P-ISSN: 1996-983X
E-ISSN: 2960-1908

مجلة المخطط و التنمية

Journal of planner and development

Vol 25 Issue 1 2020/6/1

# Mapping Paddy Rice Fields Using Landsat and Sentinel Radar Images in Urban Areas for Agriculture Planning

Haidar Razzaq Mohammed

University of Technology \ Civil Engineering Department

**Alhasan_h@yahoo.com**

**10960@uotechnology.edu.iq**

## Abstract

This research develops a new method based on spectral indices and random forest classifier to detect paddy rice areas and then assess their distributions regarding to urban areas. The classification will be conducted on Landsat OLI images and Landsat OLI/Sentinel 1 SAR data. Consequently, developing a new spectral index by analyzing the relative importance of Landsat bands will be calculated by the random forest. The new spectral index has improved depending on the most three important bands, then two additional indices including the normalized difference vegetation index (NDVI), and standardized difference built-up index (NDBI) have been used to extract paddy rice fields from the data. Several experiments being conducted to analyze and understand the strengths and weakness of the proposed new method. This research shows that spectral indices are easy and accurate tool for rapid mapping of paddy rice fields in complicated environment where urban features are dominated. The outcomes of this research could help mapping and decision makers to progress their productivity and strategic plans for better management of rice fields.

**Keywords**: random forest classifier , Paddy Rice Fields, spectral indices, Landsat OLI and Sentinel-1 satellite images

مجلة المخطط والتنمية
Journal of planner and development
P-ISSN: 1996-983X
E-ISSN: 2960-1908
Vol 25 Issue 1 2020/6/1

# إعداد خرائط لحقول الرز للمنطقة الحضرية باستخدام صور ( لاندسات و رادارية) لتوجيه التخطيط الزراعي

**المدرس المساعد حيدر رزاق محمد**
**الجامعة التكنولوجية / قسم الهندسة المدنية**
**Alhasan_h@yahoo.com**
**10960@uotechnology.edu.iq**

**المستخلص**

هذا البحث يوضِّح طريقة جديدة للكشف عن حقول الرز ضمن المنطقة الحضرية باستعمال المؤشرات الطيفية و تصنيف الغابات العشوائية وتقييم الدقة للطريقة المستعملة. سيتم اجراء التصنيف على صورة لاندسات وصورة رادار سنتنل , تم تجربة أعداد محتلفة من عينات الغابة العشوائية لتحديد الحزم الطيفية الأكثر أهميه وربطها بمعادلة لخلق مؤشر طيفي جديد وتم دمج الحزم الطيفية المنتخبة للحصول على مرئية وإجراء التصنيف عليها. تم ايضا استعمال المؤشرين الطيفيين NDVI&NDBI لاستحصال بيانات عن حقول الرز. ثم تم إجراء عملية تصنيف لمرئية أخرى ناتجه من تكامل حزم لاندسات السبعة مع الحزمة الرادارية و قيمت الدقة للصورة الناتجة, حيث اظهرت النتائج ان الدقة المستحصلة من الصورة المصنفة اولا تشبه الى حد كبير نتائج التصنيف للصورة المصنفة الثانية بفارق قليل، ويُعزى هذا الاختلاف الى وجود الحزمة الرادارية، بالإضافة الى إجراء العديد من التجارب لتحليل وفهم مواطن القوة والضعف في الطريقة الجديدة المقترحة. يوضح هذا البحث أن المؤشرات الطيفية هي أداة سهلة ودقيقة لرسم الخرائط السريعة لحقول الأرز في بيئة معقدة حيث تسيطر الخصائص الحضرية. يمكن أن تساعد نتائج هذا البحث على رسم الخرائط واعطاء صورة لصنّاع القرار للتقدّم في إنتاجيتهم وخططهم الإستراتيجية لتحسين إدارة حقول الأرز.

P-ISSN: 1996-983X
E-ISSN: 2960-1908
مجلة المخطط و التنمية
Journal of planner and development
Vol 25 Issue 1 2020/6/1

## 1. Introduction

Urban area in the most cities in the world during twentieth century has been increased due to population expansion and people displacing from rural areas to more developed regions. Rapid urban sprawls have a significant impact on the management and development of cities worldwide. Likewise, cities; villages on the other hand are also facing a rapid expansion and population growth. Once villages have expanded into cities; then they approach the threshold of being a city at an alarm rate. Overreached the maximum capabilities for the developing world's management of the cities. Thus, it appears to be that urban planning has a crucial rule to manage cities' capability to incorporate population expanding rates [1]. Nonetheless, appropriate planning within the sustainable limits will give the chance for better land use management.

In addition, shifting the settlements to the surrounding agricultural lands (e.g., paddy rice crops) may lead to planning problems; Urbanization is clustering of high density population in specific places. Beyond doubt the relationship between high population and big cities is a consequence of many aspects in our life and daily obligations like: economical, industrial, and transportation. Therefore. Significant, alterations took place to the land use of theses cities and the adjacent lands. Thus, effects of cities expansion are clearly noticeable out of their surrounding and they have vanished substantial green lands due to the massive urbanization growth and needed framework, Therefore, short and long-term plans should be carefully developed to reduce the impacts of such unorganized urban sprawls.

Remote sensing is a technology that provides access to spatial information over large areas via aerial or space-based systems. Among the spaceborne satellite systems, Landsat is a series of satellite systems provide free multispectral images

for the globe; it provides images in the visible, infrared, and thermal bands allowing exploring the Earth's surface effectively. The latest system that is in operation currently is known as Landsat 8; it provides images of 30 m spatial resolution for the multispectral bands and 15 m spatial resolution for a panchromatic image, which it could be used to enhance the spatial resolution of other bands via a process called pan-sharpening. Remote sensing techniques have been applied by several scholars for land cover mapping and change analysis [2-5].

On the other hand, geographic information system (GIS) is a software system that enables data analysts to create, store, manage, process, and visualize spatial information in a way far better than other systems. It uses the latest technology in computer science and algorithms to provide tools with user-friendly interfaces for processing geospatial data and model complex geographic phenomena [4].

Geographic Information System and Remote Sensing are technologies that contribute functional tools for, land use detection [6], ground working, and modeling [7]. so far , utilize RS and GIS techniques in urban plans can be rapidly developed for different uses of the natural resources and the protection of nature to succeed in dealing with the problems of chaotic urban spread as well as the matter of losing superior agricultural lands and forests [8]
Vegetation indicators such as vegetation density [9], cover types, and biological productivity are essential indicators for the source of food and development of the National economy. The observations using remote sensing give a scope of

monitoring, investigate the large-scale of alteration in vegetation due to climatic change, human facilities, and environmental changes.

Among agricultural crops, paddy rice is not only a highly protected crop in a strategically vital industry but also is critical for food security [10]. Rice is one of the world's two major staple foods; it accounts for 15% of the world's total cultivated area [11]. Satellite remote sensing technology has been applied to estimate crop areas and monitoring crop conditions. In the rice monitoring activity, the identification of paddy fields is one of the essential tasks of remote sensing for practical applications, but there are many difficulties in monitoring paddy rice, one of them is crop mixing with water. Therefore, an information data source for monitoring effective rice fields is an accurate way to distinguish paddy rice from other fields. Besides, estimating of rice crop area is a significant step to supply information about the policy of national food, calculation of yearly crop yields [12], and post-disaster indemnification.

The Normalized Difference Vegetation Index (NDVI) is robust, empirical measure of vegetation activity at the land surface. It enhances the vegetation signal which is received from measured spectral responses by combining two (or more) different wavebands, often in red (0.6-0.7 mm) and near-infrared (0.7-1.1 mm) wavelengths. Reflected red energy decreases with plant growth due to chlorophyll absorption within actively photosynthetic leaves. An increase of reflected near-infrared energy is due to plant growth through reflection and transmission processes in healthy leaves.

This paper presents a GIS-based method for detecting paddy rice fields using Landsat OLI and 69 Sentinel 1 radar images. The method is based on a new spectral index and random forest classification 70 at the pixel level. The proposed classification scheme is tested on real datasets over an area in Iraq.

P-ISSN: 1996-983X
E-ISSN: 2960-1908
مجلة المخطط و التنمية
Journal of planner and development
Vol 25 Issue 1 2020/6/1

## 3. Related Works

In general, vegetation mapping has been studied by many scholars using optical (Landsat TM/ETM/OLE) and radar (Radarsat and Sentinel) remote sensing [13-20]. Using only radar data, Tian et al. (2010) studied crop mapping using Radarsat-2 and TerraSAR-X images applying classification techniques of maximum likelihood classification (MLC) and minimum distance classification (MDC), this study found that C-band radar data has some advantages in mapping paddy rice[21]. De Souza et al. (2012) mapped mangrove forests in Brazil using frequency-based contextual classification of incoherent attributes derived from a multi-polarized PALSAR image; this study proved that using such data is sufficient for mapping mangrove areas. Fontanelli et al. (2014) showed that combining optical and radar images could improve crop mapping to classify an image into corn, rice, and wheat [22]. Combining C-band and X-band SAR data to maximize the improvement of rice area mapping that operational availability of satellite imagery is necessary for extracting information on crop's type and conditions [23].

Also, various methods and algorithms are established to detect paddy rice areas from satellite images (e.g., [11], [24], [25], [26]). Several methods are based on pixel-based or object-based classification, pixel-based classification is widely used because a spectral band such as red edge has potentials to detect different crop conditions in relatively homogeneous rice paddy environments [27]. For example, Ichikawa et al. (2014) used spectral information of Rapid Eye satellite image to identify paddy rice fields. In another paper, [26] and Xiao et al. [13] used spectral indices such as NDVI enhanced vegetation index (EVI) and normalized difference water index (NDWI) to map paddy rice fields.

Bridhikitti and Overcamp (2012) studied paddy rice mapping using time-series data with a

correlation-based approach for crop mapping [28]. Applications of crop yield estimation were developed by Huang et al. [12]. Advanced optimization methods like ant colony optimization algorithm are used to present image classification on the map of paddy [29].

Moreover, optical and radar imagery data are combined to detect paddy rice (e.g. [30-33]). These studies have been aimed to overcome the challenges of paddy rice mapping using only optical data. Adding radar data to the processing pipeline leads to a substantial improvement of image classification because of the unique temporal backscatter signature when the rice grows above the water surface [24].

## 4. Data and Methodology

### 4.1 Study Area

The study area is located in Iraq, in Al-Najef province as shown in Figure 1, it is a governorate in the south of Iraq. The geographic coordinates of this area are 32° 00' 00" N, 44° 32' 00" E. The subset of the area is about 1453.38 square kilometer, and the altitude varies from 52m to 61m mean sea level (M.S.L). This area is selected for this research because of its location, presence of paddy rice and the urban regions.

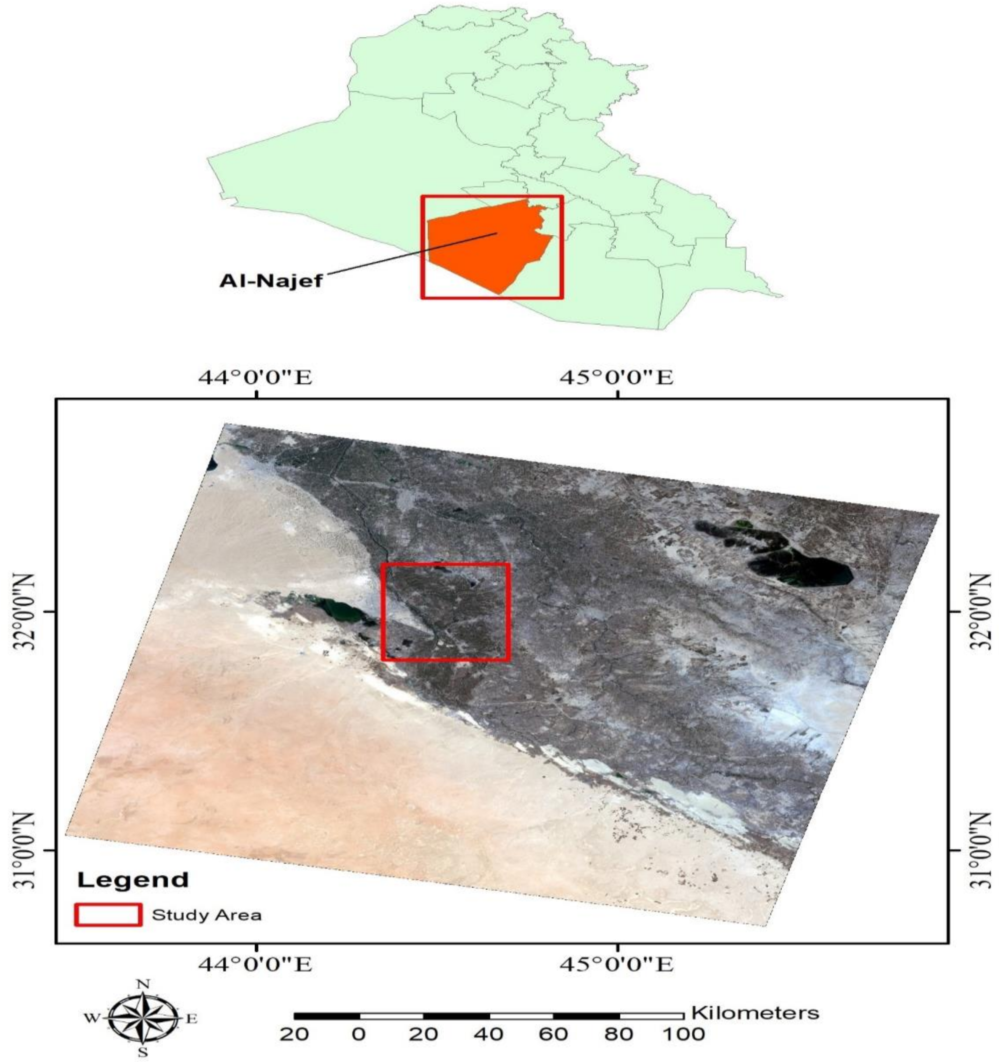



**Figure 1**: AOI (Study Area) /https: /earthexplorer.usgs.gov

## 4.2 Data Pre-processing

The images of this area of interest (AOI) were downloaded from USGS which are Landsat 8 Operational Land Imager (OLI) and Sentinel-1 as shown in **Figure 2**. Landsat 8 OLI images consist of several spectral bands (coastal: 0.43-0.45mm, blue: 0.45-0.51mm, green: 0.53-0.59mm, red: 0.64-0.67mm, NIR: 0.85-0.88mm, SWIR 1: 1.57-1.65mm, SWIR 2: 2.11-2.29mm, cirrus: 1.36-

1.38mm, TIRS 1: 10.60-11.19mm, and TIRS 2: 11.50-12.51mm, panchromatic band 0.50-0.68mm). These bands allow calculating vegetation and other spectral indices such as NDVI and NDBI. Sentinel-1. Where Radar data has used because of its advantages in vegetation mapping and penetrating the vegetation canopies. Therefore, the information regarding vegetation structure can be estimated, as well as it has other advantages, like free-cloud images, sensitive to soil moisture, and adequate data for water extraction. The characteristics of these datasets are listed in Table 1.

Ground truth data is created from Google Earth images, which are 570 samples of paddy rice and 377 samples for other class. These samples are checked and verified manually by visualizing the images and assign the correct label for each sample. The ground truth data is divided into training samples (70%) and the remaining 30% as test samples, to test the accuracy of the classification model.

In general, the raw data contains several malfunction errors. Therefore, it needs geometric and radiometric correction and calibration. The images are geometrically corrected with respect to the collected ground control points (GCPs). Second-order polynomial is used for transformation, then, nearest neighbor resampling approach has to be implemented, in which the related root mean square error (RMSE) equals 1.13 pixels. Instead, for radar data, a second-order polynomial and cubic resampling have to be applied. The estimated RMSE is 1.28 pixels. After correcting both the Landsat and Sentinel images, the area has to be put in zone 38 N in the UTM coordinate system using the WGS84 datum and WGS84 ellipsoid. The geometric calibration of the images is considered significant prior sensor integration. Landsat image pixel values are converted to radiance values; these meaningful radiance values are drawn from a conversion of the digital numbers of the image. Atmospheric correction then is applied using

P-ISSN: 1996-983X
E-ISSN: 2960-1908

dark object subtraction method. The speckle noises in the image can be reduced using enhancement filter like Lee with a kernel measurement of (3 x 3) block size.

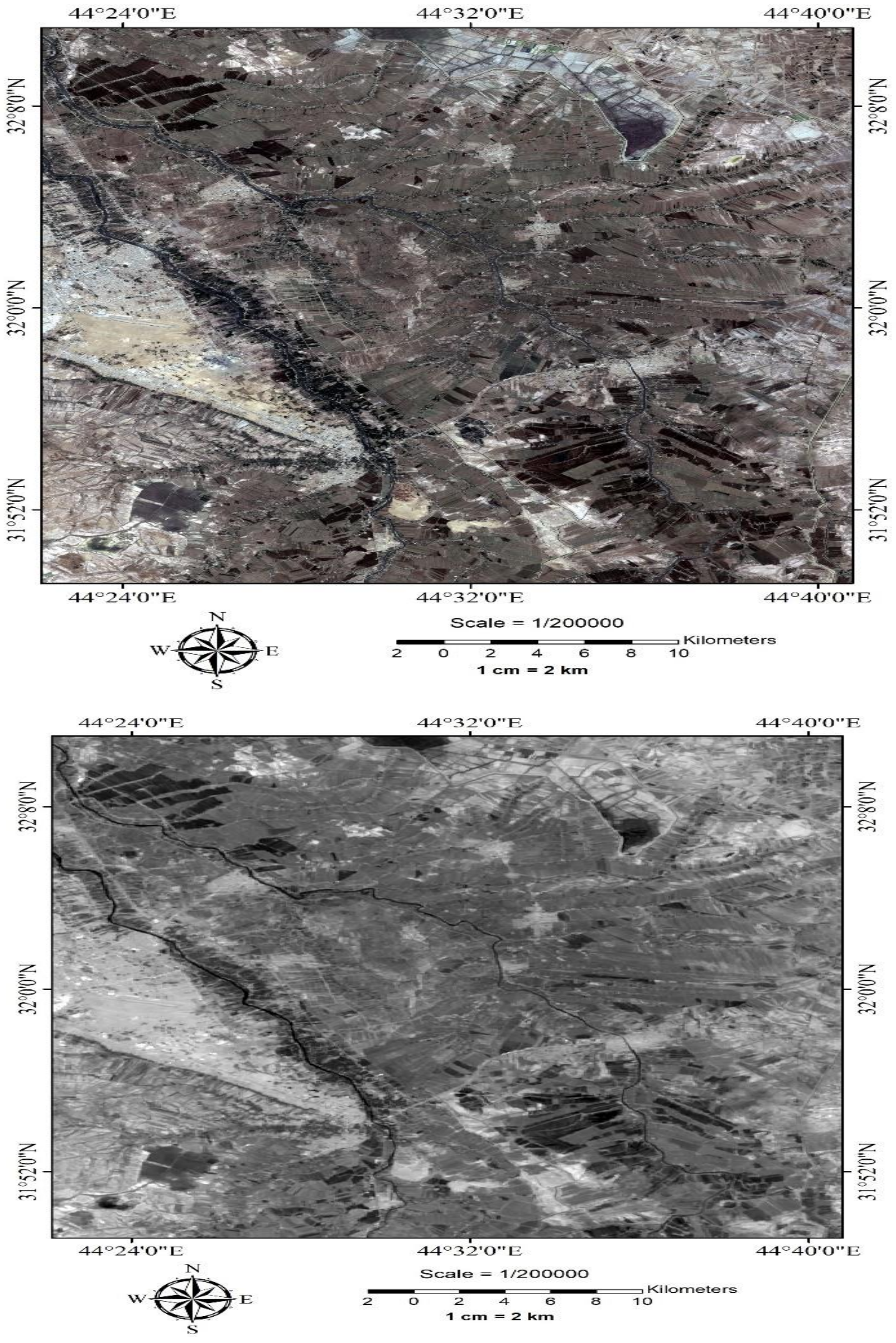



**Figure 2**: The map of Landsat (left) and Sentinel (right) images.
**Source:** https: /earthexplorer.usgs.gov

**Table 1**: The characteristics of the datasets.
**Source:** meta data of images

| Dataset | Parameter | Characteristics |
|---|---|---|
| **Landsat OLI** | Path/Raw | 168/38 |
| | Date | 2018-04-19 |
| | Cloud Cover (%) | 0 |
| | Spatial Resolution | 30 m |
| **Sentinel 1** | Date | 2018-04-19 |
| | Polarization | HV |
| | Spatial Resolution | 10 m |

### 4.3 Methodology

This section describes the overall proposed methodology to detect paddy rice areas in an integrated Landsat OLI and Sentinel-1 satellite images which consist of spectral index development, mapping paddy-rice areas using random forest method, and the accuracy assessment.

#### 4.3.1 Spectral Index Development

The main step in the proposed spectral index development involves choosing the section of the best bands according to the ability of a classier to separate paddy rice areas from other areas. The analysis is carried out using supervised random forest (500 trees) which is implemented through sklearn in Python. The relative importance of each spectral band is calculated, and the bands

are then sorted according to their importance (from most to least important band). These bands are Red, NIR, and SWIR will be used to develop a spectral index for better extraction of paddy rice from the Landsat image in comparison to the standard NDVI index. This index is developed by trial and error to get an equation out of the elected bands. The analysis suggested that (Red – NIR)/SWIR gives best assessed visually results. The aim of the spectral index is to help classifying the area by effectively separating paddy rice from other land cover types. Figure B shows the accuracy with respect to each spectral band.

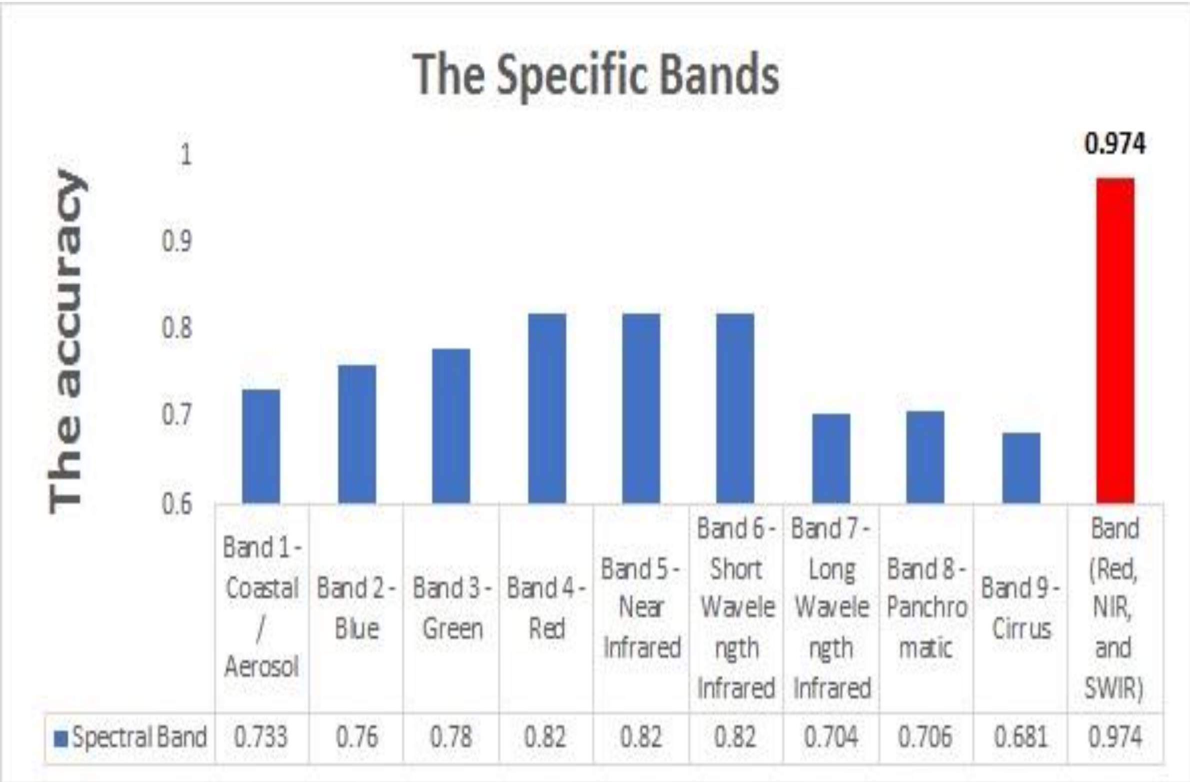



Figure B. Classification Result with respect to each band using LandSat data.

**Source:** Meta data for Land sat images

P-ISSN: 1996-983X
E-ISSN: 2960-1908

مجلة المخطط و التنمية

Journal of planner and development

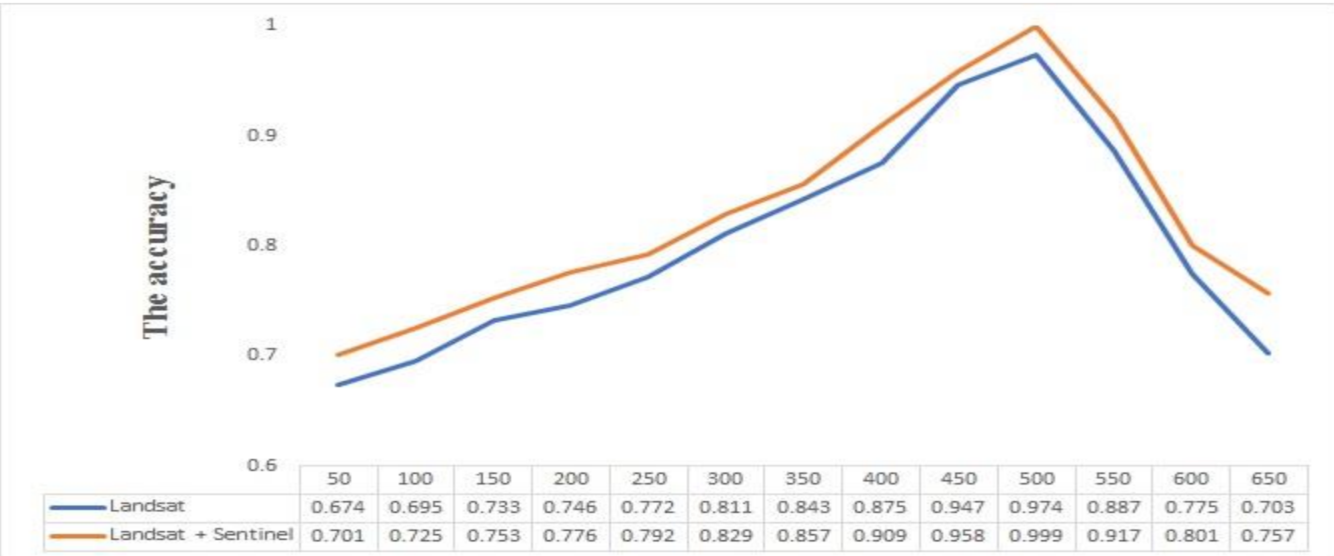
Vol 25 Issue 1 2020/6/1

### 4.3.2 Paddy Rice Mapping using Random Forest Classification

Once the spectral index is developed, other spectral indices such as NDVI and NDBI have to be calculated. The spectral indices are combined as a single image. This new image will be used as input features to the random forest classifier. The classifier is trained using the ground truth samples and its

validation bases on the validation samples. The paddy rice map is generated and the accuracy assessment of the classifier is also reported.

Besides, another classification is carried out on the same model but by adding the radar bands to the input features. A new paddy rice map is created and compared with the map that was created using only spectral indices. The results shown in Figure A, different number of trees is examined, best result has been acquired when 500 trees are used. The quantitative assessment of the classifier on Landsat and on Landsat-radar data is conducted and discussed.




| | 50 | 100 | 150 | 200 | 250 | 300 | 350 | 400 | 450 | 500 | 550 | 600 | 650 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Landsat | 0.674 | 0.695 | 0.733 | 0.746 | 0.772 | 0.811 | 0.843 | 0.875 | 0.947 | 0.974 | 0.887 | 0.775 | 0.703 |
| Landsat + Sentinel | 0.701 | 0.725 | 0.753 | 0.776 | 0.792 | 0.829 | 0.857 | 0.909 | 0.958 | 0.999 | 0.917 | 0.801 | 0.757 |

Figure A. Accuracy result using different number of trees applied on landSat and LandSat with Sentinel-1 data.

**Source:** Meta data for Land sat images

P-ISSN: 1996-983X
E-ISSN: 2960-1908

مجلة المخطط و التنمية

Journal of planner and development

Vol 25 Issue 1 2020/6/1

### 4.3.3 Accuracy Assessment

The accurate assessment based on the confusion matrix [34]. The confusion matrix gives information about how well the classifier able to separate pixel belongs to paddy rice or non-paddy rice class. The overall accuracy, user and producer's accuracies, and kappa index have to be calculated for each created map from this matrix. Producer accuracy indicates the probability of a reference pixel being correctly classified, producer accuracy is calculated by dividing the total number of correctly classified pixels on the total number of pixels that derived from reference data. User accuracy indicates the probability of a predicted pixel to be in a certain class, user accuracy is calculated by dividing the total number of correctly classified pixels on the total number of values predicted to be in that class. The Kappa index is another accuracy measure which is calculated for the two matrices that are obtained in our experiments, Kappa index is derived from the confusion matrix by comparing the reference samples with the pixels which are detected as paddy rice [34].

## 5. Results

Paddy rice mapping is an important task to analyze the land cover of an area. The current study proposes a method for paddy rice mapping using Landsat OLI and Sentinel-1 satellite images. This section presents the findings and explains the implications.

The created maps from spectral bands were used to detect the paddy rice areas in the datasets as shown in Figure 3. Figure 3a shows the created map using the spectral index development; Figure 3b shows the created map using the NDVI

spectral index, Figure 3c shows the created map using the NDBI index, and Figure 3d shows the created map using the combined spectral indices (i.e. NDBI, NDVI, and the new index instead of red, green, and blue respectively). As it can be seen from the maps, the spectral index highlights the land cover features (paddy rice, built-up, barren land) differently. Thus, when the spectral indices are combined, the classification results will give better accuracies in comparison with the classification results using only one index (NDVI). The spectral index or the combined indices could be directly applied to detect paddy rice area through threshold-based classification. This approach is a simple method to separate two or more land cover features by selecting a range of thresholds for each class. However, this threshold may not be universal. Thus, our study uses a random forest classifier with 500 decision trees to give the decision if the pixel belongs to paddy rice or not. The random forest method provides acceptable results; therefore, it can be applied to other areas.

P-ISSN: 1996-983X
E-ISSN: 2960-1908
مجلة المخطط و التنمية
Journal of planner and development
Vol 25 Issue 1 2020/6/1

The created maps of the paddy rice using our proposed method are shown in Figure 4. Figure 4a shows the produced map using only Landsat data, while the map created using Landsat and Sentinel-1 data is shown in Figure 4b, both maps show the paddy rice in green color while the background is depicted in white color. The resulted maps show all the planted paddy rice area. Figure 5 shows the good performance of the classifier when using the integrated data. This is obvious, as the created map using only Landsat image, paddy rice pixels are mixed with other classes. Moreover, the results suggested that the classifier using additional data from radar images improves the classification results.

The accuracy assessment confirms that using both datasets (Landsat and Sentinel-1) is better than using only Landsat dataset. The results of the accuracy assessment are summarized in Table 2. The producer and user's accuracies

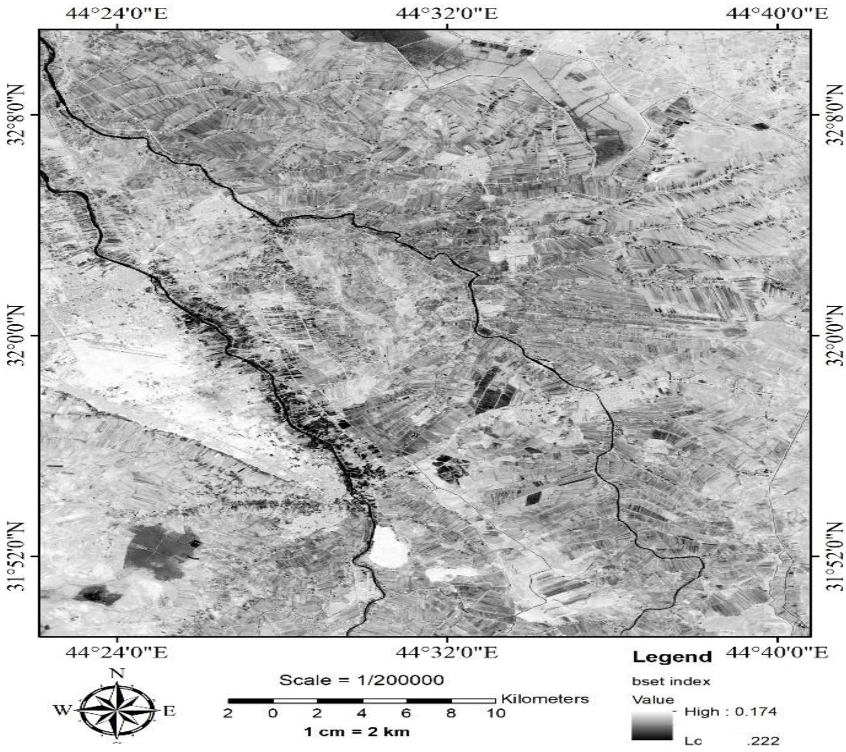
describe the performance of the classifiers to separate paddy rice areas from other classes. The accuracies are more than 0.97 indicating the effective ability of the classifier to detect paddy rice and separate them from other background pixels. The results also suggest that the additional bands of the radar data could improve the accuracy of the classification by almost 2%. The overall accuracy and the kappa describe the overall performance of the classifiers. The results using these metrics also report the advantages of the radar bands for the classification of paddy rice.

P-ISSN: 1996-983X
E-ISSN: 2960-1908

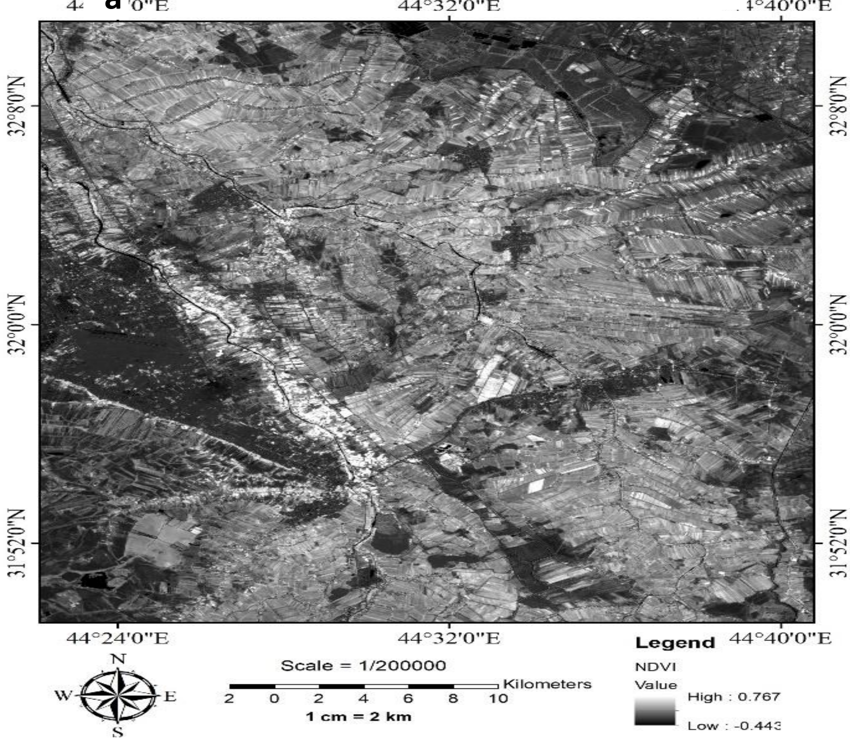
مجلة المخطط والتنمية

Journal of planner and development

Vol 25 Issue 1 2020/6/1

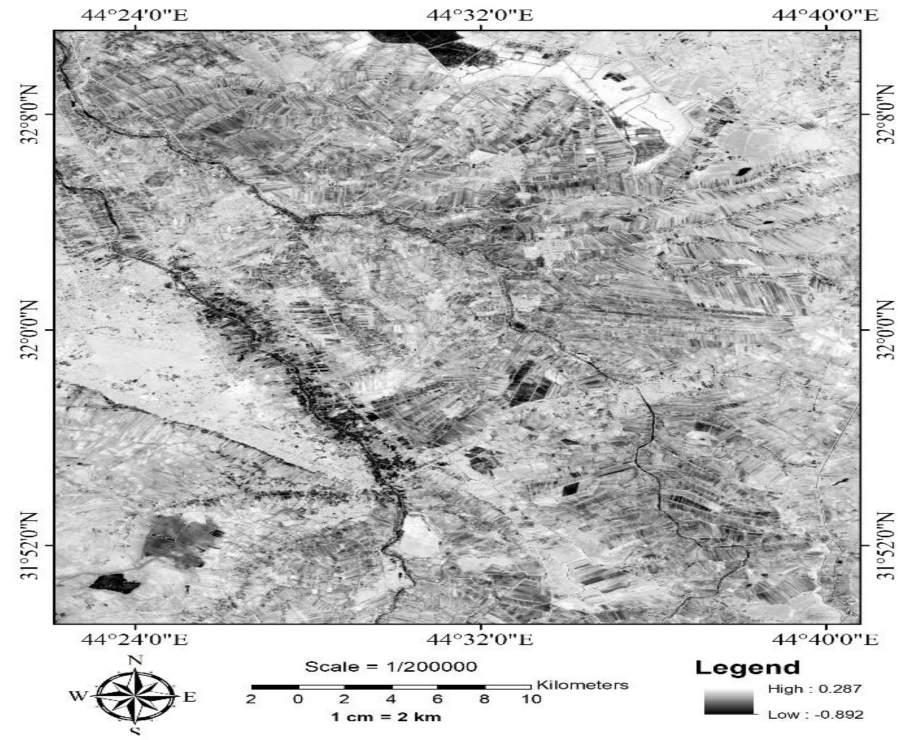



a b



P-ISSN: 1996-983X
E-ISSN: 2960-1908

مجلة المخطط والتنمية
Journal of planner and development
Vol 25 Issue 1 2020/6/1



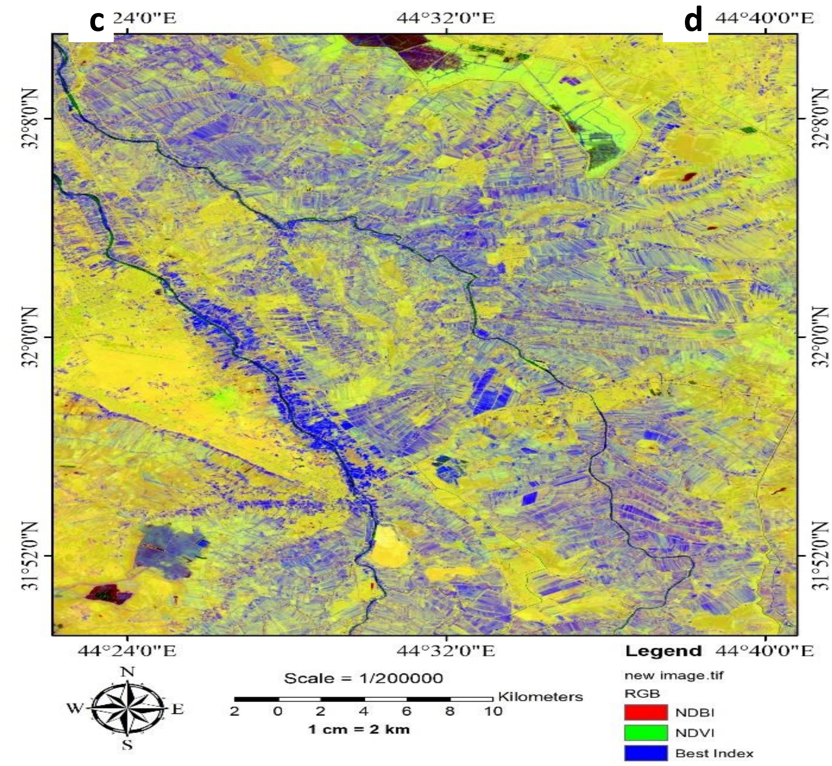




**Figure 3**: The maps of the spectral indices, **a:** map of the developed spectral index, b: NDVI spectral index, c: NDBI index, d: combined spectral indices/**Source:** Author.

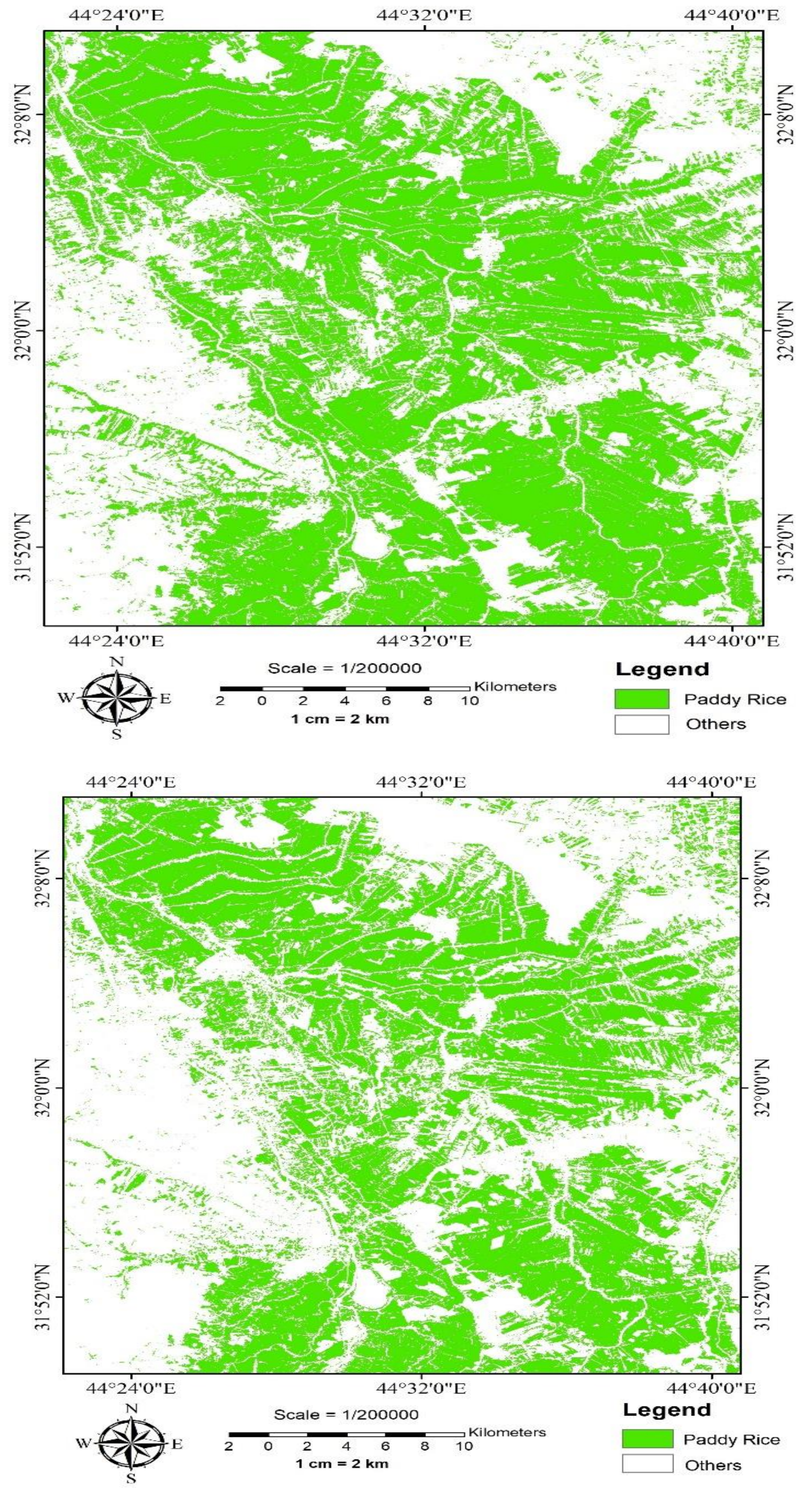



**Figure 4**: The classification maps, a: map produced by our method using the Landsat. b: the integrated Landsat and Sentinel data./ **Source:** Author

P-ISSN: 1996-983X
E-ISSN: 2960-1908

مجلة المخطط والتنمية

Journal of planner and development

Vol 25 Issue 1 2020/6/1

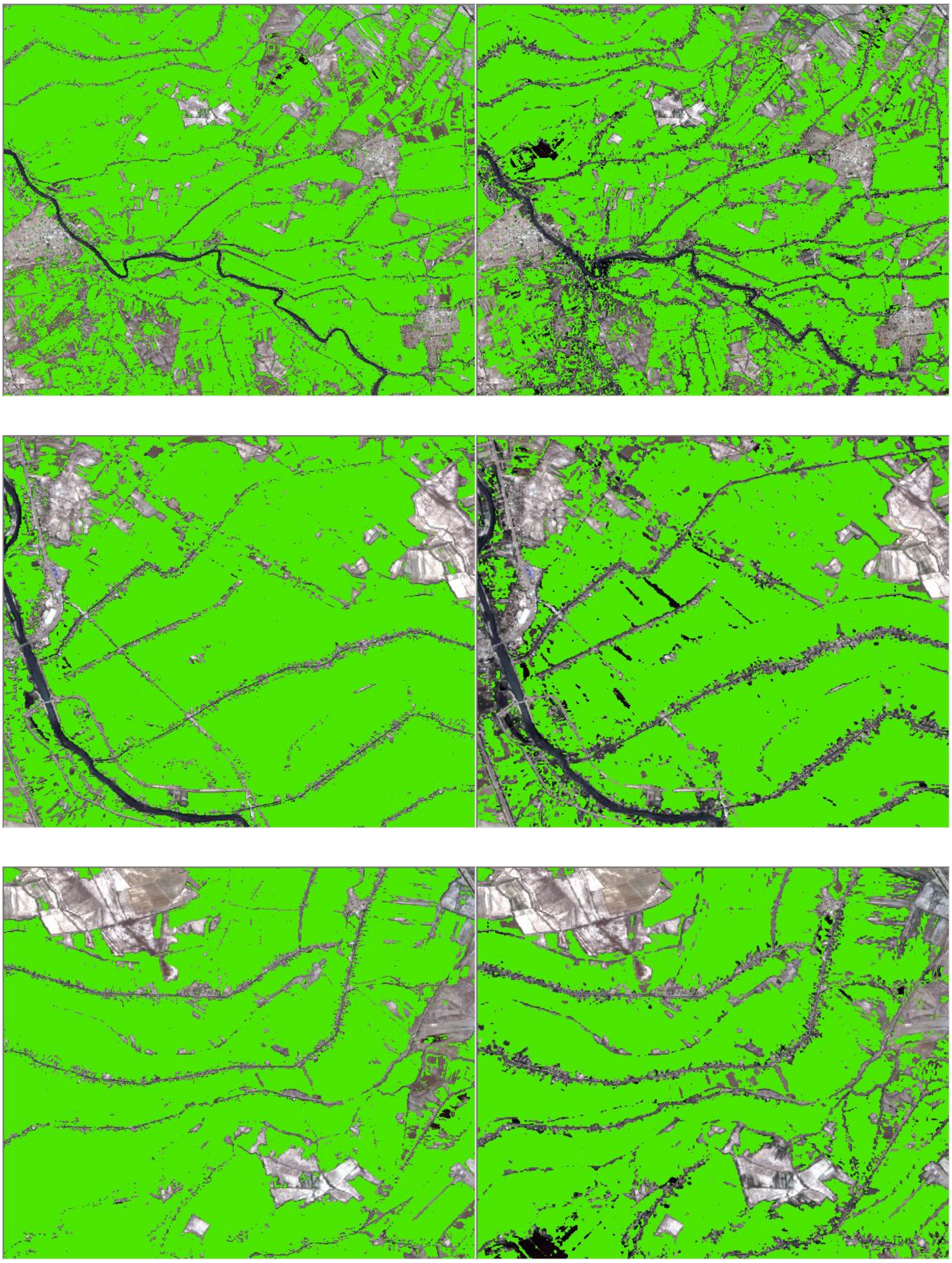


**Figure 5**: Examples of differences between the classification methods./ **Source:** Author

P-ISSN: 1996-983X
E-ISSN: 2960-1908
مجلة المخطط و التنمية
Journal of planner and development
Vol 25 Issue 1 2020/6/1

**Table 2:** Results of the accuracy assessment of the proposed classification methods./ **Source:** Author

| **Accuracy Metric** | **Landsat** | | **Landsat + Sentinel** | |
|---|---|---|---|---|
| | **Paddy Rice** | **Others** | **Paddy Rice** | **Others** |
| Producer | 0.972 | 0.976 | 0.992 | 0.991 |
| User | 0.984 | 0.958 | 0.996 | 0.982 |
| Overall Accuracy | 0.974 | | 0.999 | |
| Kappa | 0.945 | | 0.981 | |

The accuracy assessment ( overall ) of the classification was done using Kappa coefficient.

P-ISSN: 1996-983X
E-ISSN: 2960-1908

مجلة المخطط و التنمية

Journal of planner and development

Vol 25 Issue 1 2020/6/1

## 6. Discussions and Conclusion

This paper presents random forest classification method for paddy rice mapping of Najef area using Landsat and Sentinel-1 data. The classification is based on spectral indices, NDVI, NDBI, and a new proposed one, which is random forest classification algorithm. The proposed method is implemented in Python and has the potentials to be fully automated for rapid mapping and monitoring paddy rice areas with remote sensing data that are free available for all users. The proposed method is not only applied for classification, but also can be used for other applications including yield estimation and evaluation of paddy rice healthiness.

Successful planning of urban cities requires a set of planning decisions that are supported by the governmental institutions and specifying the foundations of planning. The research outputs provide information for decision-makers of urban planning institutions to make better decisions for future design of cities. As a result, investigating and studying these factors that are effected by urban sprawl and cities spreading as well shifting to the surrounded agricultural areas are very important. Therefore, this study proposes a modified method to classify paddy rice areas to find the basis of the long-term plans.

Our methods achieved high accuracy (almost 99% using integrated Landsat and Sentinel-1 data). However, further improvements should be made on the algorithm to make it scalable and fast for training and running. These improvements can be made through more in-depth analysis and conducting experiments in other areas with different environments.

## References

1. Lee R.G.; Flamm, R.; Turner, M.G.; Bledsoe, C.; Chandler, P.; DeFerrari, C.; Gottfried, R.; Naiman, R.J.;239 Schumaker, N.;Wear, D. Integrating Sustainable Development and Environmental Vitality: A Landscape240 Ecology Approach. In Watershed Management; Naiman R.J., Eds.; Springer, New York, 1992; pp. 499–521. doi:241 10.1007/978-1-4612-4382-3_20.

2. Campbell, D.J.; Lusch, D.P.; Smucker, T.A.;Wangui, E.E. Root causes of land use change in the Loitokitok Area, Kajiado District, Kenya. LUCID Working Paper 2003, 19.

3. Fan, F.; Weng, Q.; Wang, Y. Land use land cover change in Guangzhou, China, from 1998 to 2003, based on Landsat TM/ETM+ imagery. Sensors 2007, 7, 1323—1342. doi: 10.3390/s7071323.

4. Ahmed A.A.; Kalantar B.; Pradhan B.; Mansor S.; Sameen M.I. Land Use and Land Cover Mapping Using Rule-Based Classification in Karbala City, Iraq. Pradhan B. (eds) GCEC 2017, Kuala Lumpur, Malaysia, July 25—28, 2017; 1019–1027. doi: 10.1007/978-981-10-8016-6_71.

5. Ahmed, A. A.; Pradhan, B.; Sameen, M. I.; Makky, A. M. An optimized object-based analysis for vegetation mapping using integration of Quickbird and Sentinel-1 data. Arabian Journal of Geosciences 2018, 11, 280–289. doi: 10.1007/s12517-018-3632-1.

6. Silveira, E.M.O.; Bueno, I.T.; Acerbi-Junior, F.W.; Mello, J.M.; Scolforo, J.R.S.; Wulder, M.A. Using Spatial Features to Reduce the Impact of Seasonality for Detecting Tropical Forest Changes from Landsat Time Series. Remote Sens. 2018, 10, 808–828. doi: 10.3390/rs10060808.

7. Gong, H.; Simwanda, M.; Murayama, Y. An Internet-Based GIS Platform Providing Data for Visualization and Spatial Analysis of Urbanization inMajor Asian and African Cities. ISPRS Int. J. Geo-Inf. 2017, 6, 257–273. doi: 10.3390/ijgi6080257.

8. Anderson, J.R.; Hardy, E.E.; Roach, J.T;Witmer, R.E. A Land Use and Land Cover Classification System For Use with Remote Sensor Data. U.S. Geol. Survey Prof. Pap. 964; U.S. Gov. Print. Office: Washington DC, 1976.

9. Li, J.-F.; Tfwala, S.S.; Chen, S.-C. Effects of Vegetation Density and Arrangement on Sediment Budget in a Sediment-Laden Flow. Water 2018, 10, 1412–1424. doi: 10.3390/w10101412.

10. Dengiz, O.; Özyazici, M.A.; Sag˘ lam, M. Multi-criteria assessment and geostatistical approach for determination of rice growing suitability sites in Gokirmak catchment. Paddy and Water Environ. 2015, 13, 142–149. doi: 10.1007/s10333-013-0400-4.

11. Yang, S.; Shen, S.; Li, B.; Le Toan, T.; He, W. Rice mapping and monitoring using ENVISAT ASAR data. IEEE Geosci. Remote Sens. Lett. 2008, 5, 108–112. doi: 10.1109/LGRS.2007.912089.

12. Huang, J.;Wang, H.; Dai, Q.; Han, D. Analysis of NDVI Data for Crop Identification and Yield Estimation. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 2014, 7, 4374–4384. doi: 10.1109/JSTARS.2014.2334332.

13. Xiao, X.; Boles, S.; Liu, J.; Zhuang, D.; Frolking, S.; Li, C.; Salas,W.; Moore, B.Mapping paddy rice agriculture in southern China using multi-

temporal MODIS images. Remote Sensing of Environment 2005, 95, 480–492. doi: 10.1016/j.rse.2004.12.009.

14. Castillejo-González, I.L.; López-Granados, F.; García-Ferrer, A.; Peña-Barragán, J.M.; Jurado-Expósito, M.; de la Orden, M.S.; González-Audicana, M. Object- and pixel-based analysis for mapping crops and their agro-environmental associated measures using QuickBird imagery. Computers and Electronics in Agriculture 2009, 68, 207–215. doi: 10.1016/j.compag.2009.06.004.

15. Gumma, M. K.; Nelson, A.; Thenkabail, P.S.; Singh, A.N. TMapping rice areas of South Asia using MODIS multitemporal data. Journal of Applied Remote Sensing 2011, 5, 053547:1–053547:26. doi: 10.1117/1.3619838.

16. Shashikant, V.; Shariff, A. R.M.; Nordin, L.; Pradhan, B. Estimation of aboveground biomass of oil palm trees by PALSAR. IEEE Colloquium on Humanities, Science and Engineering Research, Kota Kinabalu, Malaysia, 3–4 Dec. 2012; 838–841. doi: 10.1109/CHUSER.2012.6504430.

17. Kuenzer, C.; Knauer, K. Remote sensing of rice crop areas. International Journal of Remote Sensing 2013, 34, 2101–2139. doi: 10.1080/01431161.2012.738946.

18. Widhalm, B.; Bartsch, A.; Heim, B. A novel approach for the characterization of tundra wetland regions with C-band SAR satellite data.

International Journal of Remote Sensing 2015, 36, 5537–5556. doi: 10.1080/01431161.2015.1101505.

19. Ferreira-Ferreira, J.; Silva, T.S.F.; Streher, A.S.; Affonso, A.G.; Furtado, L.F.; Forsberg, B.R.; Valsecchi, J.; Queiroz, H. L.; Novo, E. M. Combining ALOS/PALSAR derived vegetation structure and inundation patterns to

characterize major vegetation types in the Mamirauá Sustainable Development Reserve, Central Amazon floodplain, Brazil. 2015, 23, 41–59. doi: 10.1007/s11273-014-9359-1.

20. Cordeiro, C.L.D.; Rossetti, D.D. Mapping vegetation in a late Quaternary land form of the Amazonian wetlands using object-based image analysis and decision tree classification. International Journal of Remote Sensing 2015, 36, 3397–3422. doi:10.1080/01431161.2015.1060644.

21. Tian, X.; Chen, E.; Li, Z.; Su, Z. B.; Ling, F.; Bai, L.;Wang, F. Comparison of crop classification capabilities of space borne multiparameter SAR data. IEEE International Geoscience and Remote Sensing Symposium, Honolulu, HI, USA, 25–30 July 2010; 359–362. doi: 10.1109/IGARSS.2010.5651326.

22. Fontanelli, G.; Crema, A.; Azar, R.; Stroppiana, D.; Villa, P.; Boschetti, M. Agricultural crop mapping using optical and SAR multi-temporal seasonal data: A case study in Lombardy region, Italy. IEEE Geoscience and Remote Sensing Symposium, Quebec City, Canada, 13-18 July 2014; 1489–1492. doi: 10.1109/IGARSS.2014.6946719.

23. Xu, J.; Li, Z.; Tian, B.; Huang, L.; Chen, Q.; Fu, S. Polarimetric analysis of multi-temporal RADARSAT-2 SAR images for wheat monitoring and mapping. International Journal of Remote Sensing 2014, 35, 3840–3858. doi: 10.1080/01431161.2014.919679.

24. Li, K.; Shao, Y.; Zhang, F. Paddy Rice identification using polarimetric SAR data in Southern China. International Conference on Multimedia Technology, Ningbo, China, 29–31 Oct. 2010; 1–4. doi: 10.1109/ICMULT.2010.5631077.

25.Ichikawa, D.;Wakamori, K.; Suzuki, M. Identification of paddy fields in Northern Japan using RapidEye images. IEEE Geoscience and Remote Sensing Symposium, Quebec City, Canada; 13-18 July 2014, 2090–2093. doi: 10.1109/IGARSS.2014.6946877.

26.Qiu, B.; Li, W.; Tang, Z.; Chen, C.; Qi, W. Mapping paddy rice areas based on vegetation phenology and surface moisture conditions. Ecological Indicators 2015, 56, 97–86. doi: 10.1016/j.ecolind.2015.03.039.

27.Kim, H.O.; Yeom, J.M. Effect of red-edge and texture features for object-based paddy rice crop classification using RapidEye multi-spectral satellite image data. International Journal of Remote Sensing 2014, 35, 7046–7068. doi: 10.1080/01431161.2014.965285.

28.Bridhikitti, A.; Overcamp, T. J. Estimation of Southeast Asian rice paddy areas with different ecosystems from moderate-resolution satellite imagery. Journal of Agriculture, Ecosystems and Environment 2012, 146, 113–120. doi: 10.1016/j.agee.2011.10.016.

29.Chang, SH.; Wan, S. A novel study on ant-based clustering for paddy rice image classification. Arabian Journal of Geosciences 2015, 8, 6305–6316. doi: 10.1007/s12517-014-1617-2.

30.Hoogeboom, P. Classification of Agricultural Crops in Radar Images. IEEE Transactions on Geoscience and Remote Sensing 1983, GE-21, 329–336. doi: 10.1109/TGRS.1983.350562.

31.Kurosu, T.; Fujita, M.; Chiba, K. Monitoring of rice crop growth from space using the ERS-1 C-band SAR. IEEE Trans. Geoscience and Remote Sensing 1995, 33, 1092–1096.

32. Aschbacher, J.; Pongsrihadulchai, A.; Karnchanasutham, S.; Rodprom, C.; Paudya, DR.; Le Toan, T. Assessment of ERS-1 SAR data for rice crop mapping and monitoring. Proc. IGARSS, Firenze, Italy, 10-14 July 1995; 2183-2185. doi: 10.1109/IGARSS.1995.524142.

33. Premalatha, M.; Nageswara Rao, P.P. Crop acreage estimation using ERS-1 SAR data. Journal of the Indian Society of Remote Sensing 1994, 22, 139—147. doi: 10.1007/BF03024775.

34. Lillesand, T.; Kiefer, R.W.; Chipman, J. Remote Sensing and Image Interpretation. In, 7th ed.; JohnWiley & Sons: 2014.