here is analogous to that described by Dunteman (1989). PCA was performed using SPSS (version 25.0). In the present study, 26 soil physical, chemical and biological properties were used for PCA (Table 1). The objective of PCA was to scale back the dimension of information while minimizing the loss of data (Armenise *et al.*, 2013). Principal components (PC) receiving high eigenvalues were considered the best representatives explaining the variability (Andrews *et* *al.*,2002). Therefore, only the PCs with eigenvalues ≥1 were selected (Kaiser 1960). The retained PCs were subjected to varimax rotation to maximise the correlation between the PC and therefore the soil properties by distributing the variance. Additionally, PCs that specify ≥ 5% of the variability within the soil data (Wander and Bollero 1999) were included when fewer than three PCs had eigenvalues ≥1. Under a specific PC, each variable was given a weight or factor loading that represents the contribution of that variable to the composition of the PC. Only the highly weighted variables were retained from each PC for the MDS. Highly weighted factor loadings were defined as having absolute values within 10% of the very best factor loading or ≥0.40 (Wander and Bollero 1999). When quite one factor was retained under one PC, multivariate correlation coefficients were employed to work out if the variables might be considered redundant and, therefore, eliminated from the MDS. If the highly weighted factors weren't correlated (assumed to be a coefficient of correlation <0.60) then each was considered important, and thus, retained within the MDS. Among well-correlated variables, the variable with the very best factor loading (absolute value) was chosen for the MDS (Andrews *et al.* 2001).

1.2 Indicator Selection by Expert Opinion (EO)

The expert opinion (EO) approach permits to picking of easily determined soil characteristics into the MDS. If the expert who knows the soils inside the study area, crops in rotation and management practices applied on the land decides the indicators to be used, soil quality assessments are going to be more reliable and meaningful (Andrews *et al.*, 2002; Vasu *et al.* 2016).

1.3 Indicator transformation (scoring)

For transforming the indicators into scores, the MDS every observation of each MDS indicator was transformed for inclusion in the SQI methods examined. Two techniques were looked at Linear scoring and non-linear scoring. Calculation with non-linear scoring techniques requires sizable measures of information and is tedious for estimation. Due to this reason we picked the linear scoring technique for indicator transformation(Andrews *et al.* 2002b).

1.3.1 Linear scores

Chosen indicators in MDS were scored into measurement less values to standardize all indicators running from 0 to 1 utilizing a linear scoring approach (Liebig *et al.* 2001). Indicators were positioned in climbing or dropping requests contingent upon whether a higher worth was considered "good enough" or "poor" regarding soil function. For "more is better" indicators, every perception was separated by the most noteworthy watched worth with the end goal that the most noteworthy watched esteem got a score of 1. For "less is better" indicators, the most reduced watched esteem (in the numerator) was separated by every perception (in the denominator) with the end goal that the least watched esteem gets a score of 1. For some indicators, for example, pH, P, and Zn, perceptions were scored as "higher is better" up to an edge esteem (for example pH 6.5) at that point scored as "lower is better" over the limit (Liebig *et al.* 2001; Andrews *et al.* 2002 and Vasu *et al.* 2016)

1.4 Indicator integration into indices

Three soil quality records could used: an added substance SQI (ADD SQI); a weighted, added substance SQI (WTD SQI); and a various levelled decision support system (DSS SQI). In the present study, the mean SQI for each soil was determined from the weighted mean SQI of individual soil. Higher index scores were accepted to mean better soil quality.

After transformation employing a linear scoring method, scores, thus obtained for every observation were multiplied with the weighted factor obtained from the PCA results. Each PC explained a specific amount (%) of the variation within the entire dataset. This percentage when divided by the whole percentage of cumulative variation explained by all the PCs with eigenvectors >1, gave the weighted factors for identifying soil variables under each PC (Ray *et al.* 2014). After performing these steps, to urge SQI, the weighted MDS indicator scores for every observation were summed up. The SQI thus obtained were normalized with regard to the utmost possible SQI, i.e. summation of maximum PCA weighting factors of every key indicator. Weights were defined from the variance explained by each PC during PCA.

1.5 Comparison of SQI between PCA and EO method

After the development of SQI from two different methods *viz*; PCA and EO, we compare which method would give the most prominent indicator and more reliable SQI for the study area as described by Vasu *et al.*, 2016).

1.6 Statistical Analysis

The statistical analysis of the data was administered using SPSS Statistics (version 25.0, IBM, Armonk, NY, USA). Univariate analysis of variance (ANOVA) was performed for all the soil properties to find out the interaction between soil type and cropping system. One-way ANOVA was performed for all the soil properties with reference to the cropping system. Differences in individual soil properties among cropping systems were resolved using the Tukey post hoc test ($P < 0{\cdot}05$). The correlation coefficient (Pearson) was built up between the soil's physical, chemical and biological properties, and between chosen MDS in each PC.

An addition of ANOVA was done to find out the statistical difference between the mean of SQI corresponding to the cropping system. At last correlation coefficient (Pearson) was put up between SQI and yield of rice, mustard, wheat, linseed, chickpea and field pea.

Results and Discussion

Principal Component Analysis (PCA) for minimum data set (MDS)

The PCA was performed on the total data set, after getting favourable results in normality and sample sufficiency test. The results revealed that the first five PCs with eigenvalue ≥1 accounted for 75.72 % of the total variance (Table 2). Within each PC, the variable with the highest factor loading was selected as the most important contributor to the PC for MDS. The soil parameters selected from PC1 were bulk density, porosity, WHC, SOC, and Av. N. However, the multivariate correlations between these parameters indicated high correlation and only SOC, which has the highest factor loading, was retained in the MDS. Soil available Fe Mn, B and dehydrogenase activity were chosen from PC2 and after correlation (Table 3), only dehydrogenase activity was included in MDS (Andrews *et al.* 2002). From PC3, clay and WHC were selected; however, the multivariate correlations between these parameters indicated a high correlation (Table 4.). Only clay was considered as MDS because clay has the highest factor loading. Soil available S was selected in the MDS owing to the highest loading factor in the PC4. Similarly, the available N was retained as indicators from PC 5, since available N was the only highly weighed parameter in this PC. Finally, the selected MDS indicators for different Rice-based cropping systems of Alfisols were SOC, dehydrogenase activity, clay, available S and available N. The higher number of indicators in the MDS probably contributed to a greater explanation of management goal variability.

1. Weighted index

After transformation using a linear scoring method, scores, thus obtained for each observation were multiplied with the weighted factor obtained from the PCA results. Each PC explained a certain amount (%) of the variation in the total dataset. This percentage when divided by the total percentage of variation explained by all the PCs with eigenvectors>1, gave the weighted factors for identified soil variables under each PC. The weighted factors (per cent variation of each PC divided by the cumulative per cent variation explained by all the PCs) for PC1, PC2, PC3, PC4 and PC5 were 0.61, 0.18, 0.08, 0.06 and 0.06 respectively.

Table 1: Eigenvalue and variance data for the PCs

Principal components	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**
Eigenvalue	11.531	3.322	1.591	1.259	1.228
% Variance	46.126	13.287	6.364	5.034	4.914
% Cumulative Variance	46.126	59.413	65.777	70.811	75.725
Weighted factors	0.61	0.18	0.08	0.07	0.06
Factor loadings (Rotated component matrix)					
Sand	-0.659	-0.183	-0.553	-0.049	0.072
Clay	0.771	0.235	**<u>0.309</u>**	0.023	0.004
BD	**-0.861**	-0.106	0.038	-0.077	-0.150
Porosity	**0.853**	0.094	-0.052	0.108	0.153
AWHC	**0.837**	0.352	**0.303**	0.085	-0.080
SMC	**0.876**	0.296	0.148	0.101	-0.050
MWD	0.779	0.386	0.261	0.176	-0.087
pH	-0.362	-0.170	-0.262	0.261	0.112
SOC	**<u>0.888</u>**	0.252	0.008	0.141	-0.093
AN	**0.874**	0.233	0.011	0.137	**<u>0.538</u>**
AP	0.761	0.311	0.092	0.196	0.083
AK	0.612	0.322	-0.035	-0.175	-0.126
AS	0.251	0.138	0.123	**<u>0.813</u>**	-0.072
Fe	0.492	**0.797**	0.059	0.227	0.015
Mn	0.301	**0.510**	0.087	0.076	0.038
Cu	0.774	0.375	0.078	0.012	-0.174
Zn	0.585	0.372	0.071	0.097	-0.148
B	0.670	**0.402**	-0.007	-0.222	0.008
MBC	0.746	0.343	0.099	-0.046	-0.126
MBN	0.730	0.326	0.045	0.341	-0.101
DA	0.520	**<u>0.870</u>**	0.101	0.008	-0.007
APA	0.762	0.286	0.129	0.259	0.066
AlPA	0.761	0.294	0.076	0.117	-0.115
Silt	-0.033	0.042	0.009	0.099	0.053
EC	0.114	0.087	0.131	-0.167	0.049

Bold face factor loadings were considered highly weighted and underlined were retained in MDS.

Table 2: Correlation coefficient (Pearson) for highly loaded parameters in PC 1

	BD	Porosity	AWHC	SMC	SOC	AN
BD	1					
Porosity	-.976**	1				
AWHC	-.731**	.715**	1			
SMC	-.738**	.738**	.898**	1		
SOC	-.717**	.711**	.846**	.903**	1	
AN	-.713**	.706**	.834**	.886**	.985**	1

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3: Correlation coefficient (Pearson) for highly loaded parameters in PC 2

	Fe	Mn	B	DA
Fe	1			
Mn	.898**	1		
B	.568**	.439**	1	
DA	.566**	.509**	.563**	1

**. Correlation is significant at the 0.01 level (2-tailed).

Table. 4: Correlation coefficient (Pearson) for highly loaded parameters in PC 3

	Clay	AWHC
Clay	1	
AWHC	.807**	1

**. Correlation is significant at the 0.01 level (2-tailed).

4.2Soil quality index (SQI)

Soil quality index (SQI) was computed by using weighting factors derived from PCA for each scored MDS variable. The mean SQI under four different rice-based cropping systems ranged from 0.57 to 0.89 (Figure 1). The highest value of SQI was registered under the RC cropping system (0.89±0.007), whereas the lowest was recorded for RF (0.57±0.008). The SQI under the rice-legume cropping system (RC and RP) was higher as compared to RM, RW and RF cropping systems.

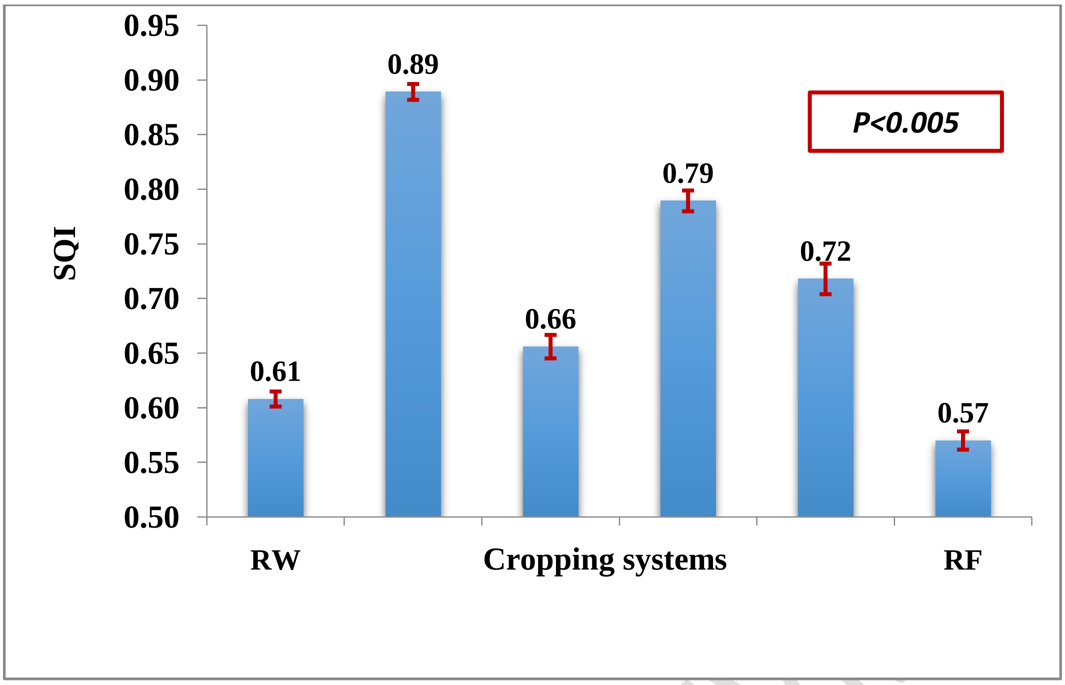

Fig 1 Average SQI among cropping systems PCA Based

4.3. Analysis of variance (ANOVA) of PCA Based soil quality index (SQI)

The SQI of soils varied from 0.56 – 0.67 (mean 0.61), from 0.0.84 – 0.95 (mean 0.89), from 0.52 – 0.72 (mean 0.66), from 0.72 – 0.88 (mean 0.79), from 0.59 – 0.84 (mean 0.72), from 0.50 – 0.64 (mean 0.57), for RW, RC, RM, RP, RL and RF, respectively (Table 3). Among the cropping systems, the SQI was found to vary significantly ($p<0.005$) (Table 4.).

Tukey's post hoc test for multiple comparisons (Table 5) indicated that the SQI of soils under the RW cropping system was significantly lower than that of soils under RC, RM and RP cropping systems. The SQI of soils under the RC cropping system was significantly higher than that of soils under RM, RP, RL, and RF cropping systems. Similarly, the SQI of soils under the RM cropping system was significantly lower than that of soils under RP and RL cropping systems. Further, the SQI of soils under the RP cropping system was significantly higher than that of soils under RL and RF cropping systems.

For other cropping systems, the differences in SQI were found to be insignificant. Results revealed that SQI under the rice-legume cropping system (RC and RP) was found to be significantly higher than that of soils under RW RM and RF cropping systems. Rice-legume cropping systems (RC and RP) have high root mass density, mean root diameter, root diameter diversity and the percentage of fine roots were all positively linked to increase in soil porosity (Bhattacharyya *et al.*, 2000), soil aggregate stability (Pagliai *et al.*, 2004), plant available water content (Mc Garry *et al.*, 2000), and reduced susceptibility to soil compaction by increasing soil organic carbon content. Moreover, it stimulates microbial activity which builds up microbial biomass into the soil (Campbell *et al.*,2000). Higher microbial biomass carbon and nitrogen under rice-legume cropping system attributed to the high SQI.

Table 5: Descriptive statistics of PCA Based SQI among cropping systems

Cropping System	Mean	Minimum	Maximum
RW	0.61	0.56	0.67
RC	0.89	0.84	0.95
RM	0.66	0.52	0.72
RP	0.79	0.72	0.88
RL	10.72	0.59	0.84
RF	0.57	0.50	0.64

Table 6: One-way ANOVA for PCA Based SQI among cropping systems

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.424	5	0.285	149.494	0.000
Within Groups	0.217	114	0.002		
Total	1.641	119			

Table 7: Multiple comparisons for PCA Based SQI among cropping systems

(I) CS	(J) CS	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
RW	RC	-.28106*	0.01380	0.000	-0.3211	-0.2411
	RM	-.04794*	0.01380	0.009	-0.0879	-0.0079
	RP	-.18131*	0.01380	0.000	-0.2213	-0.1413
	RL	-.10992	0.01380	0.000	-0.1499	-0.0699
	RF	0.03798	0.01380	0.073	-0.0020	0.0780
RC	RM	.23312*	0.01380	0.000	0.1931	0.2731
	RP	.09975*	0.01380	0.000	0.0597	0.1398
	RL	.17114*	0.01380	0.000	0.1311	0.2111
	RF	.31904*	0.01380	0.000	0.2790	0.3590
RM	RP	-.13337*	0.01380	0.000	-0.1734	-0.0934
	RL	-.06198*	0.01380	0.000	-0.1020	-0.0220
	RF	.08592	0.01380	0.000	0.0459	0.1259
RP	RL	.07139*	0.01380	0.000	0.0314	0.1114
	RF	.21929*	0.01380	0.000	0.1793	0.2593
RL	RF	.14790	0.01380	0.000	0.1079	0.1879

*. The mean difference is significant at the 0.05 level.

4.4.Contribution of retained MDS in PCA-Based SQI (Dominating factor analysis)

In the present study, the five MDS indicators were selected as the most sensitive indicators. Fig. 2 shows the specific contribution of each indicator towards the SQI for the different rice-based cropping systems. SOC gave the highest contribution towards the SQI (60.91%), followed by DA(17.55%) >clay(8.40%) >Av. S(6.65%) >Av. N (6.49%), respectively. This clearly reflected the influence of the weighting factors attributed to tough PCA. A high weighting for SOC indicated that this variable had the highest variance in the data set. It is already a well-known concept that the SOC is one of the most important predictors of soil quality (Andrews *et al.* 2002). The carbon content in soils is helpful for sustaining as well as enhancing the soil physical, chemical and biological properties of soils, which is attributed to sustaining/enhancing the soil quality of the study area.

The present study demonstrates that we need to adopt improved agronomical, soil and fertilizer management practices that can sustain and enhance the C content of soil for sustaining soil health for the next generation.

4.5. PCA Based on SQI and Crop Yield Correlation

The results indicated that a significantly positive correlation was observed between SQI and yield of rice (Fig.3), wheat (Fig. 4), chickpea (Fig. 5), mustard (Fig. 6), field pea (Fig. 6) and linseed (Fig..6) inferred that soil properties selected from the comparative data set had biological significance, and effectively evaluated the status of soil quality of rice-based cropping system (Li *et al.* 2013; Mukherjee and Lal 2014 and Vasu *et al.* 2016).

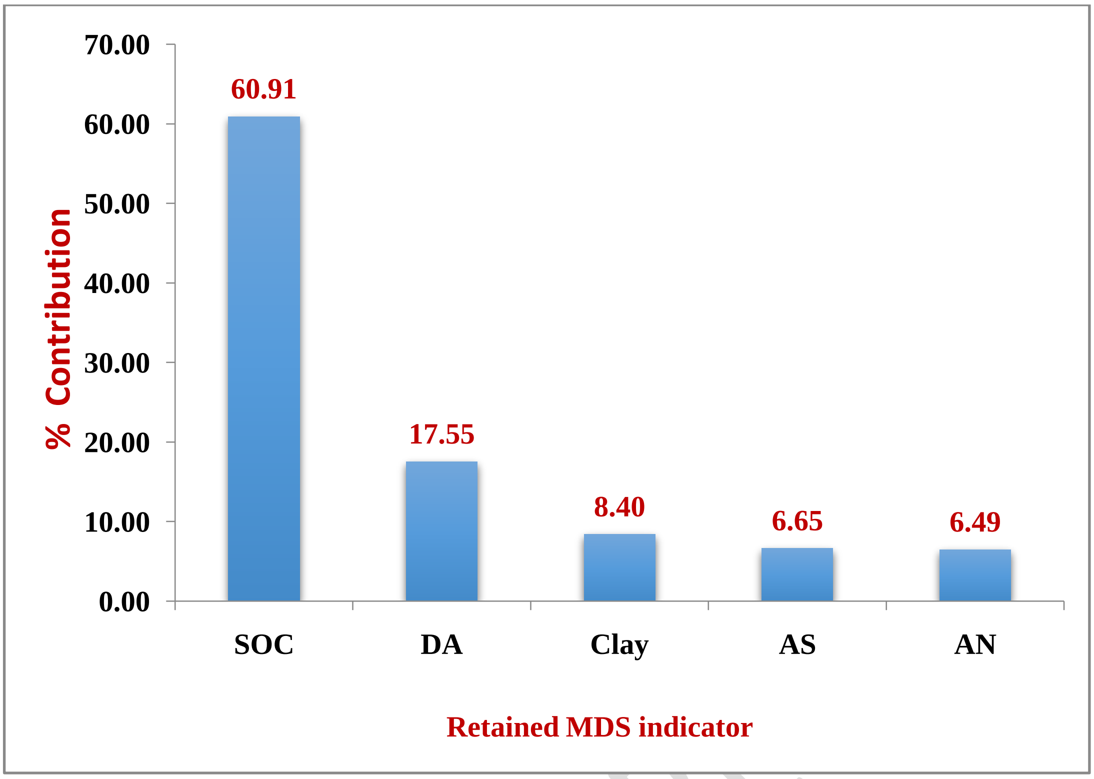

Fig. 2 Contribution of each retained MDS towards the PCA Based SQI

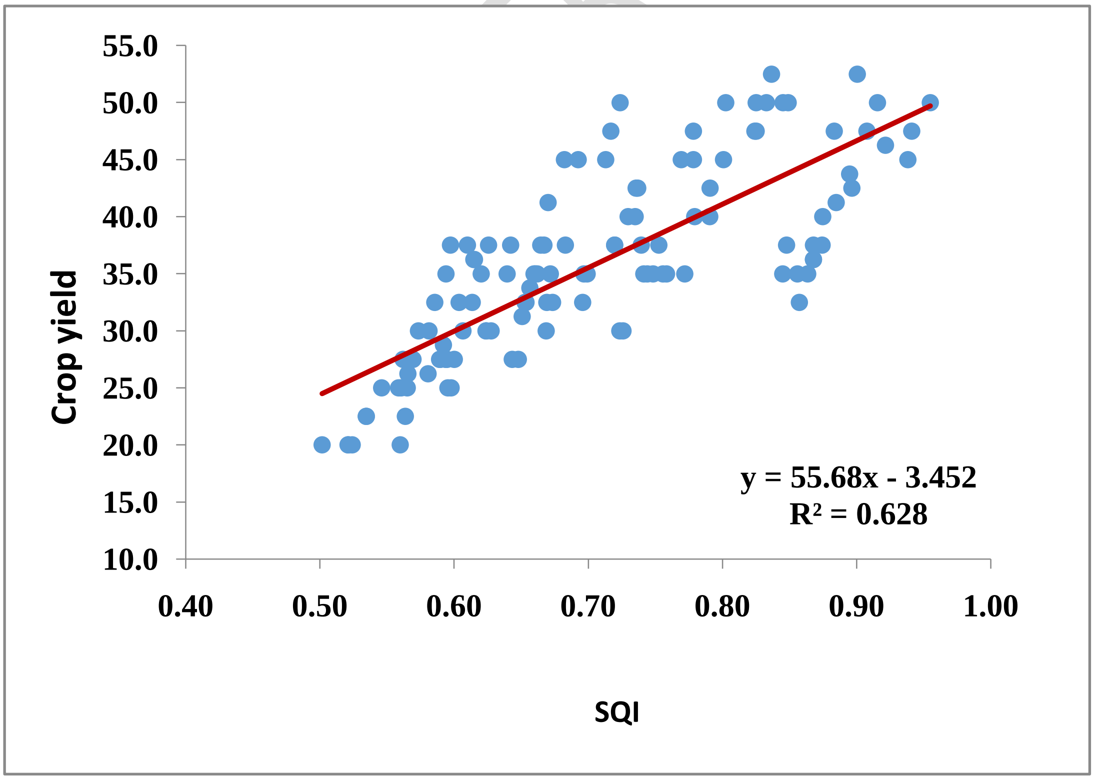

Fig.3 Correlation of SQI with yield of Rice

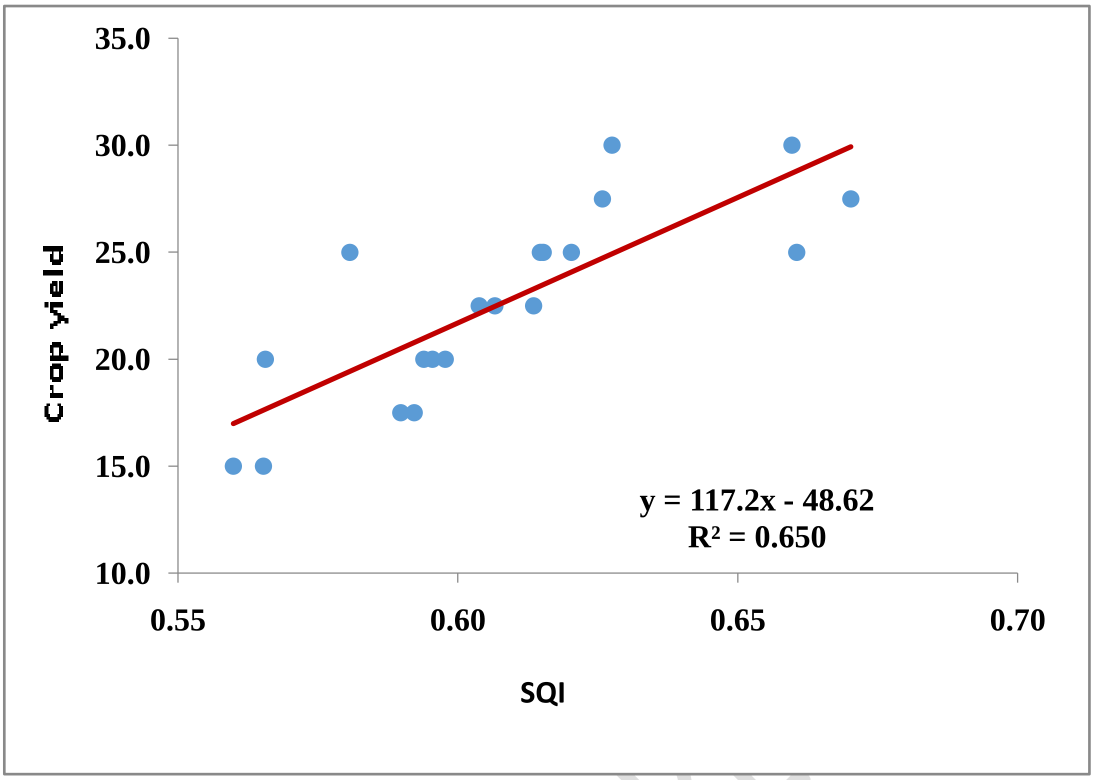

Fig4 Correlation of SQI with yield of Wheat

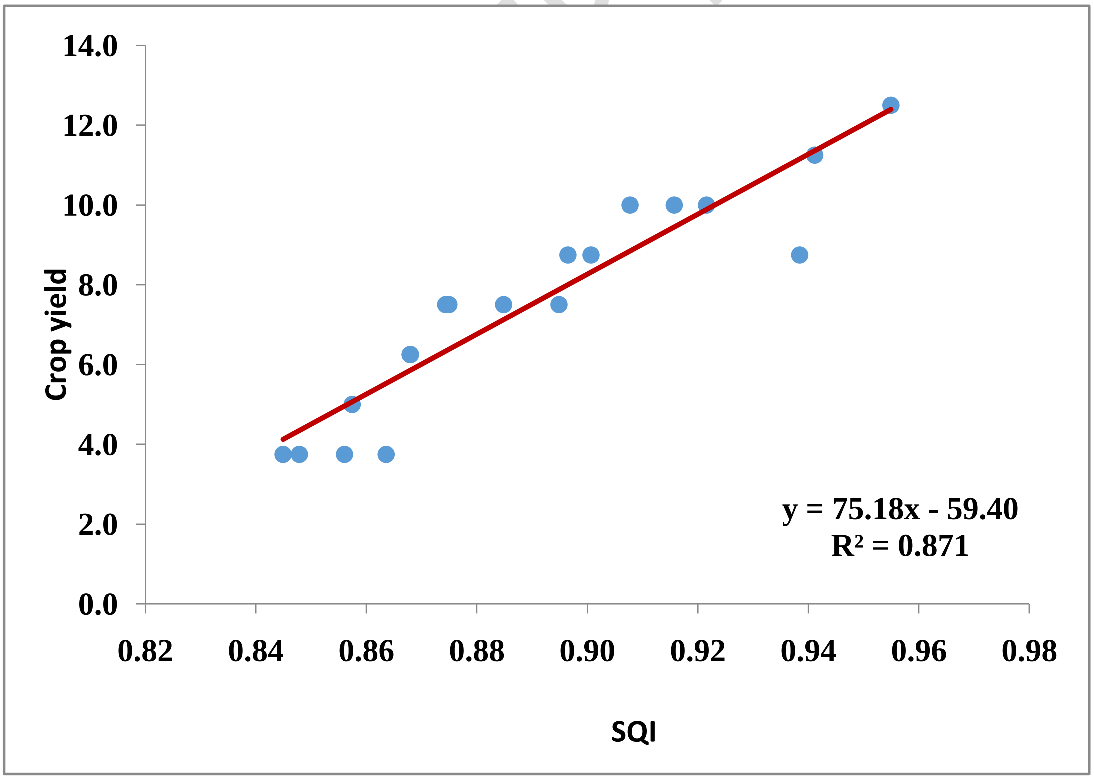

Fig..5 Correlation of SQI with yield of chickpea

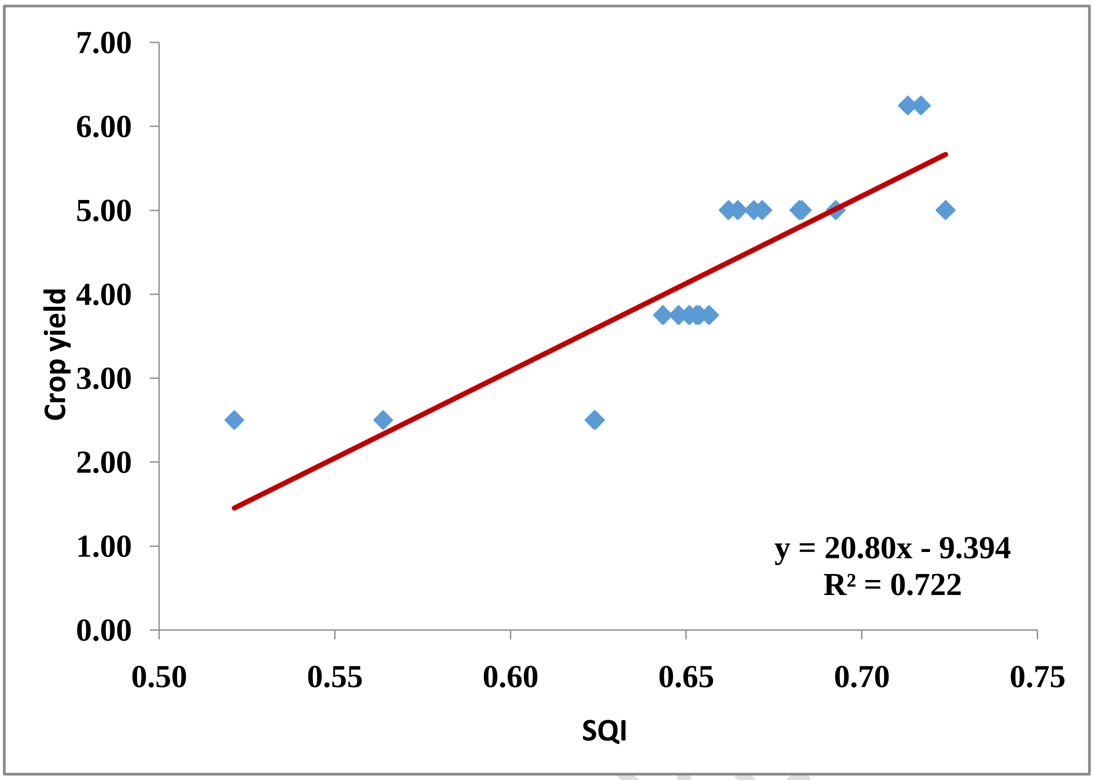

Fig.6 Correlation of SQI with yield of Mustard

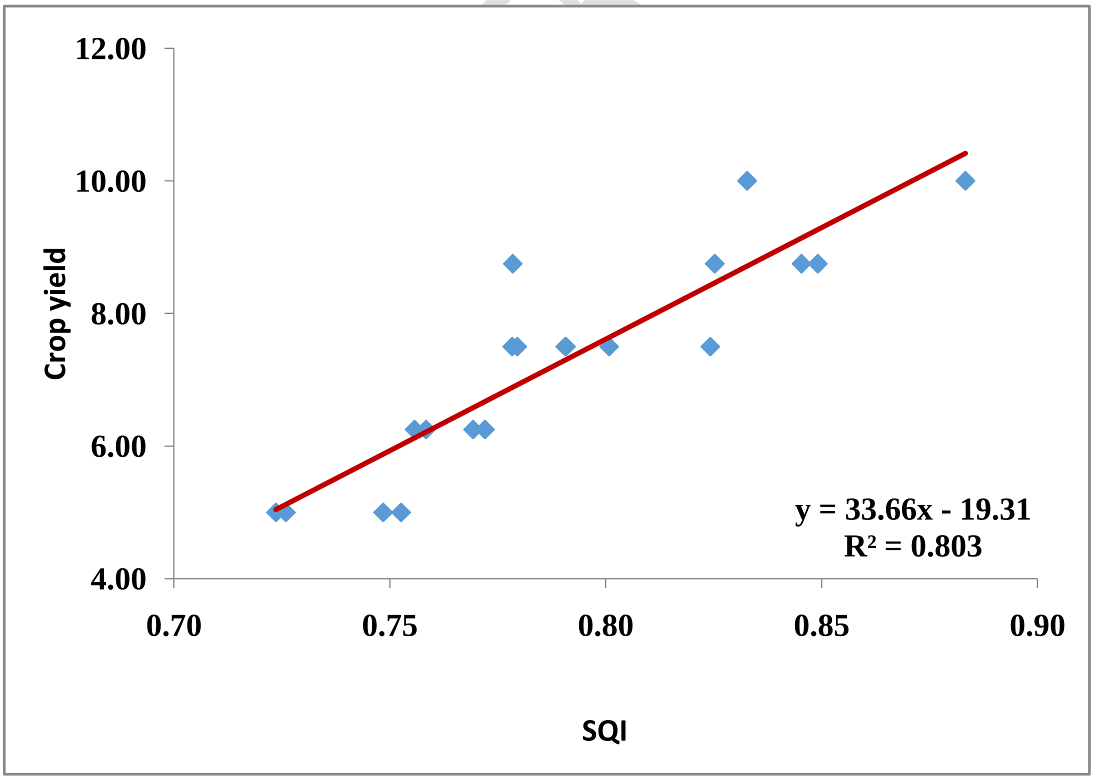

Fig. 7 Correlation of SQI with yield of Field pea

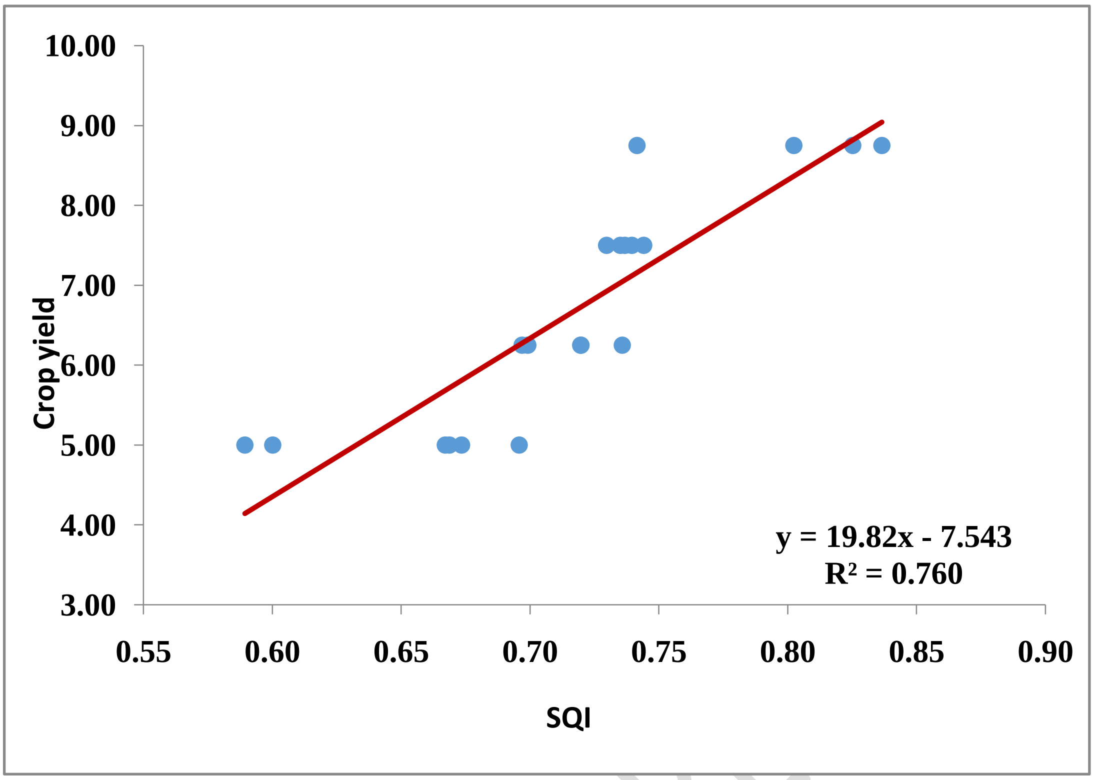

Fig..8 Correlation of SQI with yield of Linseed

4.6 Expert Opinion Method

PCA, though widely accepted, is a method of data reduction which simplifies the procedure of indicator selection. However, the authors of the present study were of the opinion that it is necessary to consider the study area characteristics such as climate, rainfall and associated pedogenic processes modifying the soil properties which determine the crop productivity before choosing variable(s) as indicators. Moreover, it is important that the selected indicator(s) should truly represent the complexity and function of the soil (Moncada *et al.*, 2014). Therefore, soil quality indicators were selected based on available data and literature pertaining to the soils of the study area.

4.6.1 Selection of MDS Indicators

Minimum soil data set properties in the EO method were selected based on the opinion giving by the experts from the subject of Soil Science and Agronomy, available soil data according to the consensus of the authors, available literature on studied soils and management concerns in the Alfisols and rice-based cropping systems of the studied area. The soil properties selected as the most sensitive MDS indicators were SOC, available P, SMC, Dehydrogenase activity and Zn.

Soil organic carbon is considered an important soil quality indicator (Lal, 2002). It plays major role in the rainfed production systems in Alfisols of northern Hill Region of Chhattisgarh, India through improving aggregation nutrient supply, moisture retention and stability of soil physical properties (Bhattacharyya *et al.*, 2007). Earlier investigations in the study area documented low OC level and it remained low (≤0.5%) over the years. The mean OC content is low (4.96 g kg^{-1}) as observed in the present study(Table 8), and it was felt that poor accumulation of OC might have played an important role in influencing the current soil quality status. Therefore, it was selected as one of the soil quality indicators.

Available P is the second most limiting nutrient for crop production. Due to the high fixation problem, the P-use efficiency of *Alfisols* is very poor. With farmer interaction, it is found that they are only using the urea as a source of N and not using the P fertilizers in a balanced manner. Therefore the P content in studied soils is very low. Hence, available P is retained as an MDS indicator.

The Northern Hill Region of Chhattisgarh is dominantly the rainfed area. In Kharif from rainwater farmers cultivated rice, while in Rabi the subsequent crop was selected according to the soil, irrigation facilities and resource availability. However, from a survey of the studied area, it is found that the productivity of rabi is very poor due to a lack of irrigation facilities. This is responsible for the poor moisture content of Alfisols. Keeping the importance of SMC is considered as another MDS indicator.

Soil biological properties are also the third important pillar of soil health. That determines the microbial population and activity. Due to the habitats of microbes in the soil, It is considered a living entity. Keeping the importance of soil microbial activity in soil health, dehydrogenase activity (the most important predictor of soil carbon) is retained as an MDS indicator.

Zn is an important micronutrient, particularly for rice and rice-based cropping systems. Earlier we stated that farmers in the study area are dominantly using urea as a source of N, only some farmers are using P and K fertilizers. The micronutrient fertilizers are not used by the farmers. Therefore the Zn deficiency appeared in the studied soils. Based on the EO, Zn is considered as MDS indicator.

4.6.2 Weighted index

After the transformation of MDS indicators using the linear scoring method, scores, thus obtained for each observation were multiplied with the weighted factor obtained from the EO method. In the EO method of soil quality assessment, the weight of particular MDS indicators was assigned as per the suggestions of different Expert in the studied area (Sharma and Arora 2010, Fernandes *et al.* 2011, Mukherjee and Lal 2014, Cherubin *et al.* 2016, Vasu *et al.* 2016). Based on the expert suggestion the weighted factors for five retained MDS indicators were 0.40, 0.25, 0.15, 0.10 and 0.10 respectively.

4.6.3 Soil Quality Index (SQI)

Soil quality index (SQI) was computed by using weighting factors derived from the EO method for each scored MDS variable. The mean SQI under four different rice-based cropping systems ranged from 0.52 to 0.85 (Figure 9). The highest value of SQI was registered under the RC cropping system (0.85±0.008), whereas the lowest was recorded for RF (0.52±0.005). The SQI under the rice-legume cropping system (RC and RP) was higher as compared to the RM, RW and RF cropping system.

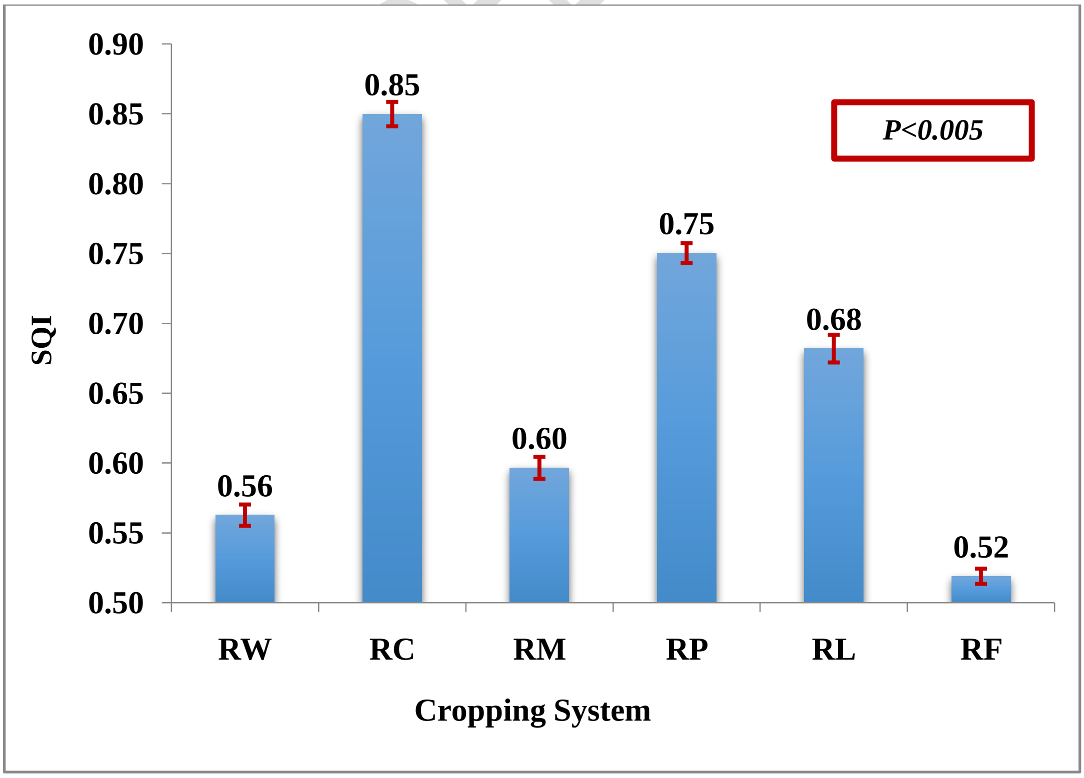

Fig. 9 EO based SQI among cropping system

4.6.4 Analysis of variance (ANOVA) of EO-based soil quality index

The SQI of soils varied from 0.49 – 0.62 (mean 0.59), from 0.77 – 0.91 (mean 0.84), from 0.51 – 0.64 (mean 0.59), from 0.70 – 0.83 (mean 0.75), from 0.60 – 0.77 (mean 0.68), from 0.48 – 0.57 (mean 0.51), for RW, RC, RM, RP, RL and RF, respectively (Table 9). Among the cropping systems, the SQI was found to be varying significantly ($p<0.005$) (Table 9). Tukey's post hoc test for multiple comparisons (Table 9) indicated that the SQI of soils under the RW cropping system was significantly lower than that of soils under RC, RM, RP and RL cropping systems. The SQI of soils under the RC cropping system was significantly higher than that of soils under RM, RP, RL, and RF cropping systems. Similarly, the SQI of soils under the RP cropping system was significantly higher than that of soils under RL, RF and RM cropping systems. For other cropping systems, the differences in SQI were found to be insignificant. Results revealed that SQI under rice-legume cropping systems (RC and RP) was found to be significantly higher than that of soils under RW RM and RF cropping systems. ANOVA study on soil physical, chemical, and biological properties was registered better for rice legume cropping systems in terms of lower BD, higher porosity, MWD, SMC, high SOC, and available macro and micronutrient content along higher microbial activities. These all are positively correlated to significantly better SQI of rice legume cropping systems (Kumar 2018, Kumar *et al.* 2020).

Table 8: Descriptive statistics of EO-based SQI among cropping systems

Cropping System	Mean	Minimum	Maximum
RW	0.56	0.49	0.62
RC	0.84	0.77	0.91
RM	0.59	0.51	0.64
RP	0.75	0.70	0.83
RL	0.68	0.60	0.77
RF	0.51	0.48	0.57

Table 9: One-way ANOVA for EO-based SQI among cropping systems

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.562	5	0.312	249.248	0.000
Within Groups	0.143	114	0.001		
Total	1.705	119			

Table10: Multiple comparisons for EO-based SQI among cropping systems

(J) CS	Mean	Std. Error	Sig.	95% Confidence Interval

		Difference (I-J)			Lower Bound	Upper Bound
RW	RC	-.28721*	0.01120	0.000	-0.3197	-0.2548
	RM	-.03395*	0.01120	0.035	-0.0664	-0.0015
	RP	-.18769*	0.01120	0.000	-0.2201	-0.1552
	RL	-.11923*	0.01120	0.000	-0.1517	-0.0868
	RF	.04378	0.01120	0.002	0.0113	0.0762
RC	RM	.25327*	0.01120	0.000	0.2208	0.2857
	RP	.09952*	0.01120	0.000	0.0671	0.1320
	RL	.16798*	0.01120	0.000	0.1355	0.2004
	RF	.33100*	0.01120	0.000	0.2985	0.3635
RM	RP	-.15374*	0.01120	0.000	-0.1862	-0.1213
	RL	-.08529	0.01120	0.000	-0.1177	-0.0528
	RF	.07773	0.01120	0.000	0.0453	0.1102
RP	RL	.06846*	0.01120	0.000	0.0360	0.1009
	RF	.23147*	0.01120	0.000	0.1990	0.2639
RL	RF	.16302	0.01120	0.000	0.1306	0.1955

*. The mean difference is significant at the 0.05 level.

4.6.5.Contribution of retained MDS in EO-based SQI (Dominating factor analysis)

The five MDS indicators were selected as the most sensitive indicators for the studied soil and cropping systems. Fig. 9 shows the specific contribution of each indicator towards the SQI for the different rice-based cropping systems. SOC gave the highest contribution towards the SQI (40.00%), followed by Available P(25%) >SMC(15%) >Dehydrogenase activity(10%) >Zn (10%), respectively.

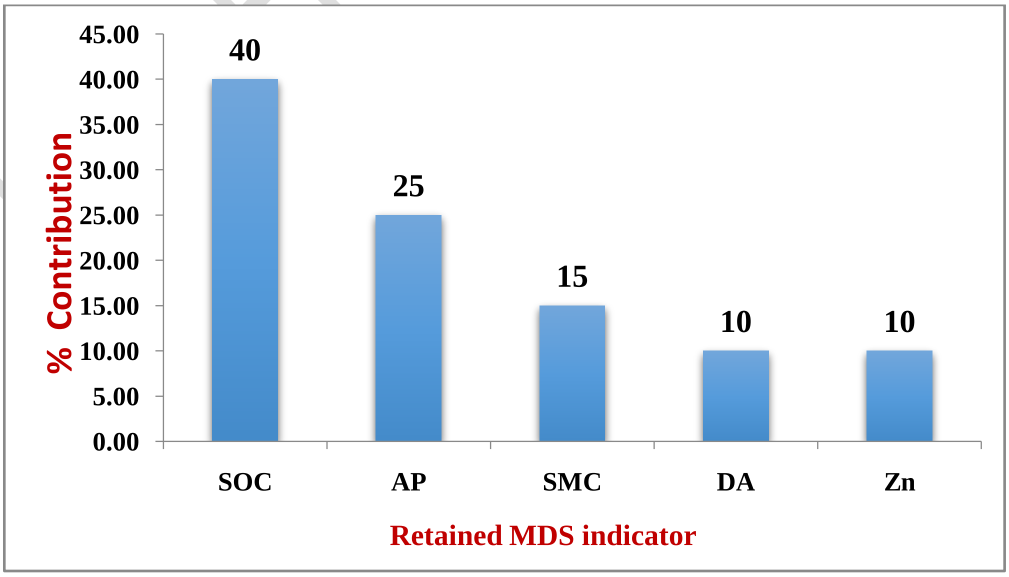

Fig. 10 Contribution of each retained MDS towards the EO-based SQI

4.6.7 EO-based SQI and crop yield correlation

The estimated SQI values were correlated with the recorded yield of crops. Result revealed that significant positive correlation was found between SQI and yield of rice (Fig. 11) (R^2 = 0.50), wheat (Fig..12) (R^2 = 0.31), chickpea (Fig. 13) (R^2 = 0.0.48), mustard (Fig. 14) (R^2 = 0.53), field pea (Fig15) (R^2 = 0.44) and linseed (Fig. 16) (R^2 = 0.61). The correlation results revealed that soil properties selected from the comparative data set had biological significance, and effectively evaluated the status of soil quality of the rice-based cropping system (Mukherjee & Lal 2014; Vasu *et al.* ., 2016). However, the PCA-based SQI were more significantly positively correlated with crop yields than that of EO-based SQI, especially for rice legume cropping systems (RC and RP). Our results are in close agreement with the findings of Vasu *et al.* (2016).

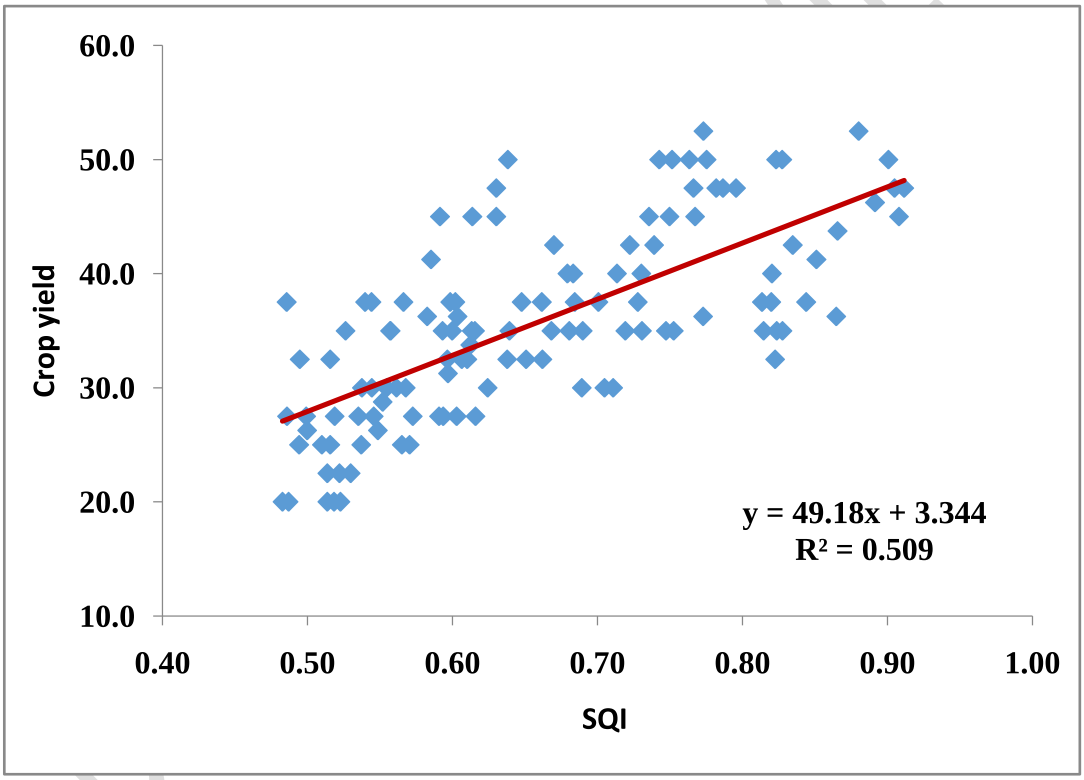

Fig11 Correlation of SQI with yield of Rice

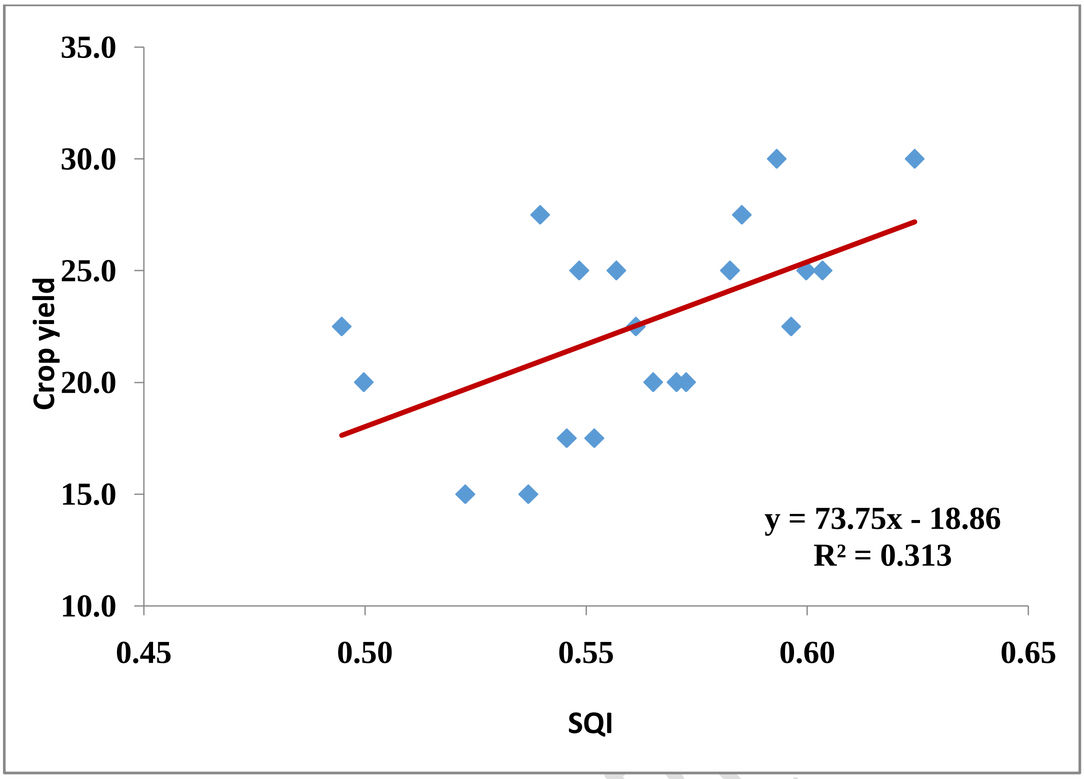

Fig.12 Correlation of SQI with yield of Wheat

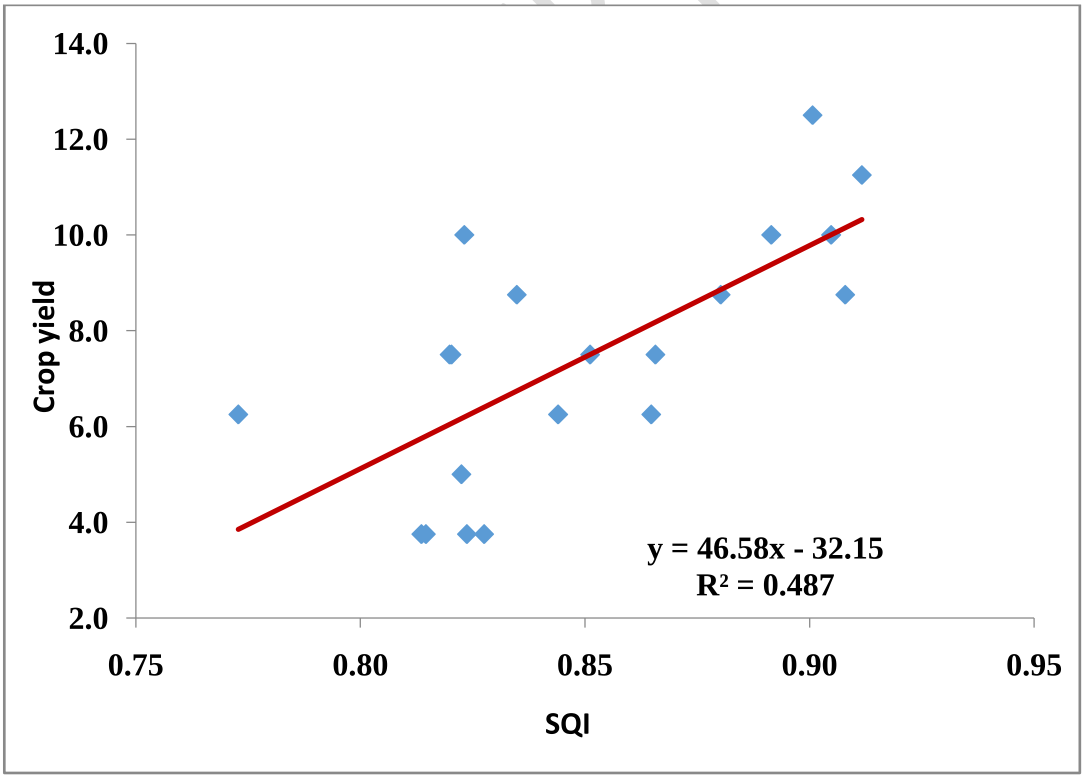

Fig.13 Correlation of SQI with yield of Chickpea

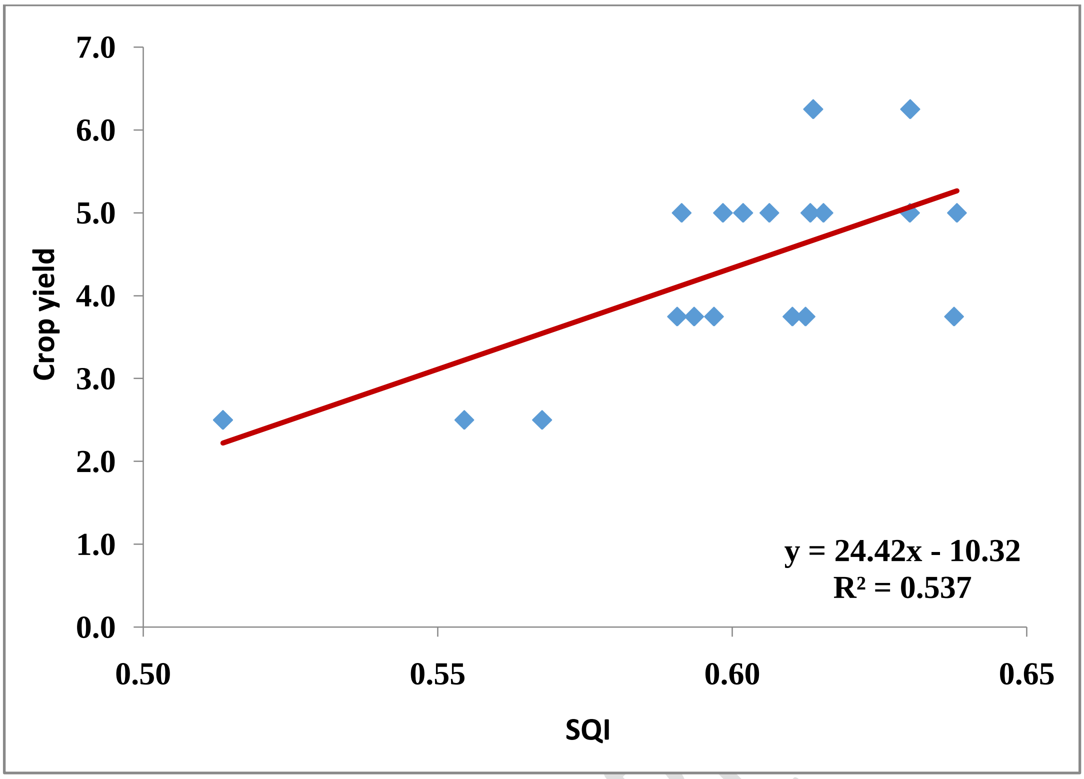

Fig..14 Correlation of SQI with yield of Mustard

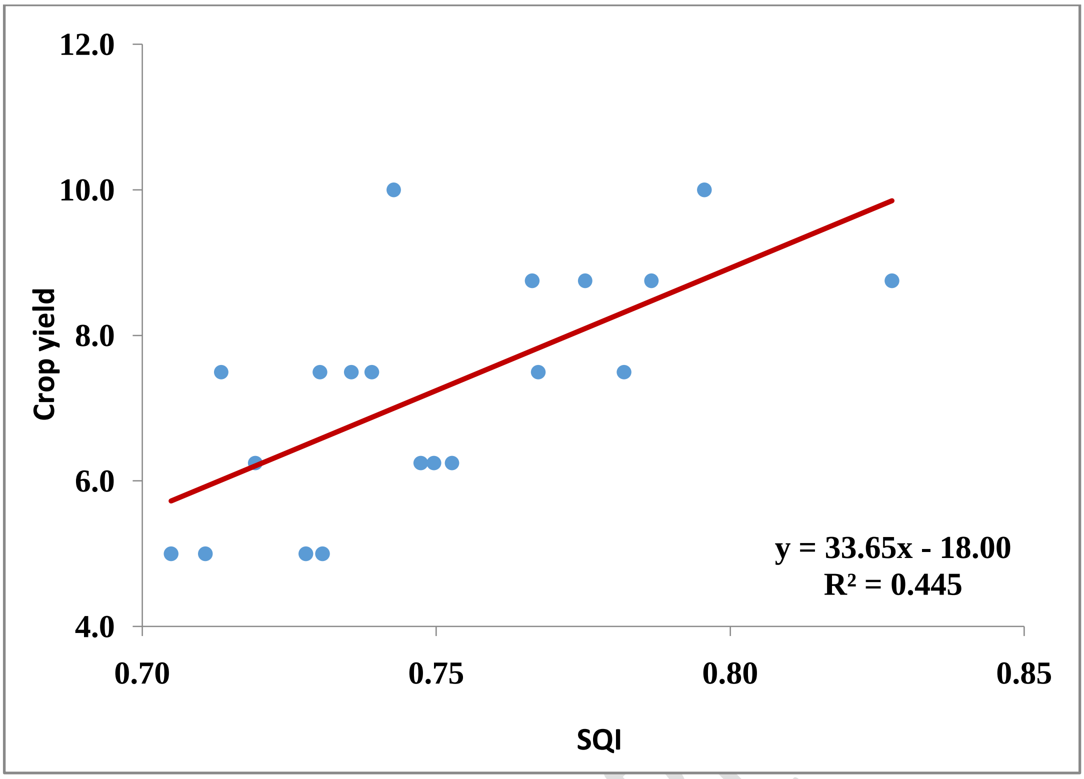

Fig.15 Correlation of SQI with yield of Field pea

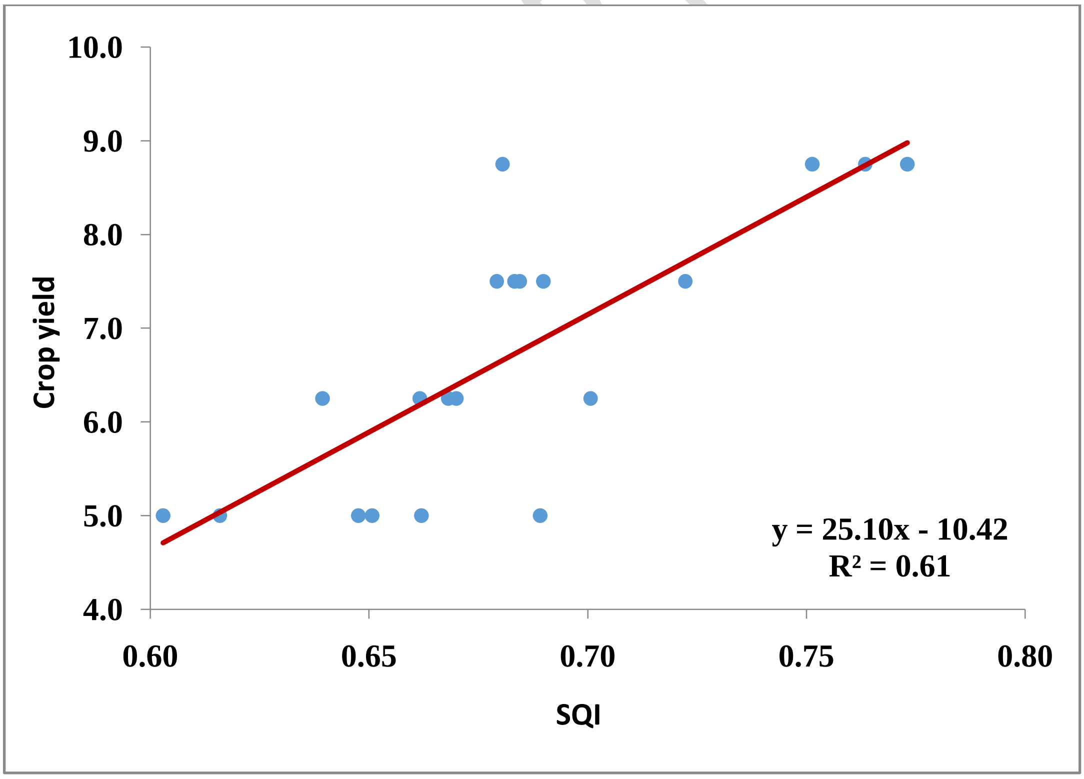

Fig16 Correlation of SQI with yield of Linseed

4.6.8. Comparison of SQI by PCA and EO method

In the present study soil quality was evaluated by using PCA and EO methods. Assessment of soil quality using PCA is well established statistical approach (Andrews *et al*., 2002; Rezaei *et al*., 2006; Govaerts*et al*., 2006; Masto *et al*., 2008; Sinha *et al.*, 2014; Cherubin *et al*., 2016; Vasu *et al.*, 2016 and Karthikeyan*et al.*, 2015).). It is the linear combination of variables that accounted for maximum variance, which reduces the dimension of data while minimizing loss of information. Results from PCA-based soil quality assessment gave the most appropriate MDS variables (SOC, DA, Clay, AS and AN) for the study area among the studied soil properties. And from each scored MDS variable the soil quality was evaluated.

While in EO based on soil quality assessment, the MDS indicators (SOC, AP, SMC, DA and Zn) were selected as per the opinion given by experts from the relevant field (Andrews *et al*., 2002; Zhang *et al*., 2004; Qi *et al*., 2009 and Cherubin *et al*., 2016). Based on the selected MDS variables weight of a particular indicator was assigned and soil quality was evaluated. However, the selection of MDS indicator and their weight through EO requires expert knowledge of the systems and may be subjected to disciplinary biases (Andrews *et al*., 2002 Cherubin *et al.*, 2016). In both the PCA and EO methods rice - legume cropping systems (RC and RP) sustain significantly better soil quality than that of other cropping systems (RW, RM and RL).

However, the PCA method was found comparatively better for soil quality assessment in the North Hill region since indicators were selected with due consideration of well-established statistical approaches with their influence on soil properties. This fact is supported by the correlation of PCA-based SQI with crop yield. The PCA-based soil quality was more significantly positively correlated (R^2) with crop productivity. The highly correlated PCA weighted index derived SQIs may be used to predict yield levels in studied soils. The low correlation levels by EO-based soil quality may be due to selected indictors, which may differ in their ability to influence crop yield. The subject of disciplinary biases for the selection of indicator and their weight (Andrews *et al.*, 2002 and Cherubin *et al.*, 2016) is also another factor that the PCA method outweighed the results obtained by the EO method.

Conclusion

Among the soil quality assessment methods, PCA explained the variation in soil properties and their interaction categorically as principal components and outweighed the results obtained by the EO method.

The significant positive correlation between SQI and crop yields revealed that soil properties selected from the comparative data set had biological significance, and effectively evaluated the status of soil quality of the rice-based cropping system.

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