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Cereal Yields Forecasting using Remote Sensing and GIS Techniques : A Case Study of Ouled Saleh Commune, Region of Casablanca-Settat, Morocco

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ABSTRACT: In Morocco, Agriculture is a key sector of the national economy, playing crucial social and economic roles. The sector accounts for around 14 to 20% of the Gross Domestic Product (GDP) and represents 43% of all employment. Winter cereals (soft wheat, durum wheat and barley) are produced all over the country, occupying nearly 65% of agricultural lands and therefore cereal yields forecasting is a major tool for decision making, allowing for planning in advance actions like annual cereal imports or aids to farmers. The present study highlights the substantial contribution of remote sensing (RS) and Geographic Information Systems (GIS) techniques in predicting soft wheat yields at the rural commune of Ouled Saleh, Region Casablanca-Settat in Morocco. The forecasting methodology was based on two steps: First, a land cover map of the study area was produced using Sentinel imagery to identify agricultural zones; second, simple linear regression models were established between the Normalized Difference Vegetation Index (NDVI), derived from the Moderate Resolution Imaging Spectrometer (MODIS) and soft wheat yields over the period 2002-2012. Our results showed high correlations between the NDVI of agricultural lands, averaged over the period from February till March or April and soft wheat yields. Therefore, NDVI can be used as a predictor index to early forecast soft wheat yields one to two months before harvest.

KEYWORDS: Remote sensing, GIS, NDVI, Ouled Saleh, soft wheat, yield forecasting.

1 INTRODUCTION

Agriculture is the mainstay of the Moroccan economy. The sector is the largest employer and plays a substantial role in the macroeconomic balance of the country. It contributes with around 14 to 20% of the national GDP and employs about 43% of the nation's workforce. Winter cereals are the major food of the population and are produced all over the country, occupying nearly 65% of agricultural lands[1]. Predicting cereal yields early before harvest is of great interest to the agricultural sector. It has economic, social and political implications on the society and directly contributes to the food security of the country since it helps to be prepared for consequences of any shortage in production through actions to reduce vulnerability to climatic risks and to plan actions like aids to farmers or cereal imports [2]. RS and GIS are one of the approaches largely used for predicting crop yields especially in the case of cereal. The availability of free or at low price satellite imagery of moderate or high resolution, have allowed analyzing interactions of crops with the climate and developing agro-meteorological indices from the spectral reflectance of the vegetation to forecast crop harvests [3], [4], [5].

In a previous study, cumulated rainfall over the cropping season, was used as a climatic predictor in a simple linear regression model with soft wheat yields at Ouled Saleh commune, over the period 2002-2012 [6]. In this study, one consider the vegetation index NDVI used as an agro-climatic predictor of soft wheat yields using the same statistical procedure and covering the same period. The results showed a strong relationship between NDVI averaged over the period from February till March or April and soft wheat yields. This approach allowed forecasting of soft wheat yields one to two months before harvest.

2 MATERIALS AND METHODS

2.1 STUDY AREA

The region of Casablanca-Settat is one of the twelve administrative regions of Morocco. It covers an area of 20.166 km² and recorded a population of 6.861.739 in the 2014 Moroccan census. It is located on the Atlantic coast. It borders the regions of Rabat-Salé-Kenitra to the northeast, Beni Mellal-Khenifra to the southeast, and Marrakesh-Safi to the south. Casablanca-Settat was formed in September 2015 by merging Grand Casablanca with the provinces of El Jadida and Sidi Bennour in Doukkala-Abda region and the provinces of Benslimane, Berrechid and Settat in Chaouia-Ouardigha region. Grand Casablanca is divided into two prefectures of Casablanca and Mohammedia and two provinces of Mediouna and Nouaceur[7]. The province of Nouaceur is spread over an area of 44.583 hectares. It is subdivided into three municipalities (Bouskoura, Nouaceur and Dar Bouazza) and into two rural communes (Ouled Saleh and Ouled Azzouz) (Figure 1).The study area of Ouled Saleh is predominantly covered by agriculture having great agricultural potentiality mainly due to its soil fertility. Its area is about 13.499 ha (30 % of total area). Useful Agricultural Surface occupy 12.260 ha and agricultural exploitations number is 1307. Cereal production is the most significant agricultural resource and winter soft wheat is the major crop cultivated in the province[8].

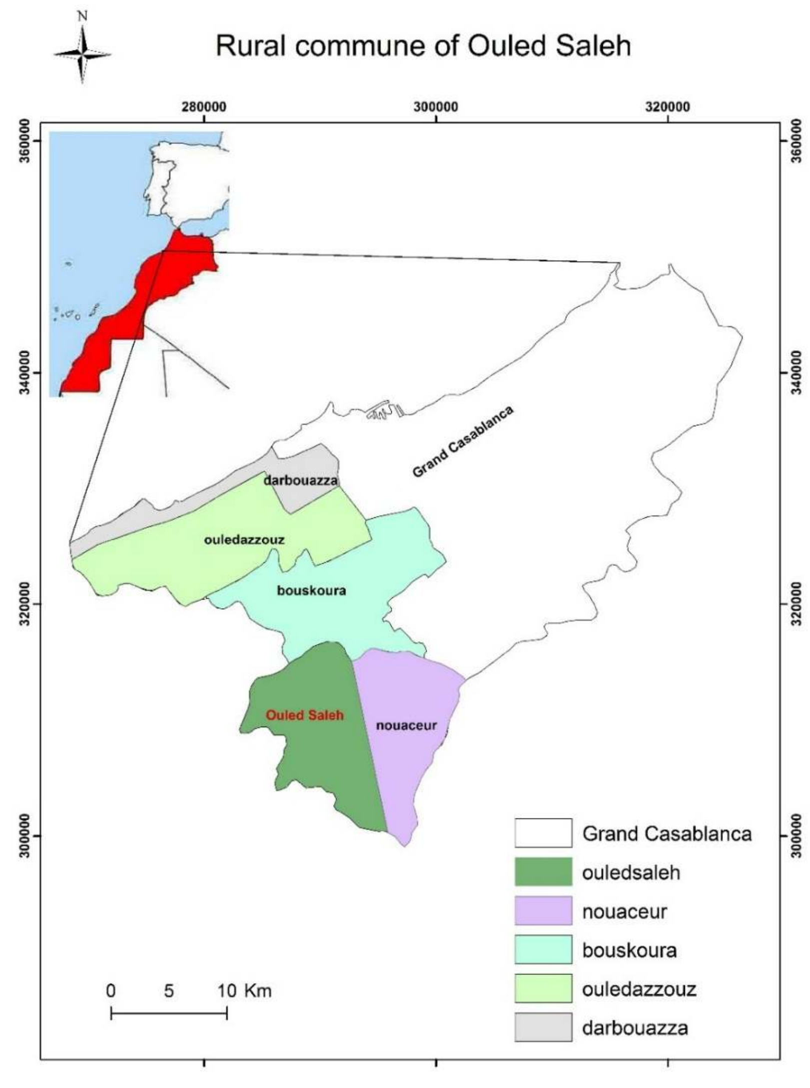

Fig. 1. Geographic location of Ouled Saleh

2.2 DATASET

2.2.1 SENTINEL SATELLITE IMAGERY

A Sentinel-2A satellite-image, covering the study area was analyzed to extract information about land cover. The image has been freely downloaded from the ESA* website. The primary criteria for scene selection were the date of acquisition for the image and little or no cloud contamination. The best available satellite imagery corresponds to 01 August 2015 with a percentage cloud cover of 0%. The choice of this period of the year corresponds to a period where the cropping season has not started yet and therefore the agricultural lands are easily recognizable. In Table1 is presented a summary of the Sentinel-2 characteristics (bands, central wavelength and spatial resolution):

Table 1. Sentinel-2 bands overview (source: https://sentinel.esa.int)

Sentinel-2 Bands	Central Wavelength (µm)	Resolution (m)
Band 1 – Coastal aerosol	0.443	60
Band 2 - Blue	0.490	10
Band 3 - Green	0.560	10
Band 4 - Red	0.665	10
Band 5 – Vegetation Red Edge	0.705	20
Band 6 - Vegetation Red Edge	0.740	20
Band 7 - Vegetation Red Edge	0.783	20
Band 8 - NIR	0.842	10
Band 8A - Vegetation Red Edge	0.865	20
Band 9 - Water vapour	0.945	60
Band 10 – SWIR-Cirrus	1.375	60
Band 11 – SWIR	1.610	20
Band 12 - SWIR	2.190	20

**ESA: European Space Agency.*

2.2.2 NDVI

Vegetation Indices are standardized methods, based on band ratios, which highlight vegetation dynamics [9]. One of the most commonly used indices is NDVI that was first formulated by [10] as the difference between near-infrared (NIR) and red visible (RED) reflectance values received by the sensors normalized over the sum of the two. NDVI, closely related to the vegetation vigor, has been recognized for its ability to monitor crops and as an estimator of crop yields since early 1980s [11], [12], [13]. One of the main benefits of using NDVI is the integration of environmental factors, in a sense that it reflects the state of global environmental stress of the vegetation, more than separate climatic variables or simulation models can do [14]. NDVI values can range from -1 (no vegetation) to +1 (abundant vegetation). Its formula is:

$$NDVI = (NIR - RED) / (NIR + RED)$$

NDVI images used in this study are delivered by MODIS sensor at 250 meters spatial resolution and at (15-days) time step and are free of charge from the EOSDIS** website.

**EOSDIS: Earth Observing System Data and Information System (http://reverb.echo.nasa.gov/).

2.3 METHODOLOGICAL APPROACH

2.3.1 LAND COVER CLASSIFICATION

Land cover classification can be defined as the process of assigning each pixels or group of pixels of the image to thematic classes [15]. The most famous types of classification techniques are the unsupervised classification which doesn't need a prior knowledge of the area and the supervised classification which needs prior knowledge of the area [16]. For this study, the methodology was essentially based on analyzing the Sentinel-2A image of 2015 in a GIS environment using ESRI***-Arc GIS 10.3 software which provides a user-friendly environment for processing raster images in a straightforward way. The ArcGIS

Spatial Analyst extension was used to perform a supervised classification in order to create a land cover map of our area of interest.

***ESRI: Environmental Systems Research Institute: An international supplier of GIS software.

2.3.2 RELATIONSHIP: NDVI- YIELDS

Agricultural zones of the created land cover map were extracted to serve as mask for NDVI images. Therefore, only values of NDVI of agricultural lands are used in establishing relationship between NDVI and soft wheat yields. It should be noted that agricultural lands in Ouled Saleh are mainly covered by cereals (soft wheat, durum wheat and barley) and other crop types[8]. Therefore, NDVI images do not specifically correspond to soft wheat areas but since the three cereal species react almost simultaneously to variation of rainfall and spontaneous vegetation (or weeds) responds to rainfall in a similar way [2], NDVI can be used as an indicator of vegetation to look for a possible relationships with the soft wheat yields. A geoprocessing model was also created using ArcGIS model Builder to automate extraction processes of NDVI values for the ten growing seasons (2002-03 to 2011-12).Therefore, we do not repeat the whole process all the time (Figure 2).

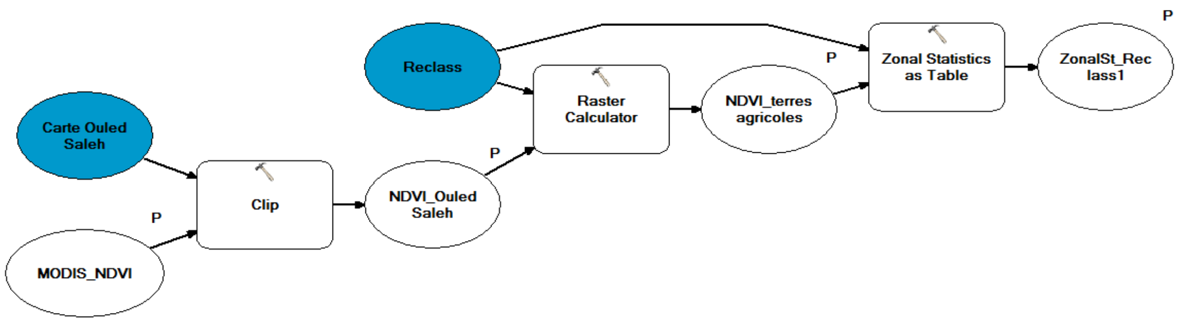

Fig. 2. Automated calculation of NDVI for the months of February, March and April (Period: 2002-2012)

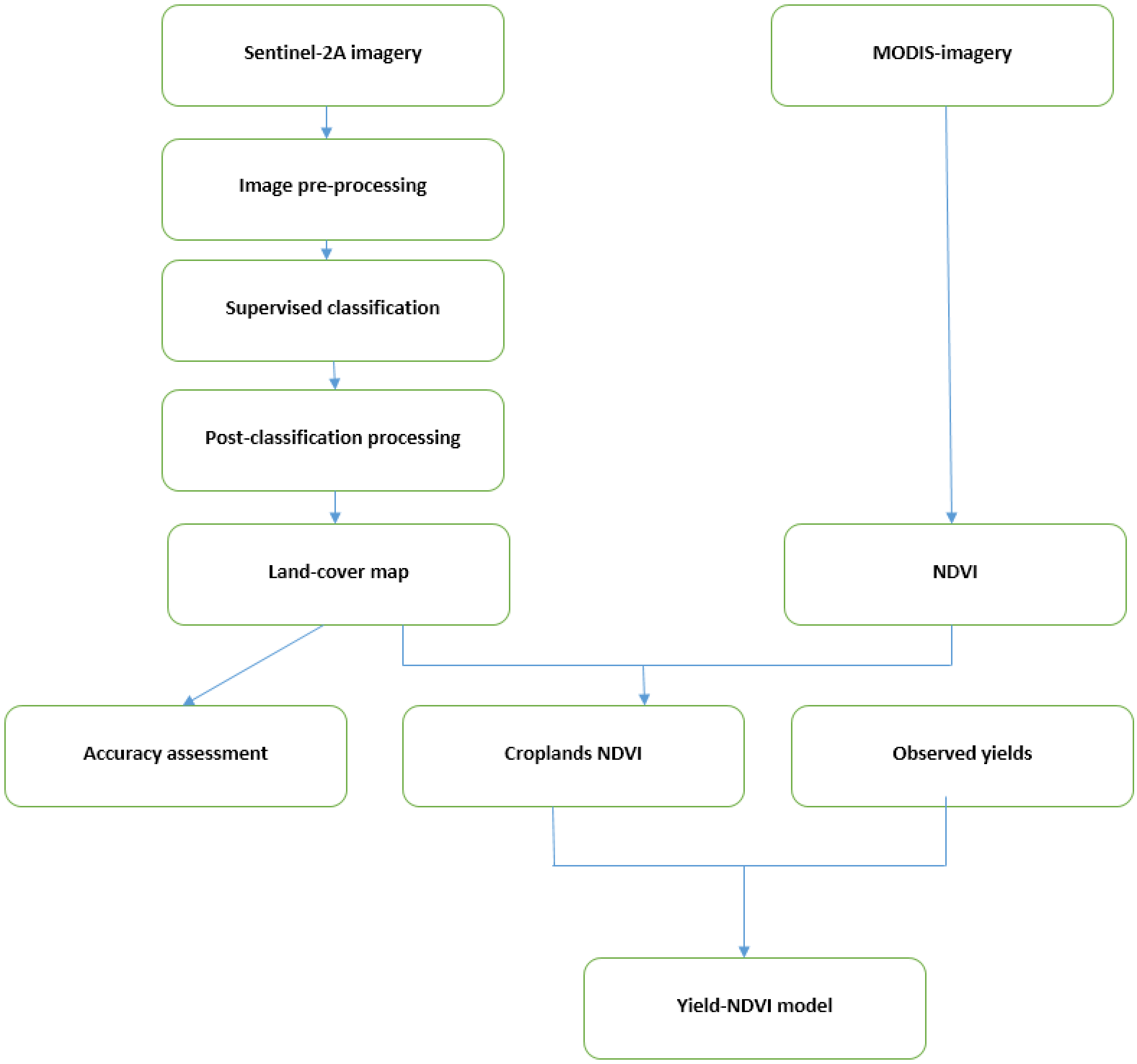

Fig. 3. Methodological workflow of remotely sensed wheat yield prediction using MODIS-NDVI

3 Results And Discussion

3.1 Land Cover Map Of Ouled Saleh

3.1.1 Sentinel Image Enhancement

Before performing different types of analyses, such as supervised classification and NDVI index, the satellite scene was pretreated (Composite Image, Band Combinations, Sub-setting...). Some radiometric, spectral and spatial enhancement techniques were also applied in the ArcGIS environment to enhance the visual qualities and to perform some analyses on the satellite image. NIR composite was used to better interpret Sentinel-2A image of the study area (Figure 4).

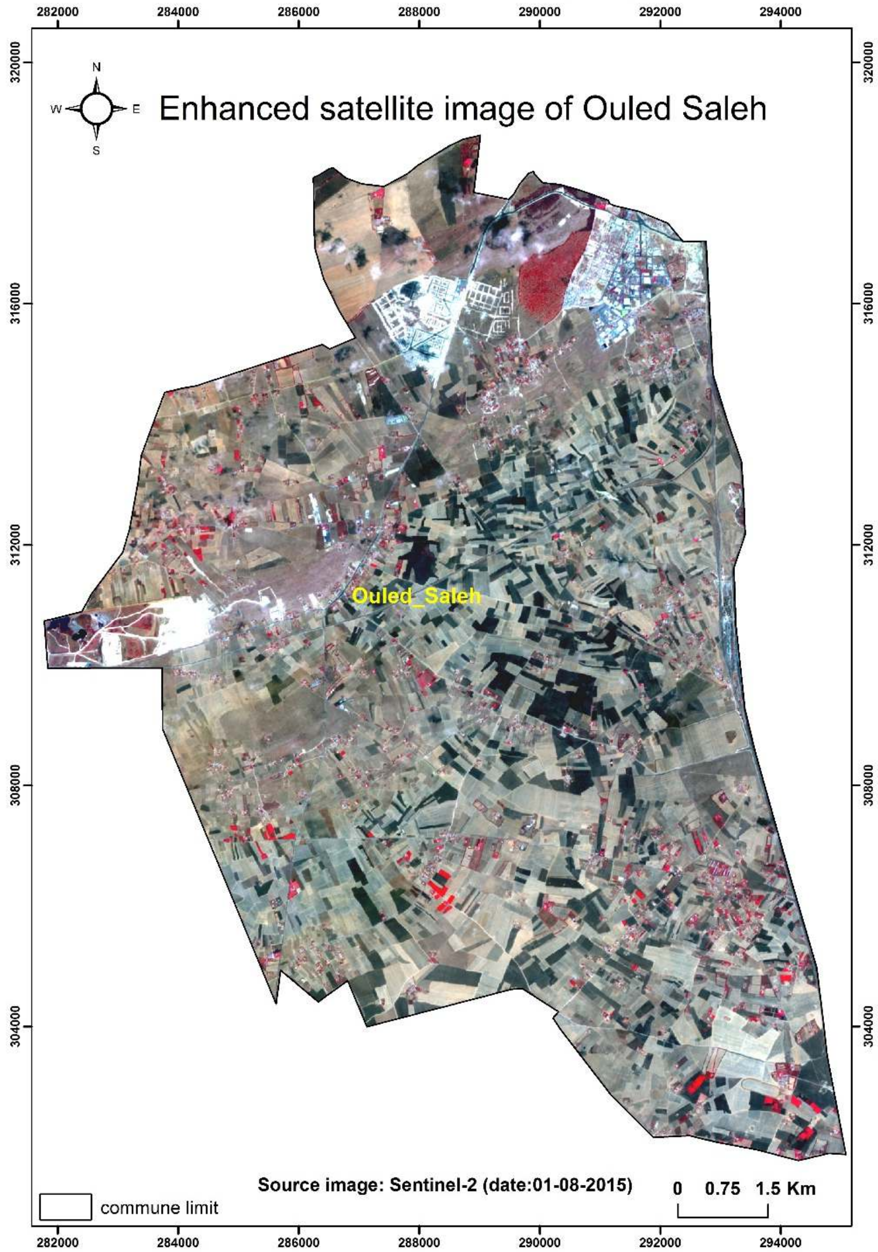

Fig. 4. Enhanced Sentinel-2A Color Infrared (vegetation) image covering the study area

Vegetation in the NIR band is highly reflective due to chlorophyll and it appears in various shades of red. Generally, deep red hues indicate healthier vegetation while lighter reds signify grasslands or sparsely vegetated areas. Urban areas are cyan blue, and soils vary from dark to light browns. Water appears very dark, due to the absorption of energy in the visible red and near IR bands.

3.1.2 Sentinel Image Classification

The classification of remote sensing images is a method of features identification in the scene. The method labels the pixels in the image through a classification algorithm, which is based on the pixels spectral characteristics, allowing for the thematic map creation [17]. ArcGIS provides a user-friendly environment for creating training samples to identify classes and calculate their signatures. Histograms, Scatterplots and Statistics tools were used to explore the spectral characteristics of different areas and to evaluate training samples to see if there is enough separation between the classes. To classify the image, the Maximum Likelihood algorithm, one of the most used supervised classifier, was chosen; that algorithm is based upon the Gaussian threshold, stored in each class signature, for assigning a class to every image pixel [18]. Once the image was classified, a post-classification processing, such as filtering and boundary cleaning was performed in order to clean up the random noises and small isolated regions to improve the quality of the output. The result is shown below (Figure 5).

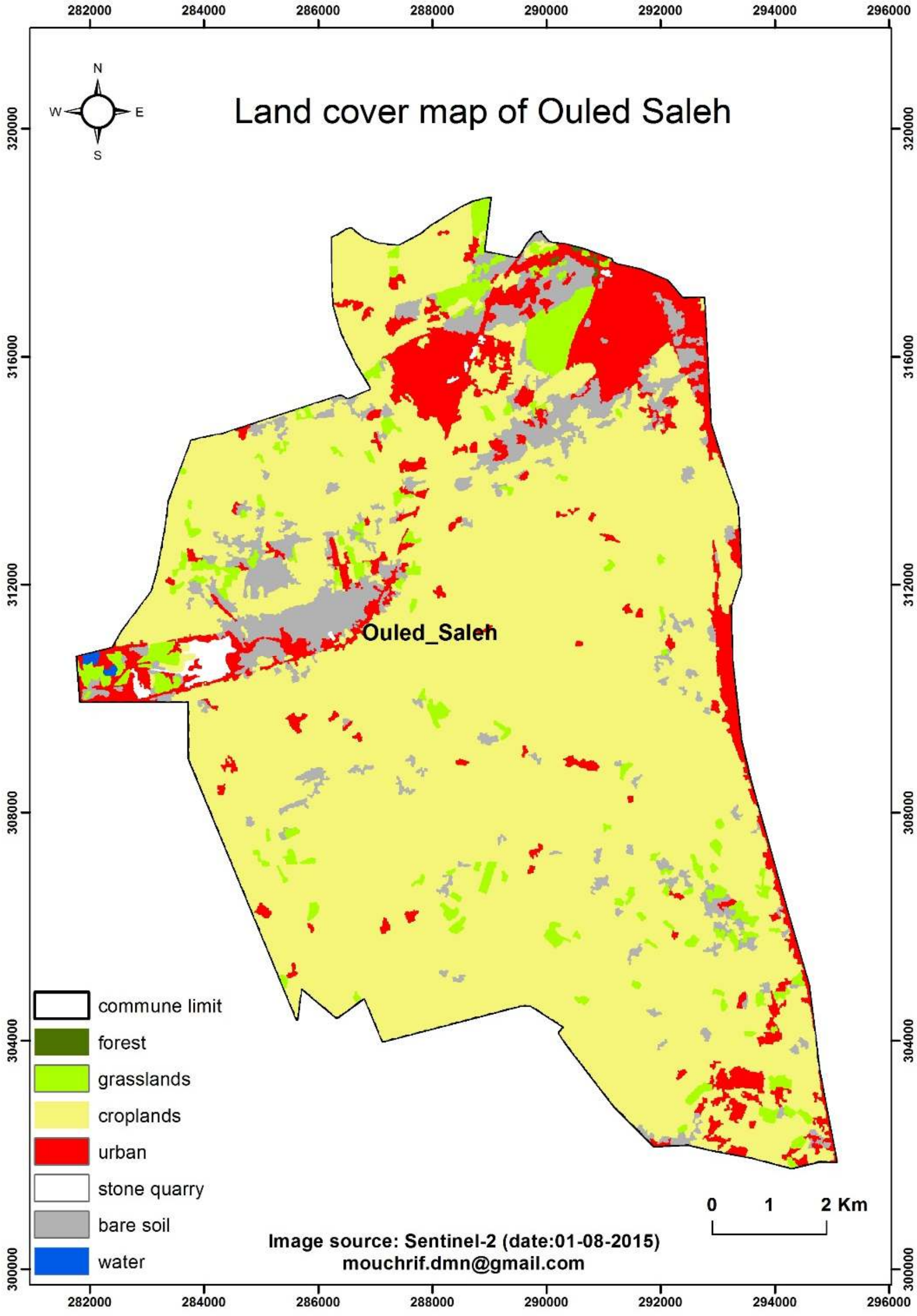

Fig. 5. Land cover map 2015 of Ouled Saleh

Seven major land cover classes were identified in the study area from the multiband raster satellite image analysis: Forest, grasslands, croplands, urban, stone quarry, bare soil and water. Proportion of each type of land cover was calculated and illustrated in Figure 6.

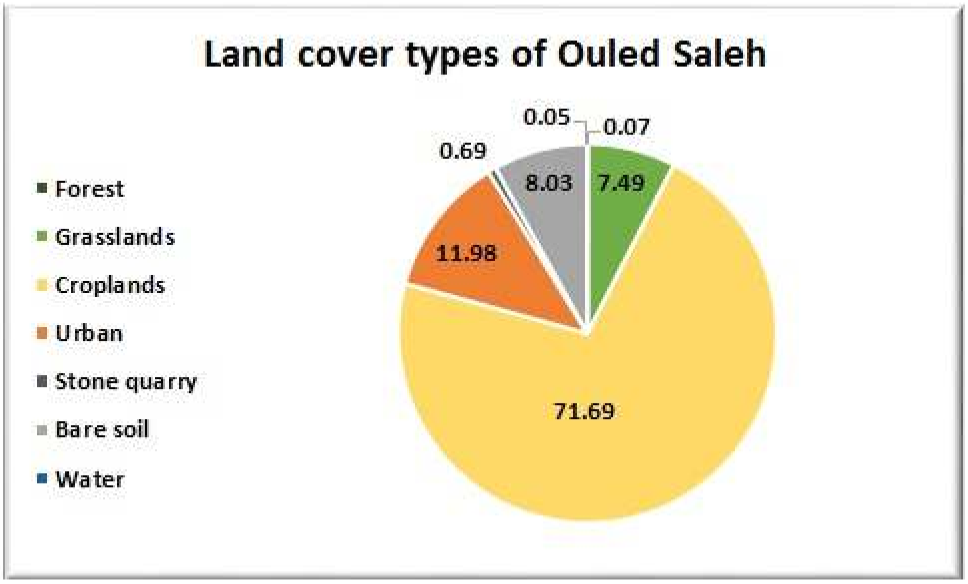

Fig. 6. Percent distribution (%) of land cover types 2015 at Ouled Saleh

This result reflects the importance of agricultural lands (71.69 %) in the territory of Ouled Saleh commune. However, one should note that in the last few years, the region has experienced significant economic growth. As a result, agricultural lands are under high demographic and urban pressure. The proximity of Casablanca, which is the economic capital of the country and the spread of land speculation, exacerbated the problem. The limited forest zone (only 0.07 %) is also threatened by urban areas (11.98 %).

3.1.3 Classification Accuracy Assessment

Accuracy assessment or validation determines the quality of the information derived from remotely sensed data. Results were checked by comparing the classified data with high-resolution imagery freely gathered from Google earth (http://earth.google.com) provided by Google Inc. The reliability of classification was tested by calculating two indices from the confusion matrix: Overall accuracy and Kappa index. Kappa can be used as a measure of agreement between model predictions and reality [19] or to determine if the values contained in an error matrix represent a result significantly better than random [20]. It ranges from 1 being perfect agreement to 0 being no agreement [21]. The final product overall accuracy and Kappa (K) was 90% and 83% respectively, which indicate an excellent agreement.

3.2 Relationship Between Soft Wheat YIELDS And NDVI

A statistical simple linear regression methodology was used to identify the relationship between soft wheat yields and the environmental indicator 15 days NDVI averaged from February till March or April over the cropping seasons 2002-2003 to 2011-2012. In Figures 7 and 8, are illustrated the strong relationship between these two variables. The results showed high linear correlations (R^2 =54% for February-March) and (R^2 =73 % for February-March-April).

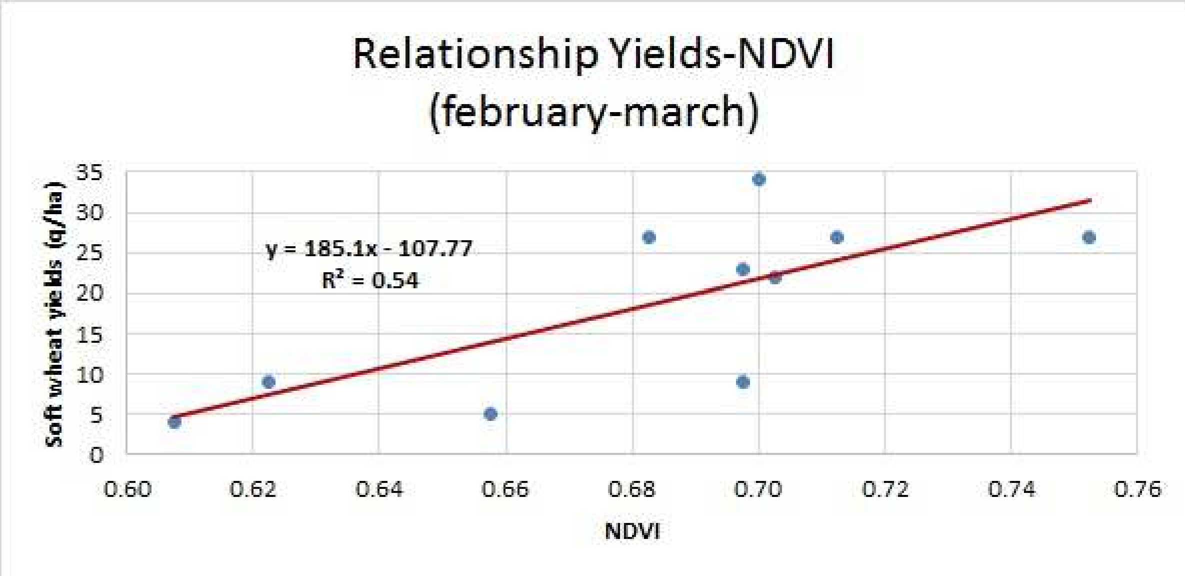

Fig. 7. Relationship between MODIS-NDVI, averaged over the period from February till March and soft wheat yields (Q/ha) at Ouled Saleh

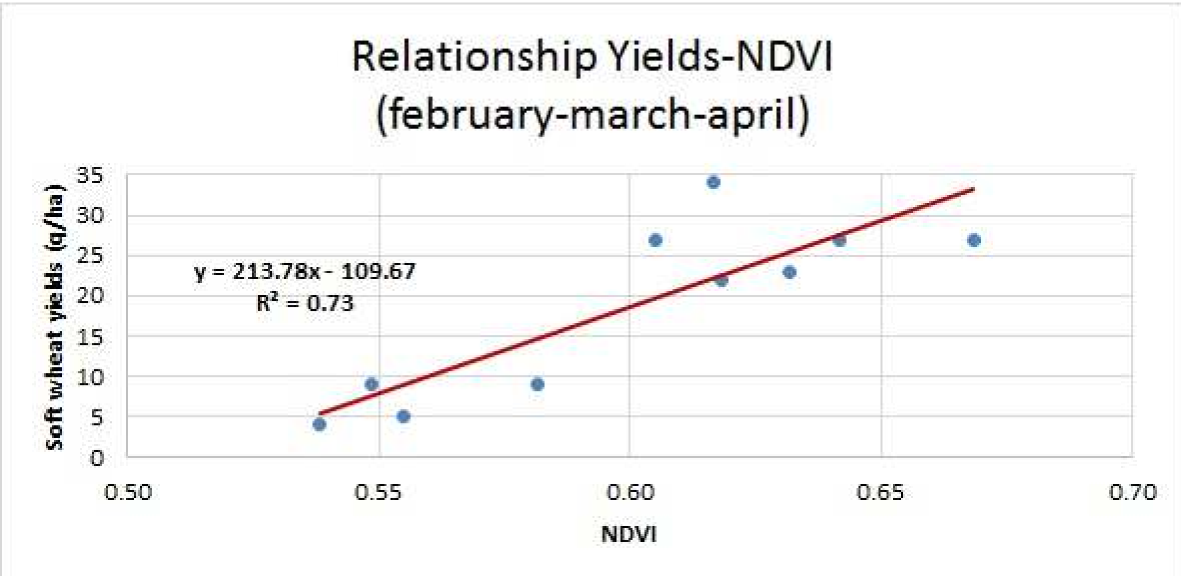

Fig. 8. Relationship between MODIS-NDVI, averaged over the period from February till April and soft wheat yields (Q/ha) at Ouled Saleh

Therefore, the NDVI index, obtained in an early, fast and inexpensive way, could be a useful indicator to estimate soft wheat yields early using the following equations:

- $Yield_{soft\ wheat}$= 185.1 $NDVI_{february\text{-}march}$ -107.77 R^2=54%.
- $Yield_{soft\ wheat}$= 213.78 $NDVI_{february\text{-}march\text{-}april}$ -106.67 R^2=73%.

It could be then considered as a promising complement to the survey based yield assessments.

4 CONCLUSION AND RECOMMENDATIONS

RS and GIS techniques were used to pre-process and classify a Sentinel-2A image using a supervised classification method to develop a land cover map and forecast soft wheat yields on the basis of MODIS NDVI at the level of the rural commune of

Ouled Saleh, Region Casablanca-Settat in Morocco. High linear correlations were identified between NDVI taken as an environmental predictor index and winter soft wheat yields. Based on a regression model approach, average NDVI from February till March or April can thus be easily used and at a low cost for yields forecasting one to two months before harvest. Therefore, we concluded that it is a useful decision-making tool for planning, management and policy decisions. Finally, we present some suggestions for further efforts to improve the quality of the results, which include:

- The use of a satellite imagery with high-spatial resolution (e.g. Spot satellite imagery) to develop a land cover more accurate and then to improve the agricultural mask.
- The use of an object-based classification to enhance the classification process and to compare it with the traditional pixel-based approach.
- The development of a map of soft wheat lands only .Therefore the new mask will closely filter NDVI images and will allow to enhance the relationship between NDVI and the yields of soft wheat.
- The use of a multiple regression model using rainfall, NDVI or temperature as predictors to improve the forecasts.

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