International Journal of Plant & Soil Science
10(3): 1-9, 2016; Article no.IJPSS.20539
ISSN: 2320-7035

SCIENCEDOMAIN *international*
www.sciencedomain.org

Precision Agriculture Using Remote Sensing and GIS for Peanut Crop Production in Arid Land

M. M. El-Sharkawy[1*], A. S. Sheta[2], M. S. Abd El-Wahed[2], S. M. Arafat[3] and O. M. El Behiery[4]

[1]Department of Soil and Water, Faculty of Agriculture, Beni Suef University, Egypt.
[2]Department of Soil, Faculty of Agriculture, Ain Shams University, Egypt.
[3]Department of Agricultural Applications, National Authority for Remote Sensing and Space Sciences, Cairo, Egypt.
[4]Department of Arid Land, Faculty of Agriculture, Ain Shams University, Egypt.

Authors' contributions

This work was carried out in collaboration between all authors. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/IJPSS/2016/20539
Editor(s):
(1) Mirza Hasanuzzaman, Department of Agronomy, Faculty of Agriculture, Sher-e-Bangla Agricultural University, Dhaka-1207, Bangladesh.
Reviewers:
(1) Muringaniza Kudakwashe Collins Ralph, Midlands State University, Zimbabwe.
(2) Yahya Farhan, The University of Jordan, Amman, Jordan.
Complete Peer review History: http://sciencedomain.org/review-history/13563

Case Study

Received 31st July 2015
Accepted 19th February 2016
Published 5th March 2016

ABSTRACT

Precision agriculture is a farming management approach for a whole field with a potentiality to solve some of management problems based on observing and measuring field crops variability using more accurate and timely information of agricultural resources. Site-specific management for farming operations and data mining using good sampling design is an effective tool on precision agriculture while remote sensing facilities are perfect tools to assess the land cover, crop situation and status as well as their changes. This work aimed to identify management zones for Peanut crop using precision agriculture management practices. GIS, GPS, sensors and soil sampling are the major technological components which were used for that purpose. The results showed that using variable rate technology and management zones for Peanut crop production is greatly responsible for lowering cost of input and decreasing environmental impact using the least amount of chemicals necessary. Furthermore, soil suitability was successfully employed to simulate soil characteristics effect on canopy structure and final yield.

**Corresponding author: E-mail: elsharkawy25518@itc.nl, mohamed200802@yahoo.com;*

Keywords: Precision agriculture; peanut; remote sensing and GIS.

1. INTRODUCTION

Precision agriculture is the term used to describe the goal of increased efficiency in the management of agriculture. It is a developing technology that modifies existing techniques and incorporates new ones to produce a new set of tools for the manager to use [1]. It's a compelling and highly active field of research typically based on large data collections and data-based decision making for agricultural operations. Since the data collections are growing rapidly, it is essential to put research efforts into methods which deal with those data sets [2]. Remote sensing is one of precision agriculture tools. According to [3] remote sensing is the art, science & technology of obtaining reliable information about physical objects and the environment, through the process of recording, measuring and interpreting imagery and digital representations of energy patterns derived from non-contact sensor systems. Information from remote sensing observations can effectively be integrated into crop modeling methodologies. Such data have been used in crop models for regional yield assessment [4,5]. One of the most important retrieved information from remote sensing is vegetation indices, which have been extensively used for monitoring and detecting vegetation and land cover changes [6,7]. One type of spectral vegetation indices is the Normalized Difference Vegetation Index (NDVI), the ratio of near infrared (NIR) and red (R) reflectance, which provides some measure of light absorption by photosynthetic tissues. The NDVI assigns a number between -1 and 1 that gives you a measure of plant greenness based on pigment content and can be correlated with seasonal plant development. Generally, soil background effects can be reduced using indices such as the soil adjusted vegetation index (SAVI) [8] especially for agricultural crops or homogeneous plant canopies [9].

SAVI is more significant when agricultural crops on widely varying soils are studied [10]. Also, Digital Elevation Models (DEM) and Remote Sensing data provide information about the earth's surface and can aid in determining characteristics of the landscape and the soil [11]. Due to terrain features of a field are significantly related to crop yield across years and crop species; it can be used to improve management zones of the crop production. Geographical Information Systems (GIS) is one of the important tools of precision agriculture. This technology allows examining and handling a wider range of spatial databases such as soils, weather, hydrology etc. and integrating with socio economic variables [2]. Simultaneous examination of these variables leads to a better understanding of various agricultural related process and their interactions over space and time. This leads to characterization of resources accurately and to identify appropriate domains to target new technologies from time to time. By interfacing these layers, GIS is emerging as a powerful spatial decision support system [12]. Mapping yield information allows a better understanding of where and why yields vary across fields [13,14]. Crop growth and yields vary because of a numerous of soil characteristics and number of permanent spatial factors that affect yield either directly or indirectly such as land-scape position and terrain attributes [15-18]. Egypt is a major peanut (*Arachis hypogaea* L.) exporting country of which 68% peanut products head to the European market [19]. Egyptian Peanut production is estimated 0.2 million tons for 2015/16, likely to be as good as at last year's production levels. Planted area is estimated similar to last year at 0.6 million hectares while area harvested is estimated at 0.59 million hectares. Planted and harvested hectares are increased 5% comparing with 2014/15 production year, which show significant benefits. The increase in planted acreage for 2015 was mainly due to lower corn and soybean prices [20]. In Salhyia and Nubaria, the largest peanut-product areas, planted area was up 25 percent from 2013. Record high yields are estimated for 2015. The objectives of the current work are producing soil productivity map for Peanut crop based on Spatial Multi Criteria Evaluation approach and providing geo-referenced field information using remote sensing techniques for precision agriculture practices.

2. MATERIALS AND METHODS

2.1 Study Area

The study area is located between 30°29′ 00″ N and 30°30′ 00″ N latitude and 31°56′ 00″ E and 31°57′ 00″ E longitude, and situated at the eastern Nile Delta, Ismailia governorate, Egypt. The study area represented by one pivot within area about 67 hectares as it shown in Fig. 1. The area cultivated with peanut crop and irrigated by center pivot system using Ismailia canal which branched from Nile River. Total Dissolved Salts (TDS) of the irrigation water = 544 mgL^{-1}.

The climate in the area is arid Mediterranean type with an average annual precipitation of about 20 mm and temperature 18°C. Meteorological data required to soil suitability assessment, collected from El-Basatin meteorological station in Salhyia for 2015. The data collected are namely average air temperature, maximum air temperature, minimum air temperature, relative humidity and average sunshine hours as shown in Fig. 2. The climate is mainly dry and rarely rainfall throughout the year. During the summer, the sun brightness hours increases and the solar radiation getting stronger that mainly increases the rates of evapotranspiration and plant water consumption.

2.2 Field Data

Twelve Soil samples collected in 2015 for the study area by symmetric random sampling from the uppermost centimeter (15 cm width × 40 cm depth) of soil (Fig. 3). The soil samples, analyzed for soil physical and chemical characteristics, were determined according to [21].

The studied soil characteristics were soil salinity (ECe) expressed in dS/ m of the extract of the saturated soil paste, soil sodicity expressed in ESP = percentage of sodium of all exchangeable cations, soil particles expressed in sand, silt and clay (percent by weight), soil reaction expressed in pH value, organic matter percentage expressed in mg/ kg, calcium carbonate percentage expressed in % and available water

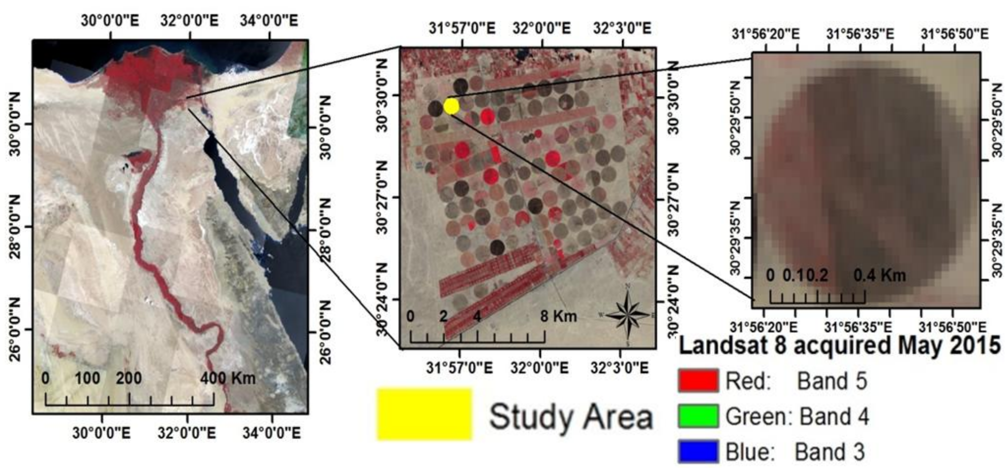


Fig. 1. Location of study area

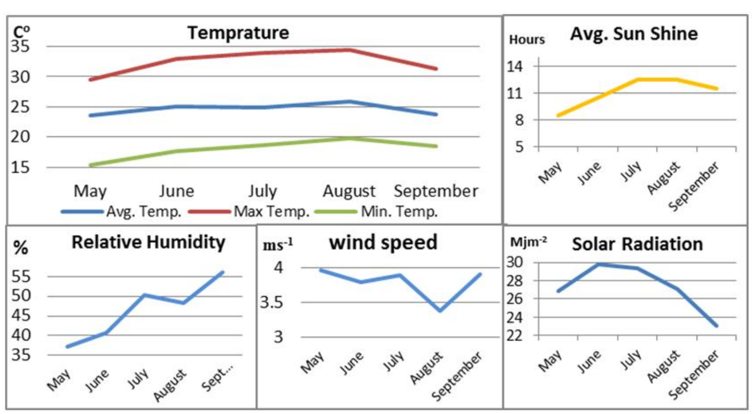


Fig. 2. Air temperature, relative humidity, wind speed, solar radiation and average sunshine

capacity expressed in cm in top one meter of the soil. The all determined soil characteristics and climate of study area used in evaluating soil according to [21,22].

However, NDVI is a good plant greenness estimator [23] but it affects by soil background, Soil Adjusted Vegetation Index (SAVI) can reduce the background effects on. Three Landsat 8 images were acquired in May, June and July 2015. SAVI computed using Equation 1 from Landsat 8 images at three different growth stages of Peanut crop to show the surface coverage condition of vegetation and to show the stage of growth of crop canopy according to [24]. Equation 1:

$$SAVI = (1+L) * \frac{(\rho_{NIR} - \rho_{red})}{(\rho_{NIR} + \rho_{red} + L)}$$

Where:

ρ *NIR* = Reflectance in the near infrared band
ρ *red* = Reflectance in the red band.
L = A parameter to minimize soil influence (ranging from 0 to 1). Its value, as determined for arid zones is 0.5.

2.3 Methodology

The methodology carried out in this study can be viewed in two parts: Soil suitability model and management zones for Peanut crop. Field survey, laboratory analysis and the climatic data were used to generate the soil productivity map; while SAVI used to validate soil productivity map.

All determined soil characteristics aforementioned used in generating digital soil maps for the study area using Kriging geostatistical method; while the suitability range for each class were determined for Peanut crop using the FAO procedure [25]. Based on the digital soil maps and the climatic data, the land productivity map for Peanut crop has been generated as an output from the Spatial Multi Criteria Evaluation tree (SMCE). Firstly, rank sum method was used to generate numerical weights from a rank order of criteria for soil characteristics [26]. The general procedure of SMCE included several phases. First, the relevant criteria (factors and constraints [27] were established. Outside the pivot and very saline soils were considered as constraints; while the groups defined according the five aspects which are highly important in establishing suitability map for crop production namely soil salinity, soil fertility, soil physical, climate, and topography as it shown in Table 1. Each group contains some spatial factors were classified based on the optimum conditions for Peanut growth in the different growth stages using the FAO procedure [20]. The SMCE method used weighted linear combination, requires that all factors must be standardized [28] into units that can be compared [29]. In this study, the factor maps were ranked according to [30]. Table 1 shows the ranking of the different classes to the different parameters. All the input layers were rasterized with cell size as 30 m in order to make an effective weighted overlay as the resolution of all the factor maps were not same. Rank sum method was used to generate numerical weights from a rank order of criteria for soil characteristics, the data weighted to express the importance of each factor relative to other factor effects on crop yield; therefore, rank sum method was used to generate numerical weights from a rank order of the groups and the factors within one group.

Land productivity levels for Peanut crop were determined for three productivity classes. The productivity levels were high production, moderate production and low production based on the structure of FAO land suitability classification. This production levels are described in Table 4 and Fig. 4.

Table 1. Rank order combined with multi criteria for getting soil suitability

Rank	1	2	3	4	5
	Salinity	**Fertility**	**Soil physical**	**Topography**	**Climate**
1	EC	pH	CaCO3	Slope	Humidity
2	ESP	O.M.	Coarse fragments	DEM	Day length
3		CEC	Texture	Location	

3. RESULTS

3.1 Soil Characteristics Maps

Soil properties values were statistically processed to determine the general features of soils studied farm. The results showed that slight variation exists in soil properties as indicated by low values of standard deviation (Std), where 80% of the farm area is of low and moderate productivity. Also, the topographic characteristics and the climatic conditions of the farm area are almost homogeneous. The standard deviation varied from 0.5 to 10.2 for pH and saturation percent (S.P.) respectively (Table 2). The table indicated that the soils are non-saline one with an averaged EC value of 3.1 dS m^{-1}. The soils alkalinity was assessed as relatively high pH values with a mean of 7.80. The low value of organic matter (O.M.) indicted that much soils had low organic content. The low values of the saturation percent and cation exchange capacity might be due to the sandy clay texture and the low O.M. contents. The CEC and low O.M. contents indicated that the soils had an insufficient or marginal supply of nutrients for all crops. The Exchangeable Sodium Percentage (ESP) varied from 1.9% to 12.2%, which is hardly affected on growing crop.

Table 2. Descriptive statistics of soil characteristics

Characteristics of soil / Descriptive statistics	EC dS m^{-1}	pH --	$CaCO_3$ g kg^{-1}	C.E.C. cmol kg^{-1}	O.M. mg kg^{-1}	S.P. %	ESP %
Mean	3.1	7.80	4.8	5.4	0.54	22	5.3
Median	3.9	7.9	4.5	4.3	0.51	19	4.8
Standard deviation	1.7	0.5	4	3.3	0.05	10.2	2.2
Minimum	0.41	7.2	0.6	2.1	0.48	9	1.9
Maximum	5.2	8.5	15	22	0.63	37	12.2

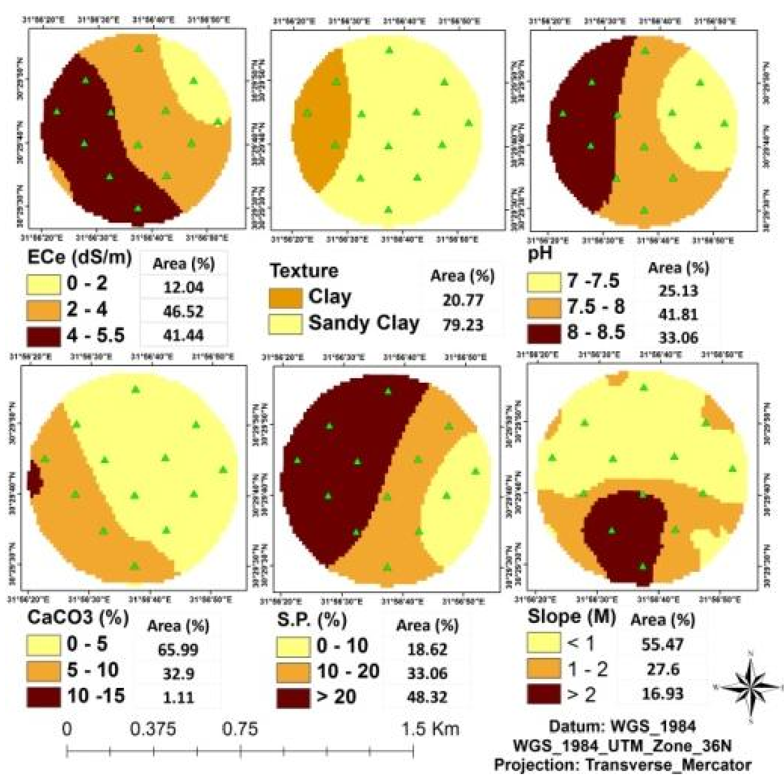


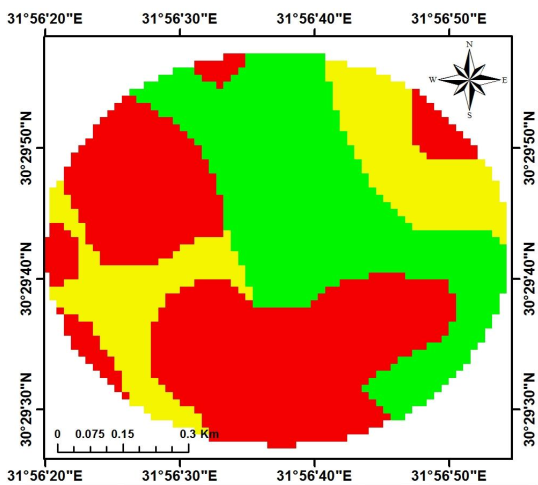
Fig. 3. Soil sample locations and digital soil characteristics maps of the study area

3.2 Spatial Multi Criteria Evaluation for land Suitability

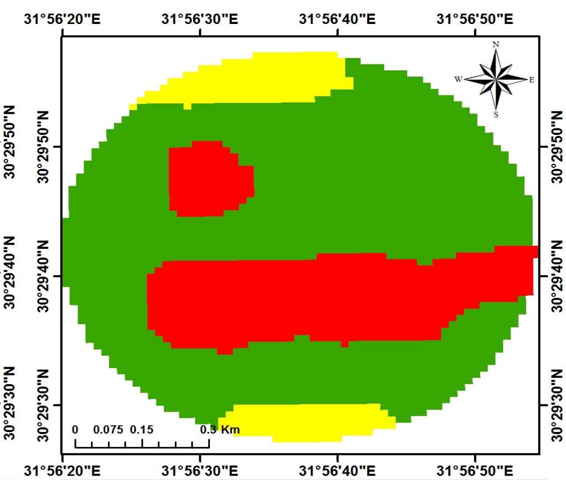
The results indicated that the area extension per hectares for each productivity class is as follows: high production 11.35 ha, moderate production 25.3 ha and low production 26.35 ha which represent 18.5%, 39.9% and 41.6% of the study area respectively.

The results indicated that high production areas were found generally in soil of EC from 0.3 to 3.9 dS m^{-1}, soil pH level (7.3 to 7.9) and $CaCO_3$ that ranged from 0.6 to 10 g kg^{-1}. Low production areas were characterized by low CEC and EC between 4 to 5.2 dS m^{-1}, soil pH level between 8 to 8.5 and $CaCO_3$ (15 g kg^{-1}). A comparison of these results with the Peanut crop requirements, in terms of soil, topography and climate conditions indicated that the area is generally suitable for Peanut crop, although the low production area need to be enhanced by nutrients supplies and organic matter. Moreover, accuracy assessment of soil productivity map showed adequate classification results with 89% overall accuracy and 0.86% overall kappa. The results of Kappa factor show a significant effect between the different classes on the model of output maps.

The result showed that using automated variable rate sprayers combined with site-specific management for herbs infection areas are greatly responsible for lowering cost of herbicides and decreasing environmental impact, through applying the least amount of herbicides necessary as shown in Fig. 4 and Table 3.



Classes	Area ha^{-1}	Area (%)
High production	23.54	35.02
Moderate production	7.11	10.55
Low production	36.58	54.43



Classes	Area ha^{-1}	Area (%)
No herbs	44.53	66.25
moderate infect	6.41	9.54
High infect	16.28	24.21

Fig. 4. A: Soil productivity B: Herbs infection

Table 3. Comparison statistics between using traditional and precision agriculture of herbicides applications

Traditional agriculture			Precision agriculture		
Classes	**Area ha^{-1}**	**Cost (%)**	**Classes**	**Area ha^{-1}**	**Cost (%)**
No herbs	44.53	66.25	No herbs	44.53	0
moderate infect	6.41	9.54	Moderate infect	6.41	9.54
High infect	16.28	24.21	High infect	16.28	24.21
		100			**33.75**

3.3 Accuracy Assessment of GIS-Mapping of Soil Peanut Productivity

Confusion matrix of 3×3 cells was selected to assess the accuracy of GIS- map of soil Peanut productivity; producers and users accuracy of map unit as well as the map entire. This accuracy assessment was based of kappa statistics is that a measure of agreement of accuracy. This measure of agreement is based on the difference between the actual and correct of confusion matrices classification (Table 3). In this matrix, the column represents the omission errors, while the errors of commission are shown in the rows. Therefore, confusion matrix enabled to determine the omitted (under estimated) and committed (overestimated) pixels of the different classes of soil Peanut productivity. The interpretation of confusion matrix indicted that:

- Thirty seven zones- test were selected (Table 4) to assess the classification accuracy of soil Peanut productivity map, while the categorical accuracy of information classes was tested by different number of zones-test. Mapping accuracy of the mapping units of high, moderate and low production, were assessed by 10, 9 and 18 zones –test, respectively.

The producer’s accuracies ranged from 85.74% to 91.67% the lowest producer’s accuracy was recorded in the case of high production class, while the highest producer’s accuracies was assigned to low production class. The producer’s accuracies ranged between 87.41% (class of low production) to 90.34% (class of high production).

Accuracy assessment showed adequate classification results with 91% overall accuracy and 0.87 overall kappa as shown on the assessment report below.

3.4 Field Management Zones

The field management zones were established based on the soil productivity map accompanied with herbs infection map and vegetation indices. The average of the mean EC, ESP, $CaCO_3$ and measured Peanut yield within each management zone were significant at $P < 0.05$ probability level, for slope and saturation percent, at $P < 0.1$ probability level. In the meantime, SAVI measurements showed higher value in zone 1 than zone 2 and zone 3. Basically, soil chemical properties were much more optimal for crop growth in the management zone 1 than in the management zone 3, where the actual yield in zone 1 was highest one whereas from 100% to 80%, while zone 3 defined as the lowest one representing the area with yield below 50%, zone 2 from 50% to 80% production.

Thus, it appears that soil properties and vegetation indices such as soil EC, pH, $CaCO_3$, ESP, slope and SAVI can be used to delineate management zones that characterize spatial variation in crop productivity.

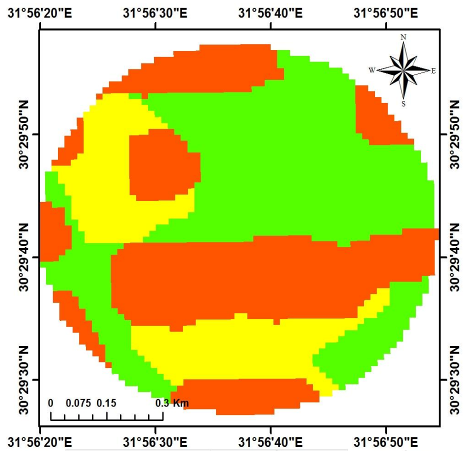
Table 4. Confusion matrix of soil productivity output data classification

Production levels	Production levels			Total zones tested
	High	Moderate	Low	
High	9	1	1	10
Moderate	1	8	2	9
Low	0	0	15	18
Total	10	9	18	37

Table 5. Classification accuracy assessment of different classes of Peanut soil productivity output data classification

Classes peanut soil productivity	Total examined cells	Classified cells	Correctly classified cells	Omission and commission errors	Accuracy (%)	
					Producers	Users
High	10	10	9	5.56	90.43%	85.74%
Moderate	9	8	8	3.57	91.76%	91.76%
Low	18	17	16	6.06	87.15%	90.26%
Totals	37	22	19	-	90.27%	88.59%

Overall classification accuracy = 89.32%



Classes	Area ha^{-1}	Area (%)
Managmenet zone 1	26.14	38.88
Managmenet zone 2	13.09	19.47
Managmenet zone 3	28.01	41.65

Fig. 5. Management zones for the studied peanut pivot

4. CONCLUSION

The conclusions drawn from this study indicate that, remote sensing imagery with soil data analyses allowed for the identification of spatial pattern of crop growth variability. The variability in soil characteristics within the field effects on Peanut yields predicted by soil suitability model. Using the soil suitability model and a sufficient number of field observations within each class, an acceptable accuracy and good spatial distribution of the suitability classification was achieved. Furthermore, compared with the crop growth models, the soil suitability model provided better detection of small areas referred to soil properties, such as Calcareous areas and saline soils. Using automated variable rate sprayers combined with site-specific management for herbs infection areas are greatly responsible for lowering cost of herbicides and decreasing environmental impact, through applying the least amount of herbicides necessary. Moreover, resulting canopy healthy and yield estimations showed a good agreement with field measurements with significant correlation coefficient.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Blackmore B. Precision farming: An introduction. Outlook on Agriculture. 1994;23(4):275-280.
2. Rub Georg. Spatial data mining in precision agriculture, PhD, Dissertation, Otto von Guericke, University of Magdeburg; 2012.
3. Colwell RN. History and place of photographic interpretation. American Society for Photogrammetry and Remote Sensing (ASPRS), 2nd edition. 1997;3-47.
4. Roebeling R, Van Putten E, Genovese G, Rosema A. Application of meteosat derived meteorological information for crop yield predictions in Europe. International Journal of Remote Sensing. 2004;25(23): 5389-5401.
5. Doraiswamy PC, Sinclair TR, Hollinger S, Akhmedov B, Stern A, Pmeger J. Application of MODIS derived parameters for regional crop yield assessment. Remote Sensing of Environment. 2005;97:192–202.
6. Liu X, Kafatos M. Land-cover mixing and spectral vegetation indices. International Journal of Remote Sensing. 2005;26:3321-3327.
7. Aparicio N, Villegas D, Araus JL, Casadesu. Relationship between growth traits and spectral vegetation indices in durum wheat. Crop Science. 2002;42: 1547-1555.
8. Elvidge CD, Chen Z. Comparison of broad-waveband and narrow-waveband red and near-infrared vegetation indices. Remote Sensing of Environment. 1995;54:38-48.
9. Rondeaux G, Steven M, Baret F. Optimization of soil-adjusted vegetation indices. Remote Sensing of Environment. 1996;55:95-107.
10. Lawrence RL, Ripple WJ. Comparisons among vegetation indices and band wise regression in a highly disturbed, heterogeneous landscape: Mount St. Helens, Washington. Remote Sensing of Environment. 1998;64:91-102.
11. Drysdale Warren GM, Metternicht GI. Utilizing remote sensing and terrain data for designing multi-scale sampling strategies of soil properties in agricultural fields. (ACT, Ed.) Proceedings of Spatial Sciences; 2003.
12. Narayana MR, Rao NH. GIS based decision support systems in agriculture. National Academy of Agricultural Research

Management. Ragendranagar, Hyderabad; 2002.
Available:http://www.sstdevgroup.com

13. Seelan SK. Remote sensing application for precision agriculture: A learning community approach. Remote Sensing of Environment. 2003;88:157-169.
14. Kaspar TC, Colvin TS, Jaynes DB, Karlen DL, James DE, Meek DW. Relationship between six years of corn yields and terrain attributes. Precision Agriculture. 2003;4:87–101.
15. Spomer RG, Piest RF. Soil productivity and erosion of Iowa loess soils. Transactions of the American Society of Agricultural Engineers. 1982;25:1295–1299.
Standardization of Coordinate Systems and Datums.
Available:http://wvgis.wvu.edu/othwrdocs/standardsndpubs/wv coordinate systems aug02
16. Stone JR, Gilliam JW, Cassel DK, Daniels RB, Nelson LA, Kleiss HJ. Effect of erosion and landscape position on the productivity of Piedmont soils. Soil Science Society of America Journal. 1985;49:987–991.
17. Jones AJ, Mielke LN, Bartles CA, Miller CA. Relationship of landscape position and properties to crop production. Journal of Soil and Water Conservation. 1989;44: 328–332.
18. Kravchenko, Bullock DG. Correlation of corn and soybean grain yield with topography and soil properties. Agronomy Journal. 2000;92:75-83.
19. FAO, Near East and North Africa Regional Network for Agricultural Policies (NENARNAP), Food and Agriculture Policy Decisions Analysis (FAPDA), Egypt Report, Food and Agriculture Organization of the UN (FAO); 2011.
20. USDA, World Agricultural Production, Foreign Agricultural Service / Office of Global Analysis, International Production Assessment Division (IPAD / PECAD), Ag Box 1051, Room 4630, South Building, Washington, DC 20250-1051; 2015. Available:http://www.pecad.fas.usda.gov/
21. Rowell DL. Soil science methods & applications. Library of Congress Cataloging in Publication data, New York, NY 10158. U.S.A; 1995.
22. Sys IC, Van Ranst B, Debaveye J. Land evaluation. Part I. Principles in land evaluation and crop production calculations. International training center for post graduate soil scientists, University Ghent; 1991.
23. Rouse JW, Haas RH, Schell JA, Deering DW, Harlan JC. Monitoring the vernal advancement and retrogradation of natural vegetation. NASA/GSFC, Type III, Final Report, Greenbelt, MD. 1974;1–371.
24. Huete A. A soil-adjusted vegetation index (SAVI). Remote Sensing of Environment. 1988;25:295–309.
25. FAO. A framework for land evaluation. Soils Bulletin 32, Rome. 1976;72.
26. Mason RL, Gunst RF, Hess JL. Statistical design and analysis of experiments with applications of engineering and science. 2nd edition, John Willey and Sons Hoboken, New Jersey, USA; 2003.
27. Eastman JR, Jin W, Kyem AK, Toledano J. Raster procedures for multi-criteria/multi-objective decisions. Photogrammetric Engineering and Remote Sensing. 1995;5:539–547.
28. Eastman JR. IDRISI 32. Guide to GIS and Image Processing. Clark Labs, Clark University, Worcester, MA, USA; 1999.
29. Malczewski J. GIS and multi-criteria decision analysis. Wiley, New York, USA; 1999.
30. Saaty TL. The analytic hierarchy process. Planning, priority setting, resource allocation, McGraw Hill, New York, USA; 1980.

Peer-review history:
The peer review history for this paper can be accessed here:
http://sciencedomain.org/review-history/13563