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# Optimisation of agricultural input application to enhance the crop quality and yield quantity in paddy under precision farming

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**RESEARCH PAPER**

## Abstract

Recently, technological advances have converged to ensure the quality and quantity of crop yield on a site-specific basis. The aim of the present work was to adapt precision farming techniques in paddy under Indian farming system using modern tools such as apparent electrical conductivity ($EC_a$) mappers, differential global positioning systems, software procedures (univariate and multivariate geostatistical modelling), principal component analysis and cluster analysis. A field experiment was conducted on paddy (*Oryza sativa*) in the research farm fields of Punjab Agriculture University, Ludhiana (Punjab), India. The results revealed that management units can easily be drawn by assessing spatio-temporal factors using geospatial technologies. Three zones were identified and validated using Fuzzy-c means and indices, respectively, to enhance efficiency and optimise input applications that can produce best quality and quantity of the yield. High-resolution and geo-referenced digital spatial variability maps of different yield-limiting factors (soil moisture, pH, $EC_a$, phosphorous and potassium) were generated to assist decision-making in various agronomic practices. The complexity in analysing the spatio-temporal factors affecting yield were correlated; yield showed a positive correlation with $EC_a$, pH, soil temperature, and available phosphorous and potassium. The yield was negatively correlated with soil moisture and soil real dielectric.

**Keywords:** crop quality and yield, geospatial technology, geostatistics, management zones, paddy, precision farming

## 1. Introduction

The emerging agricultural scenario advocates the balancing of multiple research objectives including productivity, crop quality and safety, livelihood security, environmental protection and biological diversity at an affordable cost. Precision farming (PF) is one such viable technological tool which can ensure sustainable development and meet the above expectations. PF is an outgrowth of technological developments which include: soil apparent electrical conductivity ($EC_a$) measurement that facilitates a spatial understanding of the soil-water-plant relationship, global positioning system (GPS), geographic information system (GIS), yield monitoring, on-the-go soil and crop parameter mapping sensor technologies, and variable rate technologies (VRT). Furthermore, $EC_a$ has been reliably used to improve upon primary soil properties, which have spatial dependence on $EC_a$ (Corwin *et al.*, 2003; Moral *et al.*, 2010). The future of PF rests on the reliability, reproducibility, and understanding of these technologies. Traditionally in India the 'uniform rate' approach is practiced which does not take into account spatial variability and is not the most effective management strategy. PF is the most viable approach for achieving sustainable agriculture (Corwin *et al.*, 1999). Identifying spatio-temporal variability, its analysis and useful interpretation is the first step in PF. This understanding is then used to apply best agronomic practices and employ optimal input applications on a site-specific basis. Furthermore, in PF intra-field areas known as management units/zones (MUs/MZs) are identified. These MZs/MUs are site-specific and constitute homogeneous areas which share common characteristics, such as texture, topography, nutrient levels and $EC_a$, influencing crop productivity.

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To characterise these spatio-temporal variations and enable a number of agronomic decisions, PF uses rapidly evolving information and electronics technologies. As traditional soil sampling techniques become costly and labour-intensive in PF, efficient techniques and technologies for accurately measuring sub-field variations are very important (Bullock and Bullock, 2000). Using geo-statistical techniques such as ordinary kriging (OK), co-kriging (CK), kriging with external drift (KED), regression kriging (RK) and statistical techniques, such as univariate and multivariate regression (UVR and MVR), principal component analysis (PCA), clustering, etc., $EC_a$ (secondary information) can be used to improve estimates of the soil physico-chemical properties (primary information). The main objective of the investigation was to analyse spatial variability through digital spatial maps generated by statistical and geo-statistical techniques and make use of Fuzzy-c means (FCM) and PCA techniques to create intra-field MZs for enabling customised soil input applications. Furthermore, the validation of these delineated MZs was carried out using performance measure indices (fuzziness performance index (FPI) and normalised classification entropy (NCE)) for delineation of the optimal number of zones.

## 2. Materials and methods

### Description of site

A field experiment was conducted on paddy cultivated in three different plots (P1, P2 and P3) during Kharif 2010, under loamy soil, at Punjab Agriculture University (PAU), Ludhiana, India, located between 30°54'34.752"N, 75°49'6.281"E (top left side) and 30°54'33.103"N, 75°49'5.268"E (bottom right side) and situated at 242 m above the mean sea level (datum WGS84). The region represents the central agro-climatic zone of the state of Punjab. The climate is subtropical to tropical with a long dry season from late September to early June and a wet season from July to early September. The region receives maximum rainfall of about 700 mm during July-September and a few occasional showers during winter. The experiment was conducted in a split plot design and nitrogen fertiliser was applied in different amounts with variable rates of N1, N2, N3, N4 and N5, with an average dose of 68, 75, 125, 175, and 225 kg nitrogen/ha over a crop growth cycle. Paddy-cultivar varieties of PBW-343, PBW-550, and DBW-17 were planted in three different plots P1, P2 and P3, respectively.

Field 1 (Supplementary Figure S1A) was divided into three major grids and each grid was further divided into sub-grids with a grid matrix structure of 3 columns and 5 rows, totalling 45 grid cells over the entire experimental plot, and each grid cell had dimensions of 6×5 m creating 72 points for measurement of the grid at each vertices and to observe the variability at sub-field level with the help of *in situ* field sensors. Similarly, field 2 (Supplementary Figure S1B) was divided into a 4×5 matrix structure, each cell having dimensions of 9×9 m, creating 30 points for measurement with a total of 20 grid cells. Field 3 (Supplementary Figure S1C) was divided into 11 grid cells from 1 major grid, each cell having dimensions of 9×9 m, creating 24 points for sensor-based measurement.

The geo-sensor measured spatial soil data which was collected at the vertices of each cell, whereas high density geo-referenced continuous $EC_a$ measurements were collected using a Geonics conductivity sensor (EM38-MK2, Geonics Limited, Mississauga, Ontario, Canada).

### Software and hardware tools used

The field-scale $EC_a$ of the soil was measured using the EM38-MK2 conductivity sensor, manufactured by Geonics Limited. The EM38-MK2 uses the principle of electromagnetic induction to quantify soil electrical conductivity (EC) in millisiemens per meter (mS/m). The instrument was operated in vertical dipole (CV-1.0) auto mode, providing an effective measurement depth of approximately 1.5 m. The mobile system used included a wooden trailer for carrying the EM38-MK2, a *differential global positioning systems* (DGPS) receiver, and a laptop for data acquisition. A Trimble GeoXH DGPS system (Trimble Navigation Ltd., Sunnyvale, CA, USA) with sub-meter accuracy was used to geo-reference $EC_a$ measurements. Spatial analysis was accomplished with GIS, ArcGIS 9.0 (ESRI, Redlands, CA, USA), used to compile, manipulate, organise and display all spatial data. The unscrambler (version X) statistical software (CAMO Software, Oslo, Norway) was used for describing and analysing the data set by PCA. A language platform called Matlab R2007b was used for implementing a fuzzy clustering approach to cluster data in subsets.

### Data analysis techniques

#### *Geo-statistical analysis*

To characterise the spatial distribution of soil parameters in the optimum regression model, semi-variance analyses were carried out on the selected soil variables using GIS software to determine the type of spatial structure. In this process, theoretical models were fitted to the experimental semivariograms using the method of least squares. The OK procedure was then used to estimate the values of selected soil properties at unsampled locations. Smoothed contour maps of each soil property were then constructed using the interpolated values. The procedure uses a kriging estimator to generate the spatial distribution maps of soil properties; it is considered the best linear unbiased estimator interpolation technique given by a linear combination.

$$\hat{Z}(x_0)=\sum_{i=1}^{n} w_i(x_0)Z(x_i) \tag{1}$$

Where $w_i(x_0)$, i = 1, ..., n.

In this process, the linear combination of the observed values $z_i = Z(x_i)$ with weights chosen such that the variance (also called kriging variance or kriging error):

$$\sigma_k^2(x_0) = \mathrm{Var}(\hat{Z}(x_0) - Z(x_0)) =$$

$$\sum_{i=1}^{n}\sum_{j=1}^{n} w_i(x_0)\, w_j(x_0) c(x_i,x_j) + \mathrm{Var}(Z(x_0)) - 2\sum_{i=1}^{n} w_i(x_0) c(x_i,x_0) \quad (2)$$

is minimised subject to the unbiasedness condition:

$$E[\hat{Z}(x) - Z(x)] = \sum_{i=1}^{n} w_i(x_0)\mu(x_i) - \mu(x_0) = 0 \quad (3)$$

### *Principal component analysis*

PCA is a classical statistical technique that linearly transforms an original data set of variables. The co-related soil parameters were transformed into most significant orthogonal and uncorrelated PC's. This helped reduce the data handling complexity while processing the number of soil and crop variables comprising large field observations.

### *Fuzzy c-means clustering algorithm*

In fuzzy clustering (also referred to as soft clustering), data elements can belong to more than one cluster (which normally happens in case of edaphic and anthropogenic factors influencing crop yield), and associated with each element is a set of membership levels. FCM is used for clustering the similarities within the soil properties.

The algorithm used for processing soil data was composed of the following steps (Bezdek, 1981):

1. initialise $U=[u_{ij}]$ matrix, $U^{(0)}$;
2. at k-step: calculate the centres vectors $C^{(k)}=[c_j]$ with $U^{(k)}$
   $c_j = \frac{\sum_{i=1}^{N} u_{ij}{}^{m} x_i}{\sum_{i=1}^{N} u_{ij}{}^{m}}$;
3. update $U^{(k)}$, $U^{(k+1)}$;
4. $u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{||x_i - c_j||}{||x_i - c_k||}\right)^{\frac{2}{(m-1)}}}$;
5. if $||U^{(k+1)} - U^{(k)}|| < \varepsilon$ then STOP; otherwise return to step 2.

### *Performance measure of cluster analysis*

FPI: in the present case, FPI is used to measure the degree of separation (i.e. fuzziness, range 0-1) between fuzzy c-partitions and the soil data classified through the cluster analysis. It is defined as:

$$FPI = 1 - \frac{c}{(c-1)}\left[1 - \sum_{k=1}^{n}\sum_{i=1}^{c}(u_{ik})^2/n\right] \quad (4)$$

Where c stands for cluster centroids, $u_{ik}$ are the values for each k observation and cluster i. And where '0' means high separation and '1' means high sharing.

NCE: this was used to check the amount of organization / disorganization within the spatial data. Range for values of NCE is '0' to '1'; '0' indicates high organization and '1' represents a strong disorganization.

FPI and NCE indices were used to validate the optimal number of soil MZs/SSMUs (site specific management units) that can produce enhanced quality and quantity of agri-produce at reduced inputs.

## 3. Results and discussion

During the first phase of the geostatistical study, exploratory analysis, data distribution, was described using classical descriptive statistics (Table 1). An increase in $EC_a$ was observed in depth. Thus, $EC_{a\ cv\ 0\text{-}0.5}$ averaged 21.70 mS/m and the coefficient of variation (CV) was 8.96%; $EC_{a\ cv\ 0\text{-}1.0}$ averaged 22.90 mS/m and the CV was 9.16%. CVs for soil properties indicated significant spatial variability and suggested the convenience of defining different management zones as well as interpolated spatial distribution maps. For all considered soil properties, the mean and median values were very similar, which was indicative of data coming from a normal distribution. This was ratified by the fact that low skewness values were obtained, and most of the coefficients of kurtosis were close to 0. The skewness value is based on the size of the tails of a distribution and provides a measure of how likely the distribution will produce outliers.

Thus, in this work, there were no outliers, which was significant in obtaining accurate estimation models. Although normality is not a prerequisite for kriging, it is a desirable property. Kriging will only generate the best absolute estimate if the random function fits a normal distribution (Goovaerts, 1997).

### Geostatistical analysis

Semivariograms were calculated for the soil $EC_a$ variables at both depths, as well as for the other soil properties. The following parameters are presented (Table 2): nugget effect, sill, range and model for the calculated semivariograms, in addition to structural component (C1/C0+C1), representing the amount of data variance which can be explained by spatial dependence (Isaaks and Srivastava, 1989), and error sum of squares values, which was the criterion adopted to select the best fit for each model.

Experimental variograms were computed to determine residuals. Theoretical models were selected to provide the best fit (Supplementary Figure S2). The choice of a particular variogram model is dependent upon the expected

**Table 1. Statistical analysis of sampled soil physico-chemical properties and yield data.**

| Observed variables[a] | Mean | Median | Standard deviation | CV[b] | Skewness | Kurtosis |
|---|---|---|---|---|---|---|
| $EC_{a\ cv\ 0\text{-}1.0}$ (mS/m) | 22.90 | 22.60 | 2.10 | 9.17 | 0.01 | -0.57 |
| $EC_{a\ cv\ 0\text{-}0.5}$ (mS/m) | 21.70 | 21.65 | 1.94 | 8.96 | -0.14 | -0.24 |
| Soil $Temp_{I.P.S.1f}$ (°C) | 45.13 | 44.4 | 2.04 | 4.51 | 1.13 | 0.34 |
| Soil $Moist_{I.P.S.1f}$ ($m^3/m^3$) | 0.07 | 0.05 | 0.06 | 75.28 | 0.51 | -0.91 |
| Soil $EC_{I.P.S.1f}$ (S/m) | 0.01 | 0.01 | 0.01 | 41.93 | 0.73 | -0.34 |
| Soil $RD_{I.P.S.1f}$ | 5.02 | 4.56 | 1.34 | 26.79 | 0.60 | -0.59 |
| $pH_{H.S.1f}$ | 6.31 | 6.38 | 0.62 | 9.86 | -1.25 | 1.97 |
| Soil $Temp_{I.P.S.2f}$ (°C) | 35.53 | 34.6 | 1.71 | 4.82 | 1.01 | -0.32 |
| Soil $Moist_{I.P.S.2f}$ ($m^3/m^3$) | 0.018 | 0 | 0.04 | 214.61 | 2.26 | 4.38 |
| Soil $EC_{I.P.S.2f}$ (S/m) | 0.01 | 0.01 | 0.01 | 83.48 | 1.51 | 2.59 |
| Soil $RD_{I.P.S.2f}$ | 3.19 | 2.75 | 1.27 | 39.93 | 1.36 | 1.39 |
| Soil $pH_{H.S.2f}$ | 5.92 | 5.78 | 0.58 | 9.8719 | 0.32 | 0.79 |
| $pH_{L.A.1f}$ | 7.80 | 7.98 | 0.54 | 7.03 | -1.75 | 2.33 |
| $pH_{L.A.2f}$ | 7.97 | 8.08 | 0.33 | 4.17 | -2.90 | 10.31 |
| $EC_{L.A.1f}$ (mS/m) | 0.13 | 0.12 | 0.067 | 48.71 | 2.23 | 5.14 |
| $EC_{L.A.2f}$ (mS/m) | 0.11 | 0.1 | 0.06 | 53.52 | 3.02 | 9.97 |
| $K_{L.A.1f}$ (kg/ha) | 98.66 | 96.32 | 17.98 | 18.23 | 0.64 | 0.16 |
| $K_{L.A.2f}$ (kg/ha) | 97.51 | 95.2 | 21.80 | 22.36 | 0.68 | 0.21 |
| $P_{L.A.1f}$ (kg/ha) | 37.23 | 29.43 | 17.96 | 48.26 | 1.29 | 0.98 |
| $P_{L.A.2f}$ (kg/ha) | 29.64 | 26.64 | 14.60 | 49.27 | 3.04 | 9.99 |
| Bio yield (kg/ha) | 3,318.21 | 3,483.11 | 1,263.10 | 38.06 | -0.55 | -0.40 |
| Grain yield (kg/ha) | 1,431.17 | 1,551.34 | 581.25 | 40.61 | -0.54 | -0.45 |

[a] EC = electrical conductivity; $EC_a$ = apparent electrical conductivity; H.S. = hanna sensor; I.P.S. = *in situ* pogo sensor; K = potassium; L.A. = laboratory analysed; Moist = moisture; P = phosphorus; RD = real dialectric; Temp = temperature; 1f = 305 mm depth; 2f = 610 mm depth.

[b] CV = coefficient of variation.

spatial variability. Finally, using OK spatial distribution maps were generated which estimated the values at unsampled locations showing spatial variability in smoothed contour maps (Supplementary Figure S3). Variables like soil properties can be distributed unevenly in reduced distances and exponential or spherical models are the most suitable (Isaaks and Srivastava, 1989). In this work, variograms showed a considerable nugget effect. It is a normal situation because soil property variability can occur at a scale smaller than the minimum lag distance. The nugget effect can be reduced by considering closer samples, but it is usually costly and labour-intensive, thus less popular.

Due to the exhaustive $EC_{a\ cv\ 0\text{-}0.5}$ and $EC_{a\ cv\ 0\text{-}1.0}$ data, structural analysis was more accurate for these soil properties. The theoretical stable model for $EC_{a\ cv\ 0\text{-}0.5}$ variable and circular model for $EC_{a\ cv\ 0\text{-}1.0}$ variable provided the best fit (Supplementary Figure S2).

Lower nugget values of 0.96 and 0.29 for $EC_{a\ cv\ 0\text{-}0.5}$ and $EC_{a\ cv\ 0\text{-}1.0}$ variograms were obtained, respectively, with respect to the sill values, 4.79 and 5.40 for $EC_{a\ cv\ 0\text{-}0.5}$ and $EC_{a\ cv\ 0\text{-}1.0}$ variograms, respectively, a consequence of the sampling density, although their sills were different because their variances were different as well (Table 1).

## Correlation matrix between soil properties

In one of the interesting analyses of concern, soil properties were subjected to correlation analysis. Significant correlations were observed between soil properties, $EC_{a,}$ and yield, as well as within soil properties (Supplementary Table S1). Yield was positively correlated to $EC_{a\ cv\ 0\text{-}1.0}$, soil $temperature_{I.P.S.}$, $pH_{L.A.2f}$, $pH_{L.A.1f}$, $EC_{L.A.1f}$, $P_{L.A.2f}$, $K_{L.A.2f}$ and $K_{L.A.1f}$ and negatively correlated to $EC_{a\ cv0\text{-}0.5}$, soil $moisture_{I.P.S.}$, soil $conductivity_{I.P.S.}$, soil real $dialectric_{I.P.S.}$, $pH_{H.S.}$, soil $temperature_{I.P.S.2f}$, soil $moisture_{I.P.S.2f}$, soil $conductivity_{I.P.S.2f}$, soil $conductivity_{I.P.S.2f,}$ soil real $dialectric_{I.P.S.2f}$, soil $pH_{H.S.2f}$, $EC_{L.A.2f}$ and $P_{L.A.1f}$. Strong positive correlations were observed in soil $moisture_{I.P.S.}$ and soil $conductivity_{I.P.S}$ (r=0.97).

**Table 2. Semivariogram parameters for the sampled data.**

| Observed variables[a] | Nugget effect (C0) | Partial sill | Sill (C0+C1) | Range (a) | SSE[b] | C1/(C0+C1)[c] | Model |
|---|---|---|---|---|---|---|---|
| $EC_{a\ cv\ 0\text{-}1.0}$ (mS/m) | 0.29 | 5.10 | 5.40 | 22.34 | 8.785 | 0.95 | Circular |
| $EC_{a\ cv\ 0\text{-}0.5}$ (mS/m) | 0.96 | 3.83 | 4.79 | 27.49 | 69.725 | 0.80 | Stable |
| Soil $Temp_{I.P.S.1f}$ (°C) | 3.37 | 0.99 | 4.35 | 0.00 | 137.295 | 0.23 | Hole effect |
| Soil $Moist_{I.P.S.1f}$ ($m^3/m^3$) | 0.00 | 0.00 | 0.00 | 0.00 | 0.14 | 0.39 | Rational quadratic |
| Soil $EC_{I.P.S.1f}$ (S/m) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.28 | Exponential |
| Soil $RD_{I.P.S.1f}$ | 1.04 | 0.83 | 1.87 | 0.00 | 85.83 | 0.45 | Rational quadratic |
| $pH_{H.S.1f}$ | 0.28 | 0.12 | 0.39 | 0.00 | 24.03 | 0.29 | Hole effect |
| Soil $Temp_{I.P.S.2f}$ (°C) | 0.00 | 3.76 | 3.76 | 64.04 | 8.36 | 1 | Exponential |
| Soil $Moist_{I.P.S.2f}$ ($m^3/m^3$) | 0.00 | 0.01 | 0.01 | 2,877,716.11 | 0.06 | 0.92 | Gaussian |
| Soil $EC_{I.P.S.2f}$ (S/m) | 0.00 | 0.00 | 0.00 | 2,877,716.11 | 0.006 | 0.90 | Gaussian |
| Soil $RD_{I.P.S.2f}$ | 1.14 | 7.14 | 8.28 | 2,877,716.11 | 59.956 | 0.86 | Gaussian |
| Soil $pH_{H.S.2f}$ | 0.25 | 0.39 | 0.64 | 2,877,716.11 | 9.956 | 0.61 | Exponential |
| $pH_{L.A.2f}$ | 0.05 | 0.16 | 0.21 | 52.57 | 132.38 | 0.78 | Gaussian |
| $EC_{L.A.1f}$ (mS/m) | 0.00 | 0.00 | 0.00 | 49.76 | 0.09 | 0.77 | Exponential |
| $EC_{L.A.2f}$ (mS/m) | 0.00 | 0.00 | 0.00 | 54.60 | 0.10 | 0.76 | Stable |
| $K_{L.A.1f}$ (kg/ha) | 303.30 | 36.41 | 339.71 | 17.21 | 171419.7 | 0.11 | Spherical |
| $K_{L.A.2f}$ (kg/ha) | 376.94 | 246.99 | 623.93 | 53.17 | 54167.32 | 0.40 | Gaussian |
| $P_{L.A.1f}$ (kg/ha) | 259.33 | 968.80 | 1,228.13 | 2,877,716.11 | 12,541.98 | 0.79 | Gaussian |
| $P_{L.A.2f}$ (kg/ha) | 146.32 | 135.17 | 281.49 | 10.12 | 12,048.09 | 0.48 | Circular |
| Bio yield (kg/ha) | 492,505.99 | 465,667.11 | 958,173.09 | 0.00 | 16,279,4701.2 | 0.49 | Rational quadratic |
| Grain yield (kg/ha) | 79,817.87 | 87,491.92 | 167,309.80 | 0.00 | 27,969,339.47 | 0.52 | J-Bessel |

[a] EC = electrical conductivity; $EC_a$ = apparent electrical conductivity; H.S. = hanna sensor; I.P.S. = *in situ* pogo sensor; K = potassium; L.A. = laboratory analysed; Moist = moisture; P = phosphorus; RD = real dialectric; Temp = temperature; 1f = 305 mm depth; 2f = 610 mm depth.

[b] Error sum of squares.

[c] Degree of spatial dependence.

### Delineation of management units/zones using principal component analysis

Considering that the information used to delineate subfield region MUs is inter-related and such identified intra-field regions are homogenous in nature, PCA was applied to summarise the effect. Finally, the FCM technique was imposed to identify the most optimal zones whose performance was verified using FPI and NCE indices. It was found that the strong cohesion clusters (minimal membership sharing) were obtained at three zones (FPI and NCE minimises at three). Least value of indices at three indicates best data organization (homogeneous soil characteristics) within cluster and sharing common characteristics, i.e. least sharing weights within intra-regions, whereas most dissimilar between two zones. Furthermore, the optimal PC's applied with FCM were displayed in ArcView procedures using OK interpolation (Supplementary Figure S4).

### *Performance measure of optimal zones through FPI and NCE*

Two cluster validity functions, FPI and the NCE were used to determine the optimal number of MZs. The optimal number of cluster classes (management zones) was then defined as the number at which these two indices reach their minimum value (Fridgen *et al.*, 2001). The FPI and NCE are measures of membership/amount of disorganization, whose value is constrained between 0 and 1. Plotting the values of FPI and NCE against the number of classes and choosing a classification that minimises both measures was the procedure used in determining the optimum number of classes. FPI and NCE indices (Figure 1) reached a minimum value for a division of the area into three classes (three management zones), indicating that this is the optimal number of soil MZs based on the sampled variables.

## 4. Conclusions

It is a proven fact that a high quality soil is one that provides an environment for optimum root growth, thereby enhancing crop health and productivity. Therefore, an attempt has been made to understand the spatial variability

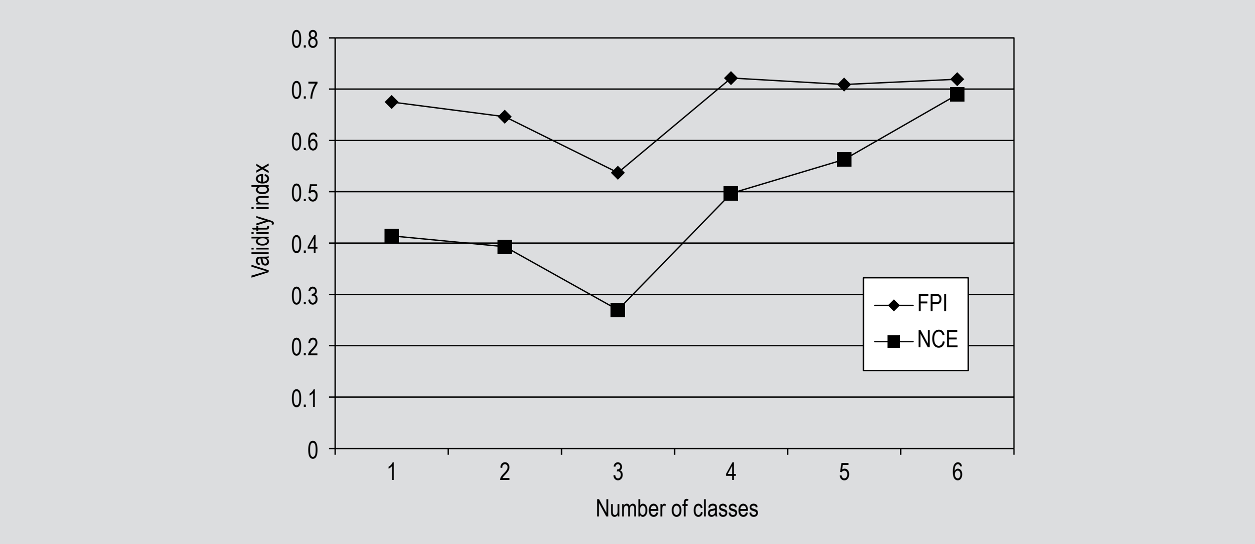

**Figure 1. Cluster performance graph. FPI = fuzziness performance index; NCE = normalised classification entropy.**

of soil properties which would help use precise agricultural inputs for improved crop quality and productivity and in turn help sustain soil health. Field-scale mobile soil $EC_a$ measurements, combined with geostatistical techniques such as kriging, successfully generated improved soil properties distribution maps. Since such geo-referenced mobile soil $EC_a$ measurements are spatially correlated with many useful edaphic and anthropogenic factors, they can be used to improve primary soil property (physico-chemical) spatial distribution maps to study site-specific spatio-temporal variabilities to govern various agronomic decisions and farming practices. This understanding is then applied on a specific field basis such that soil and crop input requirements are better matched to the applied agronomic resources and practices. This approach has special significance in light of the fact that intensive soil sampling to represent physico-chemical soil property variation of field at high resolution needs resources including extensive laboratory analysis, and is therefore unaffordable. However, field-scale mobile $EC_a$ based measurements integrate many edaphic properties responsible for crop growth, and the measurement of the same is inexpensive and rapid; it is also possible to map fields extensively. There are proven methods reported by various researchers to accurately generate spatial distribution surfaces using mobile $EC_a$ measurements (secondary information) and geostatistical interpolation techniques. It includes CK if the data are not exhaustive and KED or RK if the data are exhaustive. In the present studies OK interpolation technique has been demonstrated by fitting a suitable semivariogram (theoretical) model into experimental variograms of different soil properties whose spatial distribution was to be studied for creating optimal spatial distribution maps.

It was conceptualised that if different sources of data are aggregated, they can better predict selected agronomic soil attributes and support site specific crop management. Therefore, integrating different measurement concepts in a single mapping unit in conjunction with powerful data processing procedures can automate the agri-production system by implementing site specific crop management as a specific application of PF tool box and is one of the current topics of research.

An experimental plot was studied to prove the concept, which demonstrates the most modern ways of agronomic practices and resource applications through delineation of site-specific MUs/MZs. Novel methods to develop efficient and economic MZs are driving the current trends and future developments for the applications of $EC_a$ to PF in order to realise the 5 R's of precision agriculture (i.e. right kind of inputs, right amount, right location, right time and right technology). In developed countries, it is proven that PF is an information-driven technology which makes use of emerging engineering solutions, such as on-the-go $EC_a$ measurement, GPS, GIS, VRT, etc., and many other electronic sensors systems, otherwise primarily meant for other industries. The convergence of these emerging technologies has met with an overwhelming response in agri-fields. These modern ways and means have the potential to completely reorganise the agri-production system and make it commercially viable and environmentally sustainable.

## Supplementary material

Supplementary material can be found online at http://dx.doi.org/10.3920/QAS2012.0153.

Table S1. Correlation of soil physico-chemical properties and yield data.

Figure S1. Layout of experimental field (A) 1, (B) 2 and (C) 3.

Figure S2. Theoretical models.

Figure S3. Spatial variability distribution maps for (A) bio yield, (B) grain yield, (C) $EC_a$ cv 0-0.5, (D) $EC_a$ cv 0-1.0, (E) soil $moist_{I.P.S.}$, (F) soil $RD_{I.P.S.}$, (G) $P_{L.A.1f}$, and (H) $K_{L.A.1f}$.

Figure S4. Management units map.

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