Journal Homepage: - www.journalijar.com

INTERNATIONAL JOURNAL OF ADVANCED RESEARCH (IJAR)

Article DOI: 10.21474/IJAR01/14237
DOI URL: http://dx.doi.org/10.21474/IJAR01/14237

ISSN NO. 2320-5407

RESEARCH ARTICLE

CONTRIBUTION OF REMOTE SENSING TO ONION AGRICULTURAL SYSTEM IMPROVEMENT IN GUIDIMOUNI BASIN (ZINDER REGION)

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Manuscript Info

Manuscript History
Received: 15 December 2021
Final Accepted: 17 January 2022
Published: February 2022

Key words:-
Cartography, Cultures, Onion, Remote Sensing, WMS, RF, DT, Guidimouni, Niger

Abstract

New information and earth observation technologies, remote sensing and the Geographic Information System (T-GIS), have become very effective tools in crop mapping for better management of agricultural plots. The objective of this study is to propose a combination of spectral indexes (SI) based on a time series of sentinel-2 images by comparing the performance of three (3) classification algorithms, namely: Wide Margin Separators (WMS), the Random Forest (RF) and the Decision Trees (DT) in order to produce a map of land cover (LC) in the gardening sites of Guidimouni by analysis of pixel-based images. Five classes of land cover have been retained, namely: Onion, Other plants, Flood zones, Water, and Non-vegetation. 24 optical images were processed to draw the temporal curves of cultures that will be used for processing. 51 classification schemes were tested and evaluated. Thus, the different values of the NDVI time series made it possible to observe three stages linked to the cultural development of onion, namely stage-1 (beginning of germination and the appearance of the first leaves), stage-2 (early bulb formation and strong chlorophyll activity) and stage-3 (bulb thickening and leaf yellowing). On the other hand, the WMS classifiers made it possible to obtain a better mapping of land cover in terms of discrimination between classes by combining the five spectral indexes (NDVI, SAVI, EVI, IV, BI2) with a cartographic precision of 88.89%.

Introduction:-

In Niger, the different constraints of agricultural production systems stem from insect attacks, uncontrolled irrigation, and penetration of livestock in agricultural parcels. These problems explain the precariousness and randomness of yields, exposing rural people to the painful spectrum of famine and a chronic food shortage (Seidou

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et al. 2012). Since the droughts of the 1980s, farmers have seen the performance of their agricultural productions decrease gradually while their standard of living has deteriorated considerably (MHE / LCD, 2005).

Despite all the constraints of agricultural systems, Niger has significant assets that could ensure the development of its agriculture. Thus, alongside crops like millet, sorghum and cowpea, which will probably still remain preponderant in the majority of farmers, Niger can bet on irrigated crops and its important potential for the so-called secondary crops such as rice, corn, onion, sesame, sugar cane, soup, sorrel to develop its agriculture. These so-called secondary crops constitute a real bulwark for the main crops as a dietary supplement or as a source of income (Adam et al. 1995).

Among these different crops, onion is the second horticultural speculation produced in the world after tomato (Alessndro and Soumah, 2008). Indeed, onion is produced by more than 175 countries around the world, including Niger, due to its place in production systems, economics and food (Abdou et al. 2014). Niger is the second largest exporter of onion in West Africa (Laouali et al. 2019). Although the numbers vary according to the documents, the production of this speculation has grown significantly in recent decades. In the 1990s, the level of production was about 270 000 tons. This production was evaluated by the Regional Onion Observatory at 447 000 tons in 2008, but the 2019-2020 production was 1 212 279 tons (Prodex, 2013; RECA, 2010; MA/EL, 2021). The onion sector in Niger generates a turnover of about 47 billion F.CFA (RECA, 2011). Several studies have focused on the systems for onion culture improvements in Niger (Laouali et al. 2019, Abdou et al. 2015, Abdou et al. 2014, and Prodex, 2012). On the other hand, there is no study which has stressed the use of spatial remote sensing coupled with GIS tools to improve the onion agricultural system in Niger. However, these techniques are revealed to be the right way for monitoring and mapping our environment, in general, and crops in particular. Indeed, the satellite images offer a synoptic view of the surface of the earth, they help to go back in the past to better study the evolution of a phenomenon in time and space. Interestingly enough, these reconstituted images represent the conditions that prevail at any point in the territory when the images have been taken. Finally these images also allow us to extract biophysical variables from land objects (Mamane et al. 2020). This explains the choice of remote sensing and GIS as part of this study to propose a system for improving the onion cultivation in the Guidimouni basin through the use of a combination of indixes of remote sensing including: normalized difference vegetation index (NDVI), ground adjusted vegetation index (GAVI), improved vegetation index (IVI), greenery index (GV). Thus, our study is part of this framework to propose a supervised classification method (based pixel) of agricultural surfaces to produce an onion card for the improvement of its agricultural system in the study area.

Materials and Methods:-

Study Area

The Guidimouni rural commune, as the area considered for this study, is located in the southeastern part of the department of Damagaram Takaya of the Zinder region (Figure 1). Its geographical coordinates are longitude: 009°30'.774 and latitude: 13°41'.577. It covers an area of 660 km2, limited to the north by the rural municipality of Damagaram Takaya; to the south by those of boune, gulchi, Ouacha and Kissabana; east by the rural commune of Gouré; to the west by the rural communes of Zermou and Gafati.

According to Souley (2017), the Guidimouni basin is located in the rural commune of Guidimouni. It covers an area of about 218.26 ha. Its hydrological system is powered by two male and female ponds, one of them is permanent with an area of about 85 ha and the other semi-permanent with about 105 ha (site 2 in Figure 1). It is a flush water basin powered by several sources including Gouzgourou, Kouta, Bijari, Iggiya, Idon Gabas and Daoulawa (ADO, 2012). The water table is very shallow. It is usually less than 1.5m. The basin is characterized by black colored soil with very fertile muddy-sandy ground. One can also find, depending on places: sandy, slimy, and sandy-slimy soils.

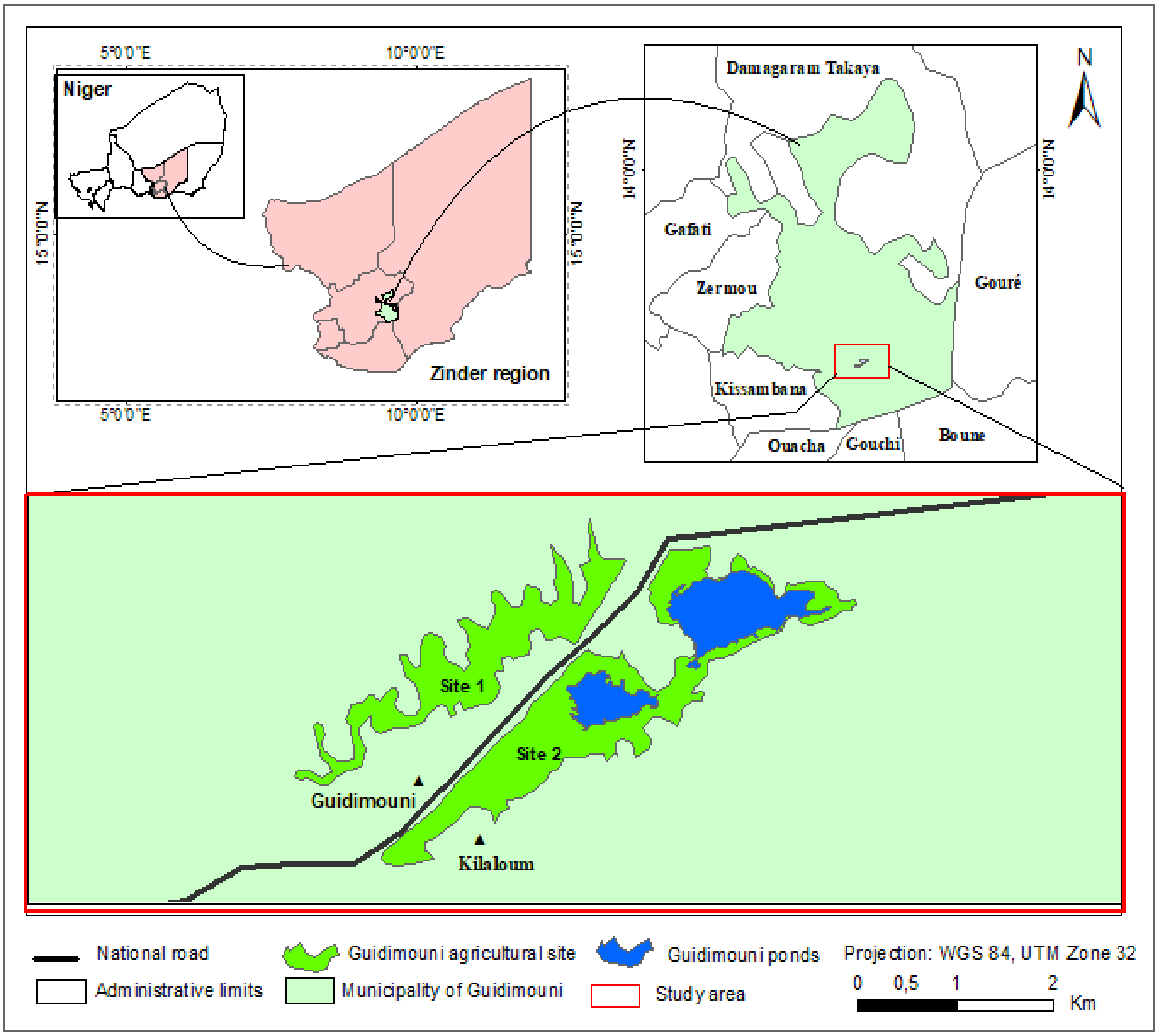


Figure 1:- Geographic Location of the Rural Commune of Guidimouni.

Exogenous and Image Data

A temporal series composed of 24 spatial resolution Sentinel-2 images covering the onion agricultural development cycle in the Guidimouni gardening site was used. From October 27 to August 29, 2020, these images are downloadable for free on the following site: https://scihub.copernicus.eu/dhus/#/home. Table 1 illustrates the list of S-2 images used for different treatments as part of this study. A shape file delimiting the rural commune of Guidimouni was used to create a NDVI mask based on the image acquisition dates.

Tableau 1:- Sentinel-2 Images Covering the 2019-2020 Agricultural Period.

Image Sentinel2	**Dates**	**Images Sentinel-2**	**Dates**
Image 1	October, 27 2019	**Image 13**	February, 4 2020
Image 2	November,1 2019	**Image 14**	February, 19 2020
Image 3	November, 21 2019	**Image 15**	March, 5 2020
Image 4	December, 1 2019	**Image 16**	March, 10 2020
Image 5	December,11 2019	**Image 17**	March, 15 2020
Image 6	December, 21 2019	**Image 18**	March, 20 2020
Image 7	December, 26 2019	**Image 19**	March, 30 2020
Image 8	January, 1 2020	**Image 20**	April, 4 2020
Image 9	January, 10 2020	**Image 21**	April, 14 2020

Image 10	January, 20 2020	**Image 22**	April, 19 2020
Image 11	January, 25 2020	**Image 23**	April, 24 2020
Image 12	January, 30 2020	**Image 24**	April, 29 2020

Data Collection and Parcel Digital Survey

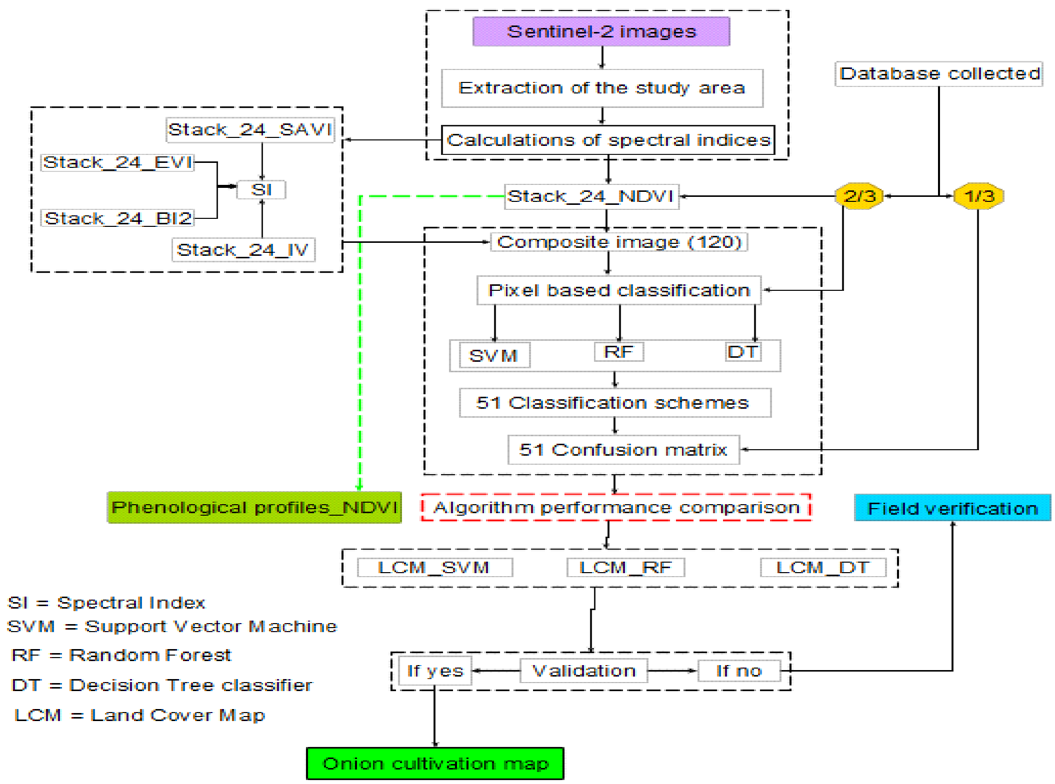
The data collection data in this study initially focused on the inquiry on the speculation cultivated on the site, then, stressed geo-location and digitalization of the farm parcels encountered on the field using the receiver GPS Etrex 10. These plots thus digitalized have been cleaned and corrected manually to avoid inter-parcelary redundancy and discriminate the phenological profiles of crops. The polygons are then superimposed on the new formed images based on spectral indexes.

Choice and calculation of spectral indexes

To meet the objectives of this study, a methodology has been adopted to produce an onion crop map for a better management of its production. After the pretreatment of the data (data exploration and extraction of biophysical parameters), 17 spectral index combinations have been tested and compared using the 2/3 of the database for calibration and 1/3 for validation. The performance of 51 classification schemes were evaluated based mainly on mapping accuracy and the accuracy for each scheme. The final maps are obtained after the field data validation. This allowed to validate the different classification results. The data processing chain is shown in Figure 2.

According to Bannari et al. (1996), a new generation of vegetation indexes has been developed with the aim of improving the variation of the spectral properties of soil and testing their potential for a more precise description of the vegetation cover recently. Thus, the vegetation indexces chosen as part of this study are: the NDVI separates the vegetation of naked soils and the urbanized surfaces, traces the phenological profiles of crops (Wardlow et al. 2007, Elmansouri et al. 2018). SAVI introduces an adjustment parameter, noted L, which characterizes the ground and its rate of overlapping by vegetation. (HUETE, 1988), IVI reduces both the sounds due to the atmosphere and the effects of soil and IV that detects vegetation in the senescence phase (harvest).

Figure 2:- Methodological Organization Chart of Calculating the Spectral Indexes.



Calculation of the Phenological Cycle of Cultures

According to Lepage and Bourgeois (2012), the term “phenology” describes the appearance of important stages in the development of a plant species. This phenology is predetermined by its genetic makeup and modulated by environmental conditions. Each phenological stage represents a specific development phase marking the phenological episodes of a crop, such as germination, emergence or elongation of the hypocotyl, appearance of leaves, flowering, fruiting, and maturity. The majority of crop mapping studies use a multi-date series of optical images under the assumption that the phenological cycle of a crop of the species is perfectly reflected on the temporal profiles of NDVI bands covering an agricultural season (Elmansouri et al. 2018; Ouzemou, 2018). Hence, the interest of using this index to stack the 24 new images of newly formed NDVI covering the crop development cycle of onion in the study area to trace its evolutionary curve during the 2019-2020 agricultural campaign.

The Algorithms that Are Used

Three (3) types of algorithms were used to classify the different images. Random Forest (RF), Decision Tree classifiers (DT) and Support Vector Machines (SVM). Indeed, According to Breiman (2001), RF or random forest classifier is a set of classification trees based on the Classification and Regression Trees (Breiman et al. 1984). This algorithm uses its internal error estimate and each tree is constructed to perform an individual learning algorithm that divides the input variable (Breiman, 2001). In fact, RF builds a number of decision trees, using a subset of about 2/3 of the data set for internal learning while keeping the remaining 1/3 for learning process error estimation (Nitze et al. 2015; Pelletier et al. 2016). Decision trees (DT) are the modeling of a classification from observations that we call an example. An example is represented by a series of attributes and an associated class, one must know the class because decision trees work on classification in supervised mode (Stuart et al. 1995).

Decision tree classification is a classification that allows decisions to be taken in several steps to highlight a particular class of object according to the spectral behavior of a band or a transformation into neo-channels (Trabi et al. 2014). Support Vector Machines (SVM), also called wide-margin separators, are supervised learning techniques intended to solve classification problems. Support vector machines exploit concepts related to statistical learning theory and bounds Vapnik and Chervonenkis’s theory. It is also a mathematical method for solving complex and heterogeneous data classification problems. It is a statistical, non-parametric and supervised method (Pal and Mather, 2005). The strength of this classification lies in its ability to make generalizations based on small data related to regions of interest for pixel image analysis (Shao and Lunetta, 2012; Hao et al. 2015) and for image analysis by objects (Teodoro and Araujo, 2016). This classification method is widely used in remote sensing for mapping of different types of crops (Devadas et al. 2012; Zheng et al. 2015).

Results and Discussions:-

System of Cultures and Production Cycle

Irrigation is the main activity practiced in the gardening site of Guidimouni given the water resources available for this purpose. The analysis of the results (figure 3), from the digital plot survey on the visited garden, shows that the cropping system in the study area is characterized by small family farming in monoculture and crops in association to ensure a production with an acceptable yield in order to effectively meet the nutritional needs of the populations. This same analysis shows that 26% of the plots surveyed (2019-2020 campaign) are occupied by onion cropping, followed by cabbage (18%). The survey also revealed 3 types of crop development cycles, namely: long-cycle (50%), medium-cycle (30%), and short-cycle (20%) crops. Table 1 illustrates the results obtained based on the information provided by farmers that the researchers found on the sites.

Figure 3:- Figures of Cutivated Speculation found in the Guidimouni Basin during the 2019-2020 Agricultural Period.

Table 1:- List of Speculations Inventory with their Development Cycle.

Speculation	Scientiic Name	Production cycle (month)
Sugar cane	Sacharum oficinarum L.	5 to 6
Carrot	Daucus carota L.	3 to 4
Cabbage	Brassica oleracea L.	3 to 4
Squash	Curcubita pepo L.	5 to 6
lettuce	Lactuca sativa L.	1 to 2
Corn	Zea mays L.	2 to 3

Cassava	Manihot esculenta Crant	5 to 8
Onion	Allium cepa L.	5 to 6
Sorrel	Rumex acetosa L.	1 to 2
Chilli pepper	Capsicum ammum L.	5 to 6

Presentation and Analysis of Phenological Curve of Onion

Figure 4 shows the evolution of onion cultivation during the 2019-2020 agricultural campaign in the Guidimouni basin. NDVI time series values vary from date to date. From these variations, three stages related to the cultural development of onion are observed: (i) an irregular variation from October 27, 2019 to January 01, 2020, this period corresponds to stage-1 of onion development. In 2002, Fritsch and Friesen proved that the first months of the onion cycle are characterized by the start of germination and the appearance of the first leaves. (ii) The variation increases from January 10 to February 19, 2020 (stage-2 A) to stabilize until March 10, 2020 (stage-2 B), it corresponds to the stage of maximum development of the onion. This phase is characterized by the beginning of the formation of bulbs and a strong chlorophyll activity with the appearance of the inflorescence and flowering for the production of onion seeds. This is the growth phase of the onion (Fristsch and Friesen, 2002). (iii) The variation becomes irregular again from March 20 until April 29, 2020 (stage-3). This period corresponds to the last stage of development, the chlorophyll activities are less important, the bulbs thicken, the leaves turn yellow and become completely dry. All these variations observed during the development cycle of the onion are in line with the results of the research work of Fristsch and Friesen (2002) on the evolution, domestication, and taxonomy of the onion (Allium cepa).

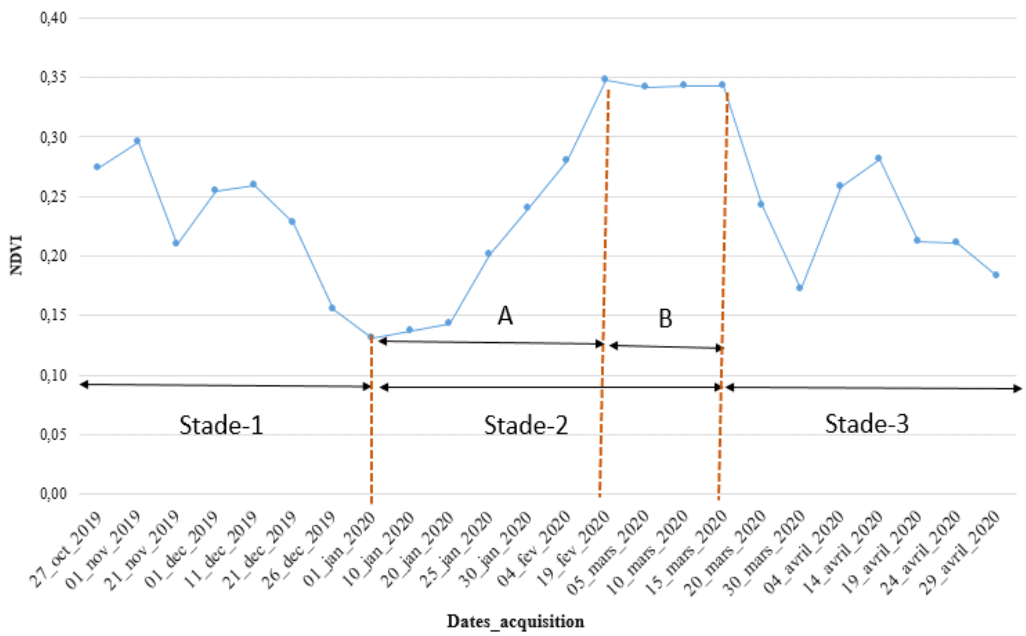


Figure 4:- Phenological Profile of Onion during 2019-2020 Agricultural Period.

Choice of index or of a combination of spectral indexes and classification algorithm to be used

Figure 5 compares the performance of the combinations and classification algorithms according to the KAPPA and cartographic precision indices resulting from the results of different schemes obtained. The analysis of this figure shows that the accuracy of classifications varies from one index or combination of spectral indices to another, depending on the classifier used. We therefore notice that WMS classifiers are best suited to the mapping of onion crops. Indeed, the values of the KAPPA indices recorded at the level of these classifiers exceed those observed at the level of RF and DT. This explains the choice to apply WMSs as a classification algorithm. Of the 17 combinations compared, the combination that better discriminates the types of crops (including onion) within the Guidimouni irrigated perimeter is the composite image that combines the NDVI, SAVI, EVI, IV and BI2 indices with a precision with a Kappa index of around 0.70 and a cartographic precision of 88.89% (Table 2) observed at the level of WMS. These results confirm the results obtained by Elmansouri who worked on Geo-Spatial Technologies to strengthen agricultural land management systems to support the management of citrus-growing areas by remote sensing in the Triffa-Berkane Plain (Morocco) in 2018.

Figure 5:- Choice of an index or of the combination of spectral indexes and of algorithm to be used for image classification

Global reference crop map obtained by SVM classifiers

Figure 6 shows the different land cover classes over the study area. The combination and the classification algorithm used made it possible to clearly classify the types of land use. There is also a clear distinction between buildings and cultivation areas. The two ponds (male and female) as well as the flood zones are very well detected. In addition, the crop classes are well classified and the onion class is well separated from other crop types. The area occupied by the gardening site is estimated at 242.57 ha against 218.26 ha declared by the Guidimouni Agriculture Department (PDC, 2018). This difference could be explained by the fact that some speculations have closely related phenological curves. If we concentrate on the estimation of the areas by speculation presented in table 2, the onion occupies 55.05 ha (i.e. 43%) of the total area of crops practiced in the basin while the other 57% concern the other gardening.

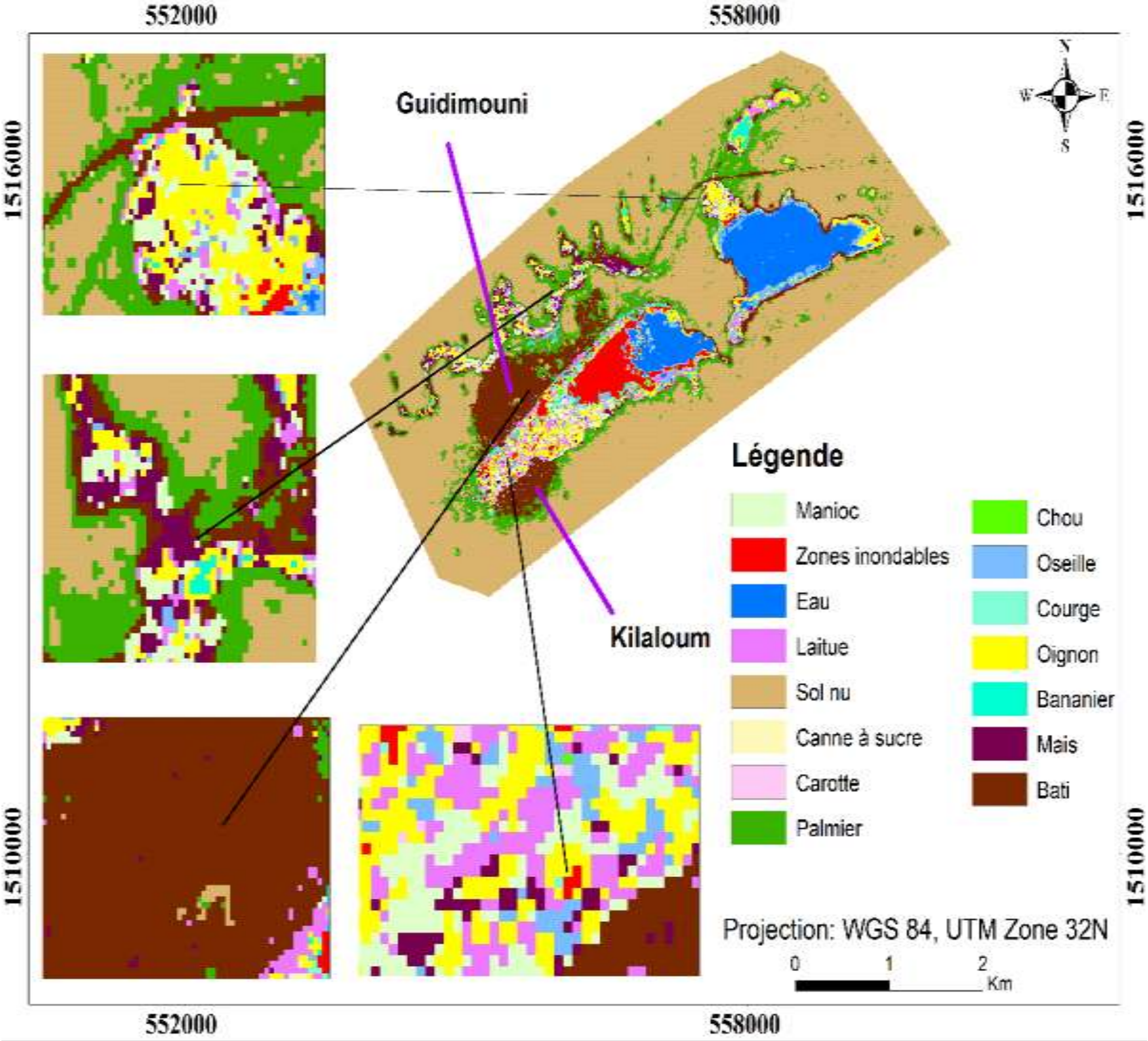


Figure 6:- Global reference map of plants obtained by WMS classifier (2019-2020 Agricultural Period).

Table 2:- Summary of onion mapping according to classifiers .

Classifiers	Cartographic precision of onion	Onion area (%)
SVM	88,89	42
RF	83,33	26,23
DT	80	10,31

Analysis of the final map of onion cultivation

To better map and analyze crop types, we have simplified the land cover classes to a reduced number of 5 classes (onion, other plantations, floodplains, water and non-vegetation). Figure 7 presents the simplified onion crop map during the 2019-2020 crop year. The analysis of the latter shows that the study area has two gardening sites. Site-1, located north of the national road (RN1) while site-2 is located between the village of Kilaloum and that of Guidimouni south of the RN1. It emerges from this analysis and that of Table 2, that the onion is the most cultivated speculation in the basin; and onion productivity is much higher at site 1 for the 2019-2020 campaign. This difference could be explained by the fact that site-2 is characterized by continuous high soil humidity (very shallow water table, presence of ponds) and the concentration of woody plants that can reduce aeration. This is justified by JGRC (2001) and Morseli (1992), which respectively confirmed that excessive humidity of the air and soil could favor the appearance of certain diseases and crop enemies, and that favorable temperature conditions could help onion development. Indeed, this development needs a certain heat to reach maturation. Finally, irrigation management is easier at site level 1 because during the growth and maturation phase of the bulb, a water shortage can accelerate maturation.

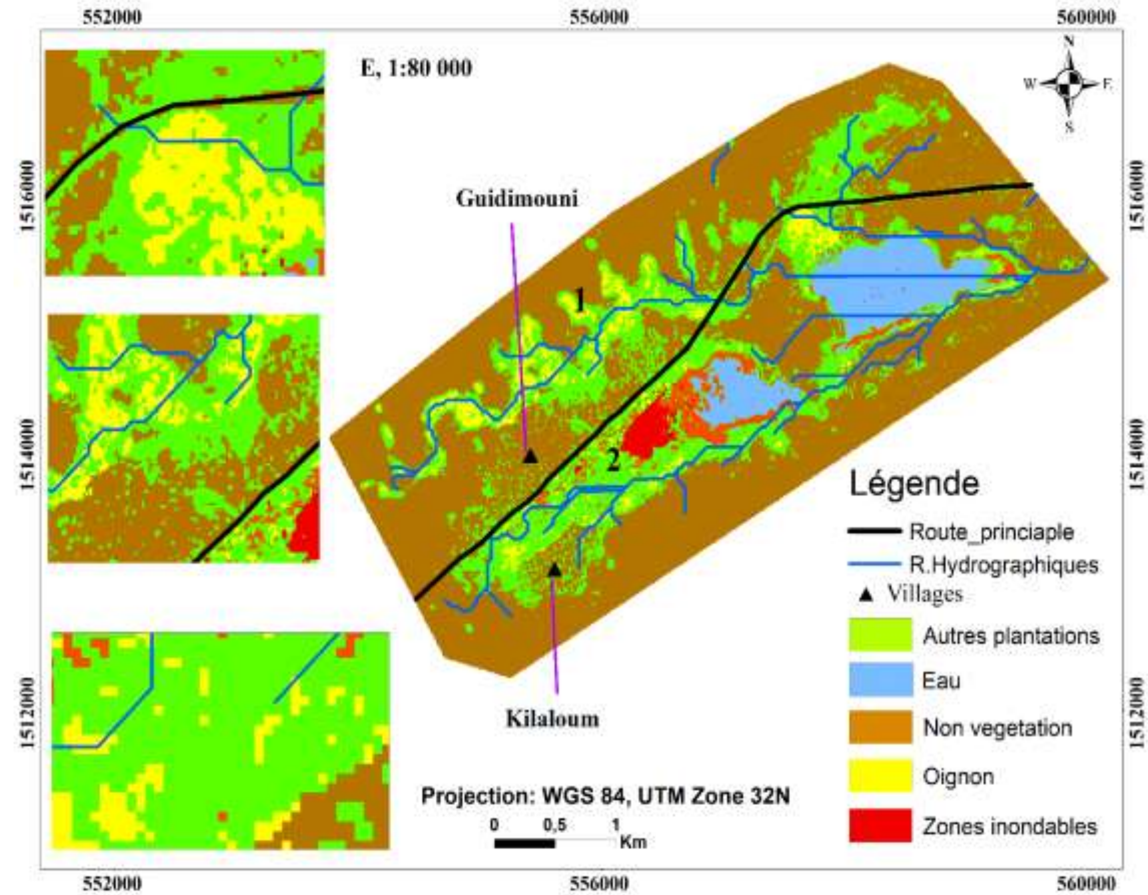


Figure 7:- Final Map of Onion Cultivation Obtained by WMS classifiers during the 2019-2020 Agricultural Period.

Conclusion:-

The current study reveals that remote sensing and GIS are essential tools for the identification and monitoring of crops. The comparison of the results from the different classifiers shows that the precision of the latter varies from one spectral index to another and depends on the classifier used. These results show that the SVM classifiers are best suited to the mapping of onion crops in the agricultural sites of the study area with an accuracy of the Kappa index of 0.70 and a mapping accuracy of 88.89%.

The results of this research could also serve as a decision-making tool for decision-makers. It will help guide farmers in identifying plots suitable for growing onions for future sowing. This will enable better management of agricultural plots by facilitating the development of farming practices in the rural commune of Guidimouni.

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