SPATIO-TEMPORAL VARIABILITY OF RICE CROP FROM REMOTE SENSING

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Abstract
In Italy there are about 150 varieties of rice and in the world, there are more than 3 thousand, each with different properties. Predicting rice yield at panicle initiation stage would provide valuable information for future planning.
In this study, RapidEye satellite images were acquired in order to provide spatio-temporal data of canopy reflectance at high spatio-temporal resolution, allowing to identify crop differences between and within fields. The study area was located in Sardinia, in a 35ha paddy field, where rice (Oryza Sativa) has been cultivated for over 30 years. Yield maps were acquired in both study years to validate the analysis.
Spectral information and reflectance analysis from remote sensing provide information about health and growth evolution. The potential of NDVI vegetation index to be used as yield estimator was investigated. A correlation analysis was performed between NDVI maps, derived from satellite images, and yield maps respectively in both study years. Correlation analysis has shown that seeding density is a determinant of yield although the NDVI index is influenced by additional factors such as the presence of weeds and plant diseases.

Key words: *yield maps, NDVI, seeding density.*

INTRODUCTION

The agricultural sector of rice growing must be set up against a background of the new challenges facing to both cultural input competition and the increasing demand for food, linked to competition on food prices caused by the globalization of markets. Agriculture, especially in developed countries, requires an approach to sustainable production from both an economic and environmental point of view (*Coppola, 2020*).
The precision agriculture approach could benefit from the use and the convergence of several technologies among which the Global Positioning System (GPS), Geographic Information System (GIS), miniaturized computer components, automatic control, in-field and remote sensing, mobile computing, advanced information processing and, wireless data transmission (*D'Antonio 2020; Gibbons, 2000*). Previous studies using remote sensing of rice crops have demonstrated relationships between the reflectance data and biophysical parameters (*Shibayama and Akiyama, 1989; Spackman et al., 2000; Cassanova et al., 1998*). These studies are characterized by the collection of ground-based radiometric data and they have successfully estimated biomass in rice, before the heading stage, by using NDVI vegetation index values. Other studies have shown that it is possible to estimate rice yield using vegetation indices from remote sensing (*Fablo and Felix, 2001; Alvaro et al., 2007*).
Rice (Oriza Sativa L.), an essential aliment in most Asian countries, accounts for more than 40% of caloric consumption worldwide (*IRRI, 2006*). Annual rice production amounted to approximately 755 million tons (*FAOSTAT, 2019*) for a yield of around 4,88 ton/ha in Asia (*FAOSTAT, 2019*). While in 2011 (*FAOSTAT, 2012*) production reached 650 million tons.
Profit from rice production rely on crop grain yield and total biomass produced. Predicting rice yield at panicle initiation stage would provide valuable information for future planning.
Yield efficiency depends mainly on accurate site-specific management, which needs a proper delineation of homogeneous zones in the field. Homogeneous zones are the result of the analysis of the combined interaction of chemical and physical soil properties, climate and plant (*Basso et al., 2016;*

Fiorentino et al., 2020; Elsharkawy et al., 2022). Homogeneous zone definition usually requires years of studies, depending on the field complexity.
Tomography, climate and canopy reflectance data provide direct or indirect management suggestions about crop canopy, nitrogen and chlorophyll content as well as weeds density.
The objective of this paper is to investigate the potential of Normalized Difference Vegetation Index (NDVI) to estimate rice yield at different growing stages. Yield maps were acquired to validate the analysis. Rice yield is strictly related to rice seedling density (number of rice seedlings per unit area)

MATERIALS AND METHODS

Site description and agronomic management

The experiment took place in Sardinia (8°43'40"E, 39°56'44"N, WGS 84) during two consecutive growing seasons, in a 35ha paddy field, where rice (Oryza Sativa) has been cultivated for over 30 years. The study area was divided in 9 sub-areas, as shown in figure 1.
In the first experimental growing season, the “Volano” (plots D and E) and “Karnak” (plots: A, B, C, F, G, H and I) cultivars, were planted. The crop cycle length was of 150 days.
The study field was a traditional paddy area continuously flooded; the wide field had the same treatment in terms of water use, fertilization, as well as disease and pest control. Two sub-areas have required some extra treatments in graminaceae weeds control, during crop cycle.
Broadcast sowing was done on 17th May, with seed density of 500 germinables seeds m^{-2}.
“Libero” (Indica subsp., plots D and E), “Karnak” (Japonica subsp., plots B, C, F, G, H and I) and “Carnise” (Japonica, plot A) varieties were planted in the field during the second growing season. The crop cycle length was of 160 days. Broadcast sowing was done on 15th May, with a seed density of 500 germinables seeds m^{-2}. Seed density showed a noticeable variability due to a mechanical fault on broadcast sowing or environmental conditions (wind and waves, seed flotating, etc).

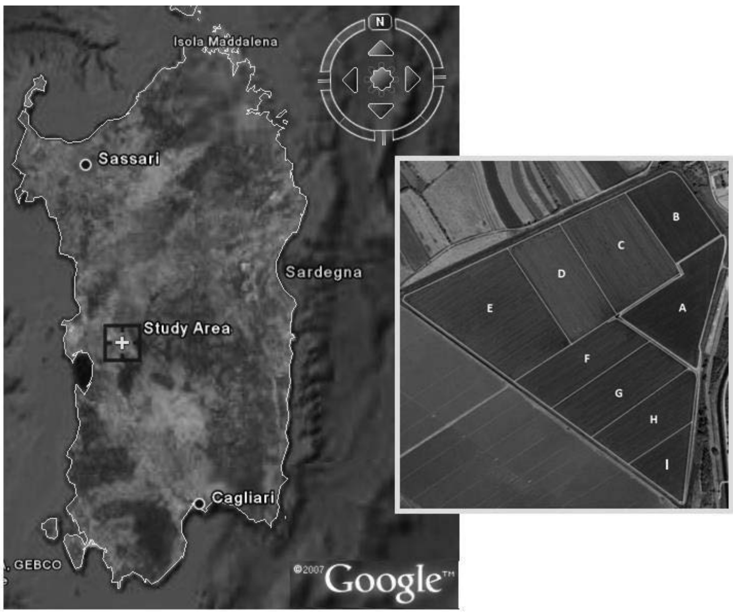
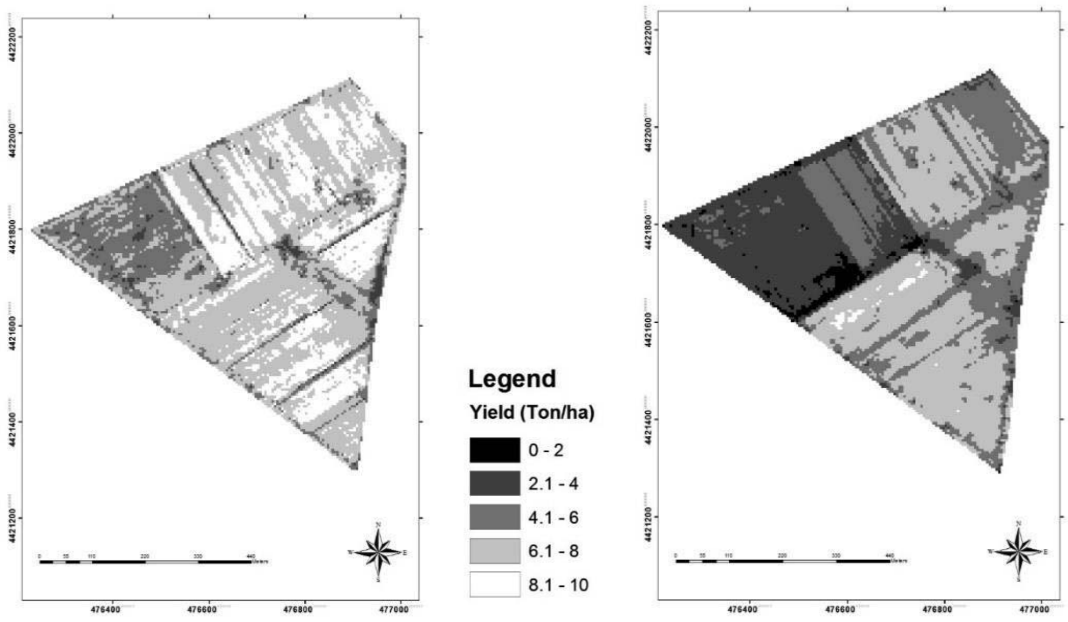


Fig. 1 Sardinia study area with the experimental plots

Field Measurements: Yield Maps

Georeferenced yield data were recorded by a New Holland combine harvester equipped with a yield monitor system (grain mass flow and moisture sensors). The data were acquired along 6 meters wide parallel transects. The average distance between two successive acquisitions was about 2 meters. Yield data were corrected based on the grain moisture content estimated by the combine harvester.
The 2 years yield maps (shown in figure 2), were obtained by plotting the yield data, elaborated by Ordinary Kriging at the nodes of a regular grid of 5 meters spatial resolution (*Goovaerts, 1997*).
It has been decided to analyzed separately the different cultivars, as a result of important discrepancies found between the mean of each yield distribution in the second year with respect to Karnak-Carmise

and Libero, while the difference was lower in the first experimental year for Volano and Karnak. The yield maps, shown in figure 2, were georeferenced and coregistrated in UTM WGS 84 zone 33N geographic reference system.



(a) (b)

Fig. 2 Yield maps for growing season 2010 (a) and 2011 (b)

Remote sensing images

A multi-temporal series of remote sensed images were acquired from the German company RapidEye A.G. (Brandeburg, DE). Satellite images were characterized by a spatial resolution of 5 meters and 5 narrow bands (spectral intervals of the electromagnetic radiation: Blue, Green, Red, Red-Edge and NearInfraRed). The images acquisition took place on 2010: 2th July, 28th July, 15th August and 10th September; and 2011: 26th June, 5th July, 16th July, 28th July 12, 20th August.

The Normalized Difference Vegetation Index (NDVI, Rouse et al., 1974) was computed as follows:

$$NDVI = (NIR - RED) / (NIR + RED) \quad (1)$$

NIR represents the wavelength in the near infrared portion of the electromagnetic spectrum (760-880 nm) and RED, the wavelength in the red portion of the spectrum (630-690 nm). All images, were geometrically and radiometrically corrected, and then, georeferenced and coregistered in UTM WGS84 coordinate system.

Correlation Analysis

A multitemporal time series of correlation maps were elaborated; the Pearson (*Hall, 1976; James, 1988*) correlation coefficients were computed at each node (5 meters equally spaced) of a regular grid associated to the corresponding pixels of the yield and the NDVI maps. The analysis has involved both studies years (2010 and 2011) at three different dates during the growing seasons. The NDVI maps involved in the analysis were: 2010 July 2nd and 2011 July 5th; 2010 July 28th e 2011 July 28th; 2010 August 15th e 2011 August 20th. The coupled dates of NDVI' maps involved in the analysis were very close, if not coincident, and relative to the same growing stage.

The spatial correlation maps, between NDVI and yield, were obtained by using a purpose-built Matlab script. Since it is not possible to consider each pixel independent from the neighbors at the spatial resolution of 5 meters, the Pearson analysis takes into account, not only of the corresponding pixels of each map, but all pixels that fall within a neighborhood centered on the pixel of interest. The neighborhood was defined as a circular moving window of a 30 meters diameter. The script produces a second output: the significance level (p-values) maps at each georeferenced location (acceptance level: p-val.<0.05).

RESULTS AND DISCUSSION

Yield maps

Figure 2 shows the yield maps for the growing season 2010 (a) and 2011(b). The average yield for the Karnak cultivar was higher in 2010 than in 2011.

In 2010 the average yield for the plots D and E, associated to the the Volano cultivar, was about 6,34 t ha^{-1}, while the remaining plots (Karnak cultivar) produced about 7,36 t ha^{-1}.

The average yields for Volano and Karnak cultivars do not show significant discrepancies.

Difference in levels of production between the fields E and D (YieldE<YieldD) (figure 2a) further supports this statement. This difference can be explained by the persistence of weeds in plot E, notwithstanding the operations of weed control.

In 2011, the average yield for the plots D and E, associated to the Libero cultivar, was about 3,31 t ha^{-1}. From the observation of figure 2b we notice that yield in plots D and E was low, particularly in the south side of plot E. In the Karnak-Carmise plots, the average yield was about 6 t ha^{-1}, lower than the previous year because of the non-uniformity in seed density that occurred in 2011.

During both study years, the yield showed a marked spatial and temporal variability. Identification of stable zone in the field from visual inspection remains difficult.

NDVI and Yield Analysis

The number of rice seedlings in the field is one of the main agronomic components for determining rice yield and the yield is also strictly correlated to the plant growth.

In this paper, the NDVI index, acquired at different phenological stages of rice crop, was correlated to the yield map in both study years. The index allows to monitor both the distribution of plants in the field and their development over time.

The spatio-temporal correlation analysis was performed including the following NDVI dates:

- 2010 July 2nd and 2011 July 5th;
- 2010 July 28th and 2011 July 28th;
- 2010 August 15th and 2011 August 20th.

The study allows both to evaluate the behavior of a single sample point of the field, but also how it behaves with respect to its neighbors.

The correlation analysis determines the geographical relationship between NDVI and yield and highlights its distribution in the space. The correlation maps are shown in figure 3.

Figure 3a shows a high inverse correlation (p value <0.001) between yield and NDVI index in plots D and E, which was already evident from the beginning of July. This was due to the presence of weeds in both 2010 and 2011study years. A further complication occurred in 2011 with the appearance of the sterility of kernels in relation to the Libero variety. In this area, this negative correlation persists even in the analysis of the two successive dates. The infertility of kernels, that occurred in plot E in the second study year, was not detectable by the analysis of the vegetation index, but it was not influenced by nitrogen management decisions or by weeding control. It would be interesting to calibrate the index limit value beyond which the crop becomes infesting itself.

The inverse correlation will always be obtained when the density of the crop is higher than its optimum, both due to the presence of weeds, as well as to the excessive sowing density or the emission of too many adventitious stalks due to too much forced fertilization in tillering. Too many stalks imply too much flowering, too much nutrient need and increasing sterility. The crop becomes infesting itself.

In the plot B, the NDVI shows a high positive correlation with yield on July 2nd/5th (2010/2011), because during the first study year (2010), high NDVI values corresponded to good yield levels, while in 2011, the poor production was due to the low seeding density (i.e. low NDVI). At the second date the correlation is reversed and it also remained negative on the last reference date (August 15th/20th). The problem, in plot B, was the re-emergence of weeds during both study years, particularly in 2011.

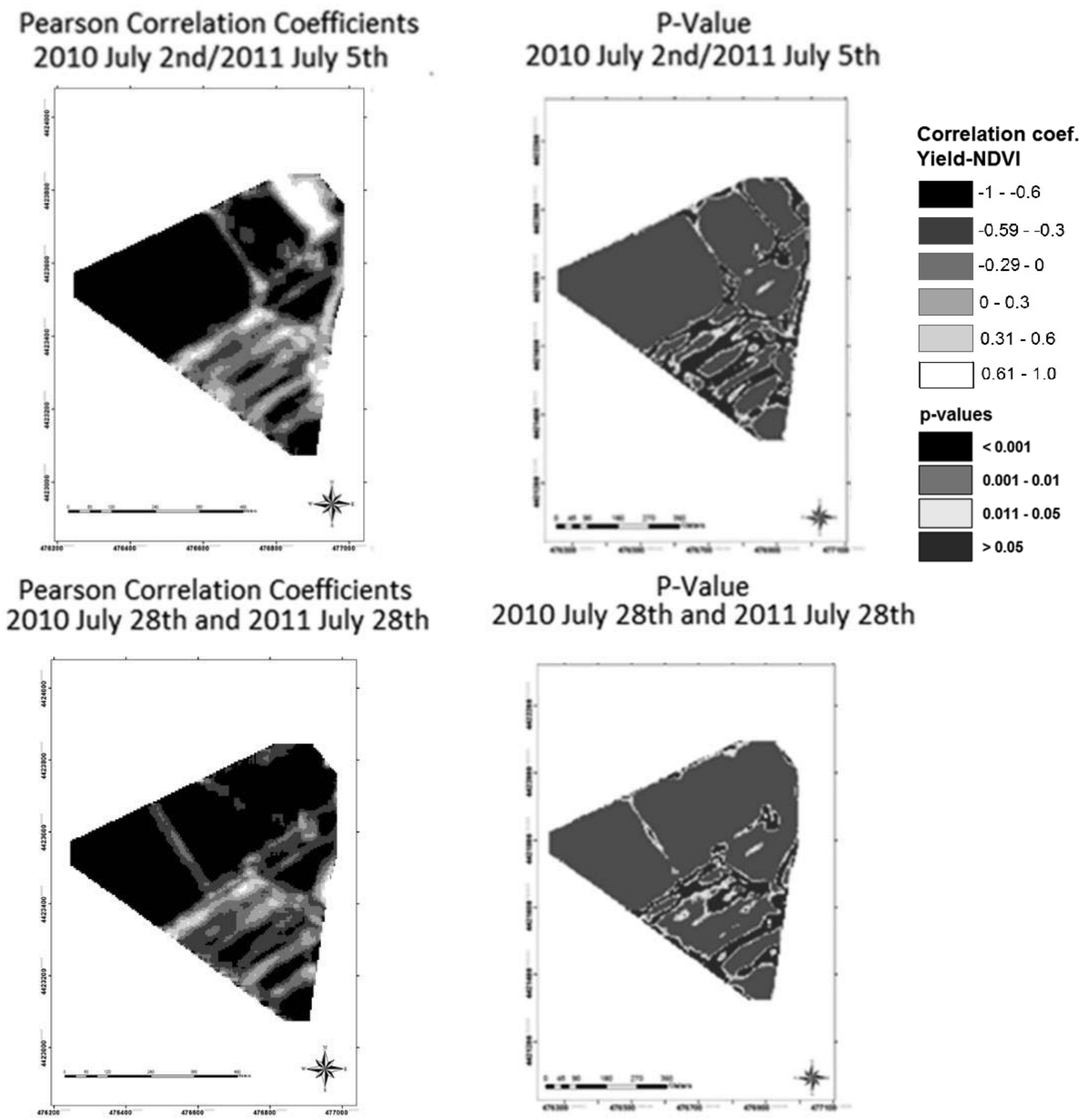
In the plot C, the strong negative correlation between NDVI and yield, already evident at the first date (fig. 3a), was strongly influenced by the presence of weeds in 2011.

In the other plots (A, F, G, H and I) the significance level of correlation (pvalue> 0.05) was poor especially in the areas at the edges of the plots. This effect is more visible on July 2nd /5th while it progressively decreases at the other reference dates.

The negative correlation, in the central portion of plot A, stems from the high seeding density which occurred in 2011. Plot F shows the lowest correlation coefficients, in turn positive and negative that became quite high in some areas. It was, probably, due to the most productive zone during the first year that became the less productive in the second.
The NDVI vegetation index proved to be a good yield estimator according to *Guam et al. (2019)*.
They used small unmanned aerial vehicles (UAVs) for determining high-resolution normalized difference vegetation index. The NDVI values were used to assess their correlations with the rice yields. *Guam et al. (2019)* observed strong correlations between NDVI and yield at the early reproductive stage or the late ripening stage for the direct-seeded rice.
The limits that this methodology presents are the same as highlighted by *Wu et al. (2019)*, they propoused a method to earlier estimations of rice yield that uses computer vision to accurately count rice seedlings in a digital image.
The main cases of failure were:

- when dark areas such as shadows appeared in the image, recognized as rice areas;
- presence of weeds in images that requires more complex tecniques to be detected.

On the other hand, the use of the NDVI index from satellite requires lower spatial resolutions (5m) than the use of a UAV in the field and allows more frequent monitoring over time.



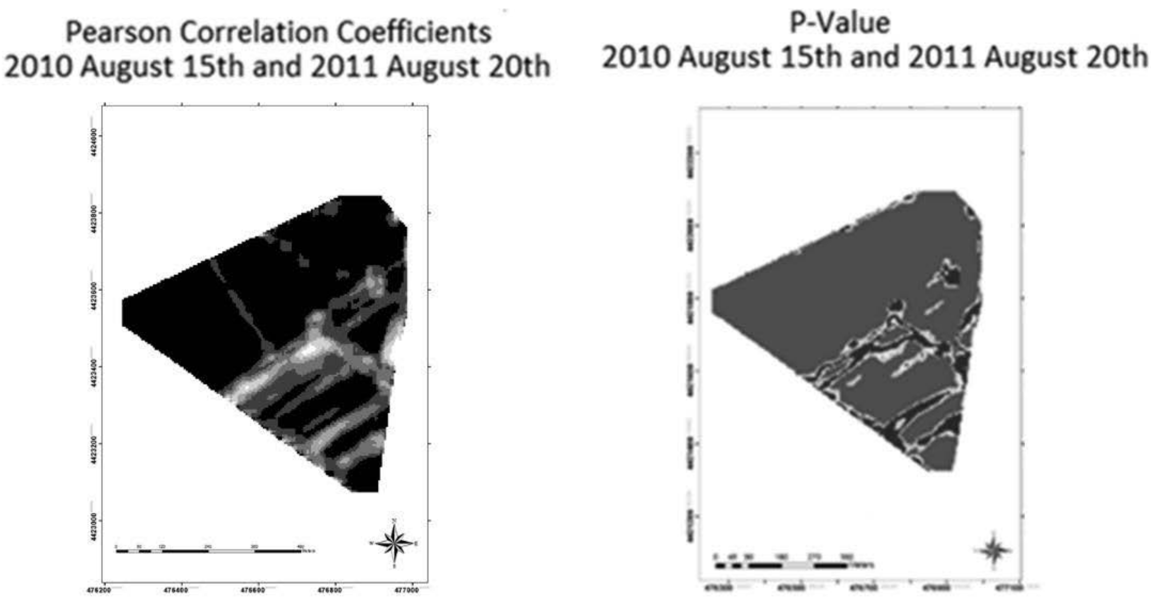


Fig. 3 Multitemporal sequence of correlation coefficients and significance maps between NDVI and yield

CONCLUSIONS

The remote sensing techniques could be an important support in the planning and management of vegetation during the growing season. They could also be used to estimate, rapidly and safely, the plant vigor and the crop potential yield.

The NDVI vegetation index, elaborated from satellite images, at different crop growing stage, was correlated with yield maps respectively in both study years. The combined study of the NDVI index and yield, has enabled the identification of potential threats related to seed density, along with the presence of pests and nutritional deficiency. Areas of high and low seeding density, as well as areas affected by weeds, were identified by
analyzing the mutual trend of NDVI index and production.

During the study years, the rice was affected by various problems, mainly the presence of weeds that made the analysis complex. In plots where no issues occurred, the NDVI index proved to be a good estimator of the yield and vegetation health during the growing season.

To address these problems, an additional analysis tool will be considered to be included in the processing chain to filter the presence of weeds from the remote sensing data.

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REFERENCES

1. Alvaro, F., L. F. García del Moral, and C. Royo. 2007. Usefulness of remote sensing for the assessment of growth traits in individual cereal plants grown in the field. Intl. J. Remote Sensing 28(11): 2497-2512.
2. Basso B., Cammarano D., Fiorentino C., Ritchie J. T., 2013. Wheat Yield Response to Spatially Variable Nitrogen Fertilizer in Mediterranean Environment. *Eur. J. Agron.*.
3. Basso B., Fiorentino C., Cammarano D., Schulthess U., 2016 Variable rate nitrogen fertilizer response in wheat usingremote sensing.Precision Agriculture, DOI10.1007/s11119-015-9414-9.
4. Cassanova D., Epema G.F., and Goudriann J.. 1998. Monitoring rice reflectance at field level for estimating biomass and LAI. Field Crops Research 55:83-92.

5. Coppola A., Di Renzo G.C., Altieri G., D'Antonio P., 2020. Lecture Notes in Civil Engineering, Preface (Editorial) Volume 67, Pages v-vii.
6. D'Antonio P., Scalcione V. N., 2020. Software and satellite technologies for precision agriculture: the potential with, EPH – International Journal of Agriculture and Environmental Research.
7. Elsharkawy, M.M., Sheta, A.E.A.S., D'antonio, P., Abdelwahed, M.S., Scopa, A., 2022. Tool for the Establishment of Agro-Management Zones Using GIS Techniques for Precision Farming in Egypt. Sustainability (Switzerland), 14 (9), art. no. 5437.
8. Fablo M., and R. Felix., 2001. Analysis of GAC NDVI data for cropland identification and yield forecasting in Mediterranean African countries. Photogram. Eng. and Remote Sensing 67(5): 593-602 RRI. 2006.
9. FAOSTAT. 2019.Agricultural Statistics Yearbook: 2018.
10. FAOSTAT. 2012.Agricultural Statistics Yearbook: 2011
11. Fiorentino C., Donvito A.R., D'Antonio P., Lopinto S., 2020. Experimental Methodology for Prescription Maps of Variable Rate Nitrogenous Fertilizers on Cereal Crops Lecture Notes in Civil Engineering 2020, 67, pp. 863–872
12. Gibbons G., 2000. Turning a farm art into science */an overview of precision farming. URL: http:// www.precisionfarming.com.
13. Goovaerts P., 1997. Geostatistics for Natural Resources Evaluation. Oxford University Press, New York
14. Hall E.H., Computer Image Processing and Recognition, Academic, New York (1979), pp. 480-485.
15. Guan S., Fukami K., Matsunaka H., Okami M., Tanaka R., Nakano H., Sakai T., Nakano K., Ohdan H. and Takahashi K., 2019. Assessing Correlation of High-Resolution NDVI with Fertilizer Application Level and Yield of Rice and
16. Wheat Crops using Small UAVs. Remote Sens., 11, 112; doi:10.3390/rs11020112
17. James M., Pattern Recognition, John Wiley and Sons, New York (1988), pp. 36-40.
18. Rouse J.W., Haas R.H., Schell J.A., Deering D.W., 1974. Monitoring vegetation systems in the Great Plains with ERTS. Third ERTS Symp., NASA SP-351 1, pp. 309–317.
19. Shibusawa S., 1998. Precision Farming and Terra-mechanics. Fifth ISTVS Asia-Pacific Regional Conference in Korea, October 20 Á/22.
20. Spackman S., McKenzi G., Lamb D., and Louis J., 2000. Retrieving biophysical data from airborne multispectral imagery of rice crops. International Archives of Photogrametry and Remote Sensing B7:1447-1451
21. Tennakoon S. B., Murty V. V. N., and Eiumnoh A., 1992. Estimation of cropped area and grain yield of rice using remote sensing data. Intl. J. Remote Sensing13(3): 427-439.
22. Wu J., Yang G., Yang X., Xu B., Han L. and Zhu Y., 2019. Automatic Counting of in situ Rice Seedlings from UAV Images Based on a Deep Fully Convolutional Neural Network. Remote Sens., 11, 691; doi:10.3390/rs11060691

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