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Method for estimating exploited areas; case of the woloni and Tounga plains

Méthode d'estimation des surfaces exploitées ; Cas des plaines de woloni et de Tounga

Auteur 1 : DEMBELE Abdramane,
Auteur 2 : DAOU Ibrahima
Auteur 3 : COULIBALY Kadidiatou,
Auteur 4 : KONARE Mahamadou

DEMBELE Abdramane, (https://orcid.org/0000-0001-5017-5464*, PhD)

École Nationale d'Ingénieurs (ENI-ABT), GEC, Bamako-Mali

DAOU Ibrahima, (https://orcid.org/0000-0001-8610-5281, PhD)

Institut Polytechnique Rural de Formation et de Recherche Appliquée de Katibougou (IPR/IFRA de Katibougou)

COULIBALY Kadidiatou, (MSc)

Société De Géomatique Et De Système D'information (SGSI MALI sarl)

KONARE Mahamadou, (https://orcid.org/0000-0003-4005-1200, PhD)

Université Thomas SANKARA, Bobo-Burkina-Faso

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Abstract

The major direction of this work was on evaluating the exploited regions of the Tounga and Woloni plains. Due to the fact that these areas are now assessed using conventional procedures, which are lengthy, expensive, laborious, and prone to human error. It is intended to accomplish this by creating an approach using remote sensing. This technique assesses and monitors the evolution of exploited regions in the Tounga and Woloni plains. To do this, we digitized topographic maps of the study area to extract the boundaries of the plains. We used the maximum likelihood supervised classification method to elaborate the land use maps. We perform statistical analyses to extract the values of the exploited areas, then make forecasts of exploited areas for 2030, 2040 and 2050. The results obtained from the statistical analyses are as follows: on a projected area of Tounga 27126.30 ha, the areas exploited in 2018, 2020 and 2021 are respectively 9739.82 ha, 10423.20 and 10663.26 ha. And as for Woloni, on a projected area of 5488.03 ha, the areas exploited in 2018, 2020 and 2021 are respectively 2240.93 ha, 2309.55 ha and 2498.08 ha. The annual exploitation rate between 2018 and 2021 increased by 1.5% in the Tounga plain and by 1.09% in the Woloni plain. To verify the accuracy of our results, a comparison was made between the 2018 exploited area values obtained and the 2018 exploitation report of the Office des Moyen Baní. After the comparison, we find a variation of about 2%.

Keywords: remote sensing, land use, statistical analysis, forecasts, plains

Résumé

L'évaluation des superficies exploitées des plaines de Tounga et Woloni fut la direction majeure présent travail. À cet effet, il s'agissait d'élaborer une méthodologie au moyen des données de la télédétection pour évaluer et suivre l'évolution des superficies exploitées dans les plaines de Tounga et Woloni étant donné que ces superficies sont actuellement évaluées par des méthodes classiques qui sont toutefois longues, coûteuses, fastidieuses et sujettes aux erreurs humaines.

Pour se faire, nous avons digitalise des plans topographiques de la zone d'étude pour extraire les limites des plaines. Nous avons traité par la méthode de classification supervisée par maximum de vraisemblance pour élaborer les cartes d'occupation du sol et effectuer des analyses statistiques afin d'extraire les valeurs des superficies exploitées, puis faire des prévisions des surfaces exploitées pour 2030, 2040 et 2050. Les résultats obtenus des analyses statistiques sont les suivants : sur une superficie projetée de Tounga 27126.30 ha, les superficies exploitées en 2018, 2020 et 2021 sont respectivement 9739.82 ha, 10423.20 et 10663.26 ha. Et s'agissant de celle de Woloni, sur une superficie projet de 5488.03 ha, les superficies exploitées en 2018, 2020 et 2021 sont respectivement 2240.93ha, 2309.55 ha et 2498.08 ha. Le taux de l'exploitation annuelle entre 2018 et 2021 a augmenté de 1.5% dans la plaine de Tounga et de 1.09% dans celle de Woloni. Pour vérifier l'exactitude de nos résultats, une comparaison a été effectuée entre les valeurs de la superficie exploitée de 2018 obtenue et le rapport 2018 d'exploitation de l'Office des Moyen Baní. Après la comparaison, nous constatons une variation de l'ordre de 2%.

Mots clés : télédétection, occupation du sol, analyse statistique, prévision, plaines

Introduction

Mali is a Sahelian country whose economy is dependent on the primary sector, dominated by agriculture, livestock, fishing and forestry. These sectors employ more than 80% of the active population and participate fully in the creation of wealth (Fida, 2020). Agriculture, being all of the work done on the soil with a view to plant production, is essentially rain-fed in Mali and has become increasingly uncertain since the major droughts of the 1970s (DEMBELE & Al., 2021). This serious disruption has had a negative impact on the economics and evolution of agricultural production (Bied-charreton, 2018).

Indeed, the government has been forced to resort to increasingly heavy and costly imports of cereals, particularly rice, in order to cover the country's food needs. Analysis of this situation has led it to consider that securing food production necessarily involves controlling water in order to remove agriculture from its heavy dependence on rainfall. It was with a view to increasing the security of agricultural production that the Middle Bani Plains Development Program (PMB) was identified (Du et al., 2009). The program's intervention zone is located in the center of the country, in the Segou region, which is one of the regions most affected by the drought. Submerged rice cultivation, which has always been practiced in this area, is a traditional crop; however, it has become practically impossible due to the decrease in the flow of the Bani River, a tributary of the Niger River, whose natural floods can no longer submerge the crop plains. The design of the PMB is based on the principle of raising the level of the Bani River, through the construction of a diversion weir, in order to dominate the plains (Keita, 2016; Zachwatowicz & Gietkowski, 2010).

Given that the cultivated area of the country represents only 4% of the territory (Hollinger & Staatz, 2015; Wang et al., 2022), it is therefore essential to monitor and evaluate the exploited area in order to ensure food security. However, in order to carry out this evaluation, it is essential to have information on the areas planted and their yield. This information must be updated frequently to forecast food availability (Global Strategy on Agricultural and Rural Statistics (GSARS), 2017), economic planning activities and agricultural market management. Therefore, in order to better understand the management of the PMB plains, a team is mobilized on site to estimate the area planted after each harvest using conventional methods in order to have a rough idea of the annual production. However, these methods of estimating cultivated areas are long, costly, tedious and subject to human error (Campus Awolowo, Obafemi State, 2012). Wishing to explore this work culture, its importance was introduced in the form of a research article entitled "Method for estimating exploited areas; case of the woloni and Tounga plains".

To overcome these problems, remote sensing is an alternative due to its synoptic and multi-temporal capabilities. These data can be used to map the exploited areas and analyze the dynamics of their evolution. The general objective of this study is to establish a method to evaluate the exploited area of the plains through the use of new technologies of remote sensing and Geographic Information Systems (GIS) specifically.

- ✓ Produce plains occupation maps;
- ✓ Evaluate the occupation units of the maps to extract the exploited area of the plains;
- ✓ Confirm the exploited areas obtained from remote sensing methods with other data;
- ✓ To study the dynamics of the evolution of the plains.

The assumptions are the following:

- ✓ Land use studies in the Tounga and Woloni plains make it possible to evaluate the exploited areas.
- ✓ The evolution of the exploited area of the Tounga and Woloni plains can be detected by remote sensing methods.

Our study plan is structured in 6 parts:

The abstract which exposes a condensed version of the whole article

The introduction It highlights the general context of the subject and the objective, explains the subject and shows the state of knowledge.

Material and study area: exposes the different tools, and gives a detailed situation of the work.

Methodology: detail all the operations used in this work

Results: shows the different results from all the processes

Finally, we will end this article with the conclusion and future perspectives where we will find a confirmation of the details highlighted above and recommendations.

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1 Study Area and Materials

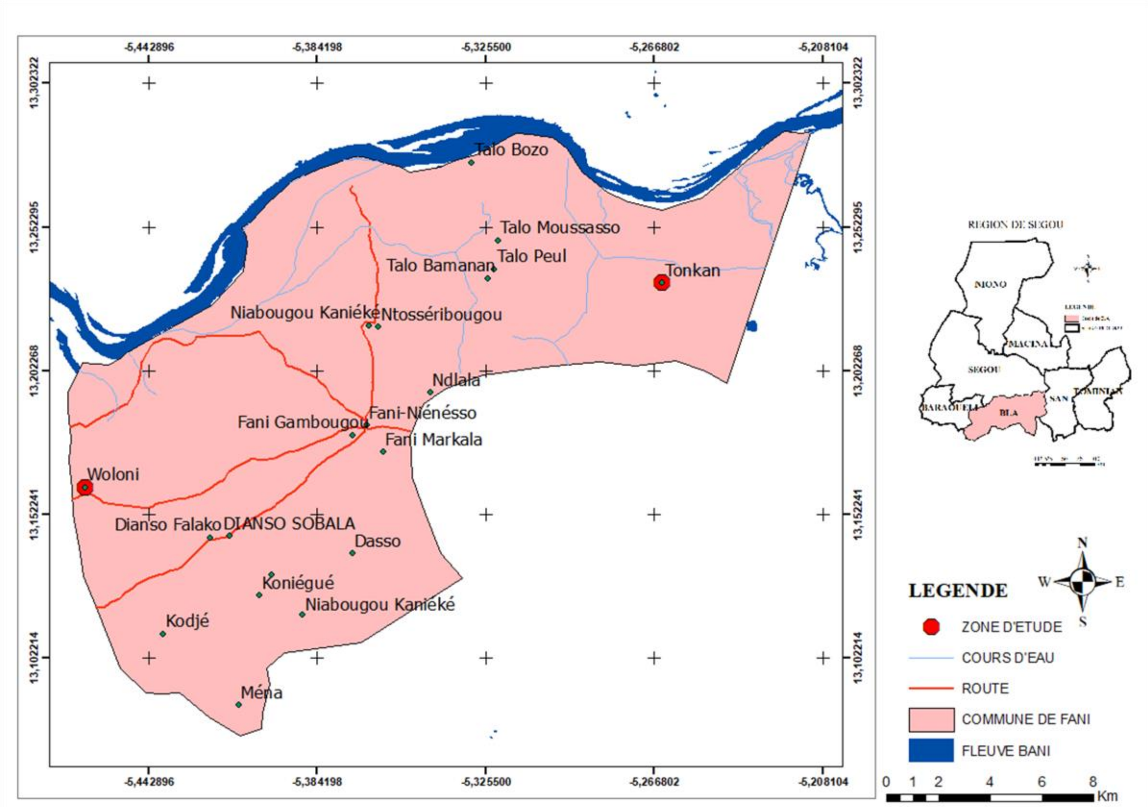
This chapter presents the geographical framework of the study, the materials and used to develop our project.

1.1 Presentation of the study area

The Woloni and Tounga plains that are the subject of our study are part of the development projects of the Programme de Développement de l'Irrigation dans le Bassin du Bani et à Sélingué (PDI - BS). They are located in the rural commune of Fani and border on 5º09'39" and 5º45'21" W longitude and 12º57'24" and 13º19'42" N latitude (Figure 1), with an area of 460.70 km^2.

The vegetation is shrubby in the savannah composed of thorny species (acacias) and herbaceous in the plains (grasses). The average annual rainfall is variable from year to year and ranges from around 600 to 1000 mm. The temperature is often high and varies from 18 °C to 40 °C. The relief of the area is not very uneven, consisting mainly of plains and lowlands favorable to rice cultivation and elevation. The soils are alluvial clay-sand or silty clay. The climate is Sudanian.

Figure 1 Carte de la commune rurale de Fani



Source: Group production

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1.2 Materials

This part exposes the tools and the data used to develop our project.

* **Tools**

The tools used in this study are as follows:

Computer, The Gamer brand computer was used for data processing and report preparation.

Scanner, An HP Designiet T2500 type scanner was used to scan the topographic maps from previous studies of the Paper Forming Plains into digital format

DGPS S800

Software

The software used during our work are: Autocad18-Covadis17; ENVI 5.3; ArcGIS 10.4; Google Earth; Wordoffice and Excel

* **Data**

Several types of data were used in our work. These are:

- Sentinel-2 satellite images;
- The topographic study plan for the area,

spatial resolution	: From 10 to 60 m depending on the bands
spectral resolution	: 13 spectral bands from visible to mid-infrared
temporal resolution	: 5 days allowing to have many quality images
The satellite swath	: 290 km of swath to cover our study area
Website (freely available)	: https://scihub.copernicus.eu/

The data are ready to use, i.e. the ortho-rectification atmospheric corrections are already included

Due to the date the study was conducted, the topographic plans are only available in paper format. These plans were digitized to delineate the boundaries of the Tounga and Woloni plains

- Field data from the study area

The field data were used for the validation of the classification

- The 2018 operating report of the Office des Moyen Bani,

Data from the 2018 OMB operations report was used as a source of verification for the areas obtained after satellite image processing

- The topographic and agronomic study report.

Data from the topographic and agronomic study reports were used to geo-reference the topographic study plans and to delineate the maximum water level (

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Table 1).

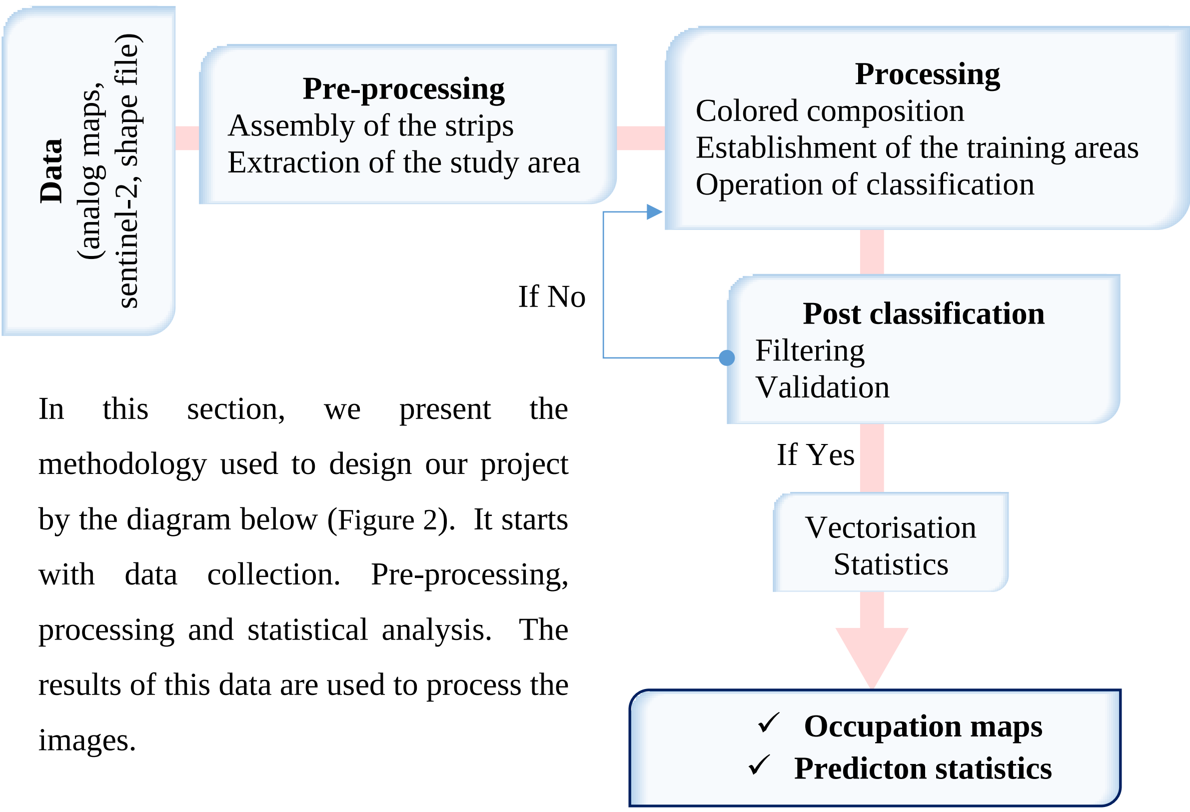
Table 1 Data Characteristics

Data	**Resolution/scale/accuracy**	**Source**	**Formats**	**Utilities**
Sentinel-2	10 à 60 m	https://earth	Digital	Land Use Unit Map
The report of the	Digital	Middle Bani	Digital	Check the area
Topographic plan	1/10 000	Technical study	Analog	Extract the limits of
Topographic and agronomic study reports Paper	Analog Papers	Technical study office	Analog Paper	Geo-referencing and delineation of the topographic plans of
Field data	1mm	Field	Digital	Validation of the

Source: Group Production

2 Methodology

Figure 2 Processing flow chart



In this section, we present the methodology used to design our project by the diagram below (Figure 2). It starts with data collection. Pre-processing, processing and statistical analysis. The results of this data are used to process the images.

Source: Group production

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2.1 Data collection

The data collection consisted of viewing all the necessary documents used to

How it works

Once at the site, we made a rough visit to identify the boundaries of the exploited areas in the plains and the different land-use units. We surveyed samples of each land use class by recording their geographical coordinates in the differential GPS. These data are then transferred to the computer, processed and converted to shapefile format to serve as the basis for supervised classification. The list of points is shown in Appendix.

2.2 Pre-processing

2.2.1 Digitisation of topographic plans

Having obtained the topographic plans in digital form (PDF), we used AutoCAD 2018 and Covadis 17.0 software to digitise and reconstitute the topographic plan of Tounga and Woloni. This digitisation was carried out as follows:

* The recalibration of the topographic plans of Tounga and Woloni

After loading the points on AutoCAD 2018-Covadis 17.0, we proceeded to the recalibration of the topographic plans through the Helmert method. However, the known markers well distributed on the plan were chosen as the point of alignment of the topographic plans. Thus, each sheet was re-aligned independently.

After the georeferencing of the plans, we proceeded to the reconstitution of the different plans of Tounga and Woloni by associating the 3 sheets of Tounga and the two sheets of Woloni. To do this, we apply the following approach:

in the woloni file window, select the entire drawing and on the toolbar click on edit and then in the menu that appears select copy, then open a new window, click on edit in the menu that appears select paste to original coordinates

* Reconstruction of topographic points

We used the covadis software to reconstitute the topographic points existing on the analog plan.. In the dialogue box that appears, we take care to choose the appropriate parameters.

Once this setting has been validated, simply click on the symbol representing a topo point, then enter its coastline using the keyboard and validate to move on to the next point. All the topographic points are thus reconstituted.

2.2.2 Drawing of other details

This step consists in drawing with the appropriate commands each detail (villages, dikes, milestones, etc.) in their corresponding layers.

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At the end of these steps, we proceeded to the spinning of the contour lines and to the comparison of the reconstructed plan with the image plan, the objective of which would be to verify the digitised plan and to correct any errors that may have occurred during digitisation (for example, some points may have been incorrectly captured). With the points reconstructed in three dimensions, we created the DTM and spun the contour lines.

After digitisation, we proceeded to identify the boundaries of the farms proposed in the studies. This identification is done by taking as a basis the dimensions provided by the agronomic study report. Then we identified the corresponding contour lines and drew the boundaries.

After digitising the topographic map of Tounga and Woloni, we recorded their boundaries in Shape-file format using Arc Gis software.

- Assembly of the strips

The Sentinel-2 images are provided as individual strips in Geotiff format. The stitching process consists of stitching the individual strips of Sentinel-2 images together to form a multi-spectral image. It also makes it easier to manipulate the images without making mistakes. Bands 1, 9 and 10 were excluded due to their sensitivity to aerosols and clouds and their spatial resolution (60m)[20]. We used the Layer Stacking tab in ENVI Classic to stack our bands and get a multi-band image in TIFF format.

- Extraction of the study area

The objective of this phase is to extract the study area from the image in order to speed up the processing. Indeed, the Sentinel-2 images have a size of 290 x 290 km for a ground resolution of 10 to 60 m depending on the band, with such a large area, it would be useful to extract the study area from the scene beforehand in order to facilitate the processing. We used the vector file of the topographic study plan to extract the study area through the Windows tool (Image Analysis) of the ArcGIS software.

2.3 Processing

We started by applying the false colour composition to the images, as it is of great visual interest to better appreciate the land use of an area (Mariam, 2019). We assigned to each of the three channels (red, green, blue) in the ENVI software a spectral band of the pre-processed images. For our study, bands 11, 8 and 4 (SWIR, PIR and red) were used. This allowed us to identify 4 main classes through the good knowledge of the study area (Figure 3).

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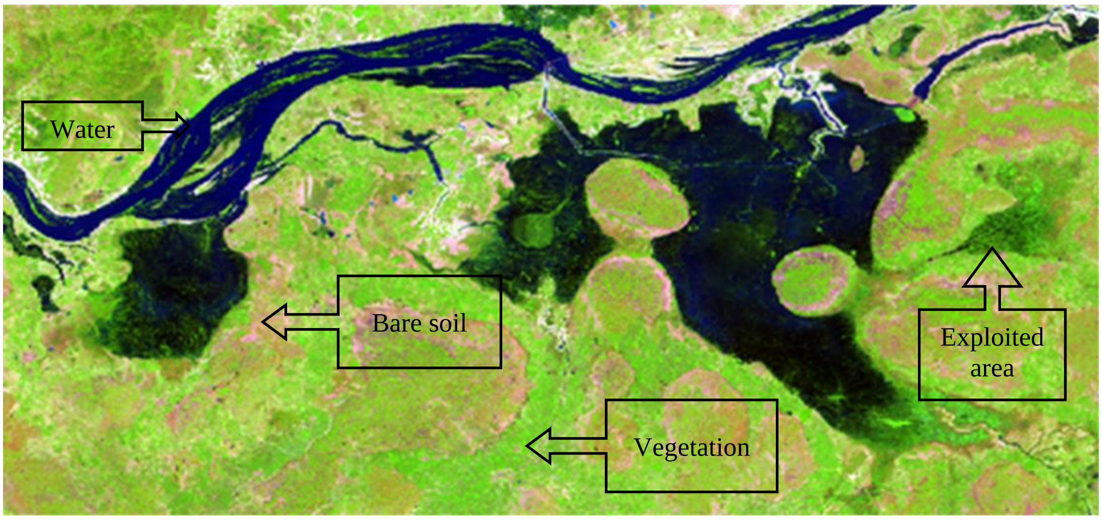
Figure 3 Colored Composition



Source: Group Production

- **Establishment of training areas, also called regions of interest (ROIs)**

We created training data (Regions of Interest ROI) based on the vector files from the field data collection. Then, through photo-interpretation of multitemporal images, we identified the different classes. The results of the field data collection were used both to select samples for training the classification algorithm and as validation samples for the classification (Daou Ibrahima, 2021; Zachwatowicz & Gietkowski, 2010).

- **Supervised classification**

Following a colour composition, samples of homogeneous areas were identified and materialized on each image (training areas). This made it possible to perform a supervised classification on the images using the Maximum Likelihood classification algorithm implemented on the classic ENVI software.

The maximum likelihood algorithm is based on Bayes' rule and calculates for each pixel its probability of belonging to one class rather than another. The pixel is assigned to the class with the highest probability of membership.

After the classification of the images, we refined the images by applying the majority/minority functions.

- **Validation of the classification**

After the classification, we validated the results of the classification by the "Confusion Matrix" algorithm of the ENVI software, which is used to estimate the quality of the classification according to the file of the training sites representing the ground truth.

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The result is given in the form of a matrix called confusion matrix which contains two indices:

Overall accuracy:

It is equal to the total number of correctly classified pixels (diagonal of the confusion matrix) divided by the total number of verification pixels (Sbai et al., 2016).

The Kappa index:

It indicates how well the data to be classified agrees with the reference (ground truth) data. It is a reliable measure in the evaluation of thematic classifications, as it examines all elements in the confusion matrix and takes into account both omission and commission errors.

It is given by the following equation (1):

$$\boldsymbol{K} = \frac{(Observed - Expected)}{(1 - Expected)} \tag{1}$$

The Observed quantity is equal to the sum of the diagonal elements divided by the total number of samples (the confusion matrix).

The expected quantity is equal to the sum of the diagonal elements divided by the total number of samples (the row x column product matrix).

The kappa coefficient ranges from 0 to 1 and is divided into five (5) categories: very low agreement from 0 to 0.20; low agreement from 0.21 to 0.40; moderate agreement from 0.41 to 0.60; substantial agreement from 0.61 to 0.80; and near perfect agreement from 0.81 to 1.

Statistical calculations of the area of the different classes

The statistics of the different land use units and their annual rates of change were determined as follows:

- Rate of coverage of land use units :

$$\boldsymbol{Rc} = \frac{occupied\ area}{total\ area} * 100 \tag{2}$$

Rc= Recovery rate

- The annual rate of change of land use units is calculated by the formula proposed by equation (3):

$$\boldsymbol{ARc} = (\frac{S2 - S1}{S} * 100)/n \tag{3}$$

ARc = annual rate of change; S1 = area year 1; S2= area year 2; S= total area; 100 is constant and n = year difference.

Positive values of ARc represent an increase in the area of the class during the period analysed and negative values indicate the loss of area between the two dates (Foi, 2017). Values close to zero indicate that the class remains relatively stable between the two dates.

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2.4 Prediction

Concerning the prediction to be seen on the landscape, we applied the simple linear regression on each of the classes following the three years 2018, 2020 and 2021 (DEMBELE & Al., 2021; Gao et al., 2011). The characteristic equation applied is of the form equation (4):

$$y = \beta_0 + \beta_1 * x + \varepsilon \qquad (4)$$

$$\beta_1 = \frac{Cov(x,y)}{V(x)} = \frac{\overline{xy} - (\bar{x} * \bar{y})}{\overline{x^2} - (\bar{x})^2}$$

$$\beta_0 = \bar{y} - \beta_1 * \bar{x}$$

y : Year — β_1 : coefficient or slope

x : Classe — β_0 : Intercept or constant

ε : error of the term

The linear correlation coefficient r was calculated by the equation (5):

$$r = \frac{Cov(x,y)}{\sigma(x) * \sigma(y)} = \frac{Cov(x,y)}{\sqrt{V(x)} * \sqrt{V(y)}} \qquad (5)$$

$\sigma(x)$: Deviation on x
$\sigma(y)$: Deviation on y

From the equations generated for each of Woloni's and Tounga's classes, we calculate forecasts of the areas occupied by the different classes, mainly the "exploited areas" from 2030 to 2050.

3 Results and Interpretation

3.1 Quality of classification

The accuracy assessment consists of an evaluation of the confusion matrix on the degree of reliability, accuracy and the main confusions and omissions made during the classification of the three images.

Table 2 Confusion matrix of the 2018 image

		Ground truth data						
Classified data 2018 in %.	Unit	Water	Exploited	Vegetation	Bare	Total	Precision	Error
	Water	99.54	0.00	0.00	0.00	23.87	99.54	0.46
	Exploited area	0.00	100	0.00	0.00	13.53	100	0.00
	Vegetation	0.00	0.00	100	0.10	28.30	100	0.00
	Bare ground	0.45	0.00	0.00	99.90	34.30	99.90	0.1
	Total	100	100	100	100	100		
	Accuracy for	100	100	99.87	99.69			
	Commission	0.00	0.00	0.31	0.10			

Source : Group Production

After the classification of the 2018 image, we obtain the following values:

The overall accuracy is: 99.85% for a kappa coefficient of 0.98.

Looking at Table 2, the confusion matrix based on the Sentinel-2 2018 image classification, a number of permutations of pixels between some classes are noticeable. There were pixels of bare soil that ended up in other classes with an omission error of 0.46%. This class is followed by vegetation with 0.10% omission error. However, the best represented class is the harvested area and vegetation with 100% accuracy followed by the bare soil class with 99.90% and lastly water with 99.55%.

Table 3 Confusion matrix of the 2020 image

		Ground truth data						
Classified data 2020 in %.	**Class unit**	Water	Exploited area	Vegetation	Bare ground	Total	Precision for production	Error Omission
	Water	98.96	0	0.37	0	21.39	98.96	1.04
	Exploited area	0	100	2.77	0	37.72	100	0.00
	Vegetation	0.73	0	96.86	0	23.70	97.86	3.14
	Bare ground	0.31	0	0	100	17.19	100	0.00
	Total	100	100	100	100	100		
	Accuracy for use	99.58	98.22	99.34	99.61			
	Commission error	0.42	1.78	0.66	0.39			

Source : Group Production

The overall accuracy of the 2020 image is: 98.01% for a kappa coefficient of 0.97.

The confusion matrix in Table 3, which assesses the accuracy of the 2018 image classification, gives the four land use classes defined in order of accuracy: 100% for the Utilised area and Bare soil, 98.96% for Water and 97.86% for the Vegetation class.

Table 4 Confusion matrix of the 2021 image

		Ground truth data						
	Class unit	Water	Exploited area	Vegetation	Bare ground	Total	Precision for production	Error Omission
Classified data 2021 in %	Water	97.05	0.00	0.00	0.00	28.71	97.05	2.95
	Exploited area	0.00	100	0.00	0.00	22.80	100	0.00
	Vegetation	0.44	0.00	100.00	0.78	22.86	100	0.00
	Bare ground	2.51	0.00	0.00	99.22	25.54	99.22	0.78
	Total	100	100	100	100	100		
	Accuracy for use	100	100	97.09	98.59			
	Commission error	0.00	0.00	1.41	2.91			

Source : Group Production

According to Table 4, the confusion matrix of the 2021 image, the best ranked land cover is Harvested area and Vegetation with an accuracy of 100% followed by Bare soil with 99.22%

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accuracy. Water comes last with 98.93% accuracy. The matrix has an overall accuracy of 98.19% with a Kappa coefficient of 0.98%.

The evaluated Kappa coefficient of the three images 2018, 2020 and 2021 is 0.98, 0.98, 0.97 respectively. It shows us the reliability of the results.

Overall, by observing the kappa coefficient, we can conclude that the results of these classifications are statistically good, because according to Landis and Koch, this index is Excellent when it is equal to or greater than 0.81.

After validation of the classification, the data were exported to GIS software (ArcGIS 10.5) for mapping and statistics.

3.2 Land use analysis of the plains (Woloni and Tounga*)*

The land use analysis of the plains will consist of the presentation of the 2018, 2020 and 2021 map of Woloni and Tounga and their respective statistics.

Land use analysis of the Woloni plain in 2018, 220 and 2021

The Woloni plain is made up of four (4) main classes (water, bare soil, vegetation, and exploited area) represented in different proportions according to the dates.

According to Table 5 and **Erreur ! Source du renvoi introuvable.**, we observed on 2018 that for a total area of 5488.03ha, the exploited area occupies the largest area 2240.93ha or 40.83%, followed by vegetation with 20.88%, bare soil with 19.65% and water with 18.64%.

The following results of 2020 shows that from the total area, the exploited area occupies the largest area of 42.08%, followed by vegetation of 36.82%. Bare soil and water occupy 23.54% and 2.55% respectively

According to 2021, out of the total area of 5488.03ha, the land use units are as follows: the exploited area occupies 45.52% followed by vegetation 20.24%; then bare soil with 23.36 and water with 10.88%.

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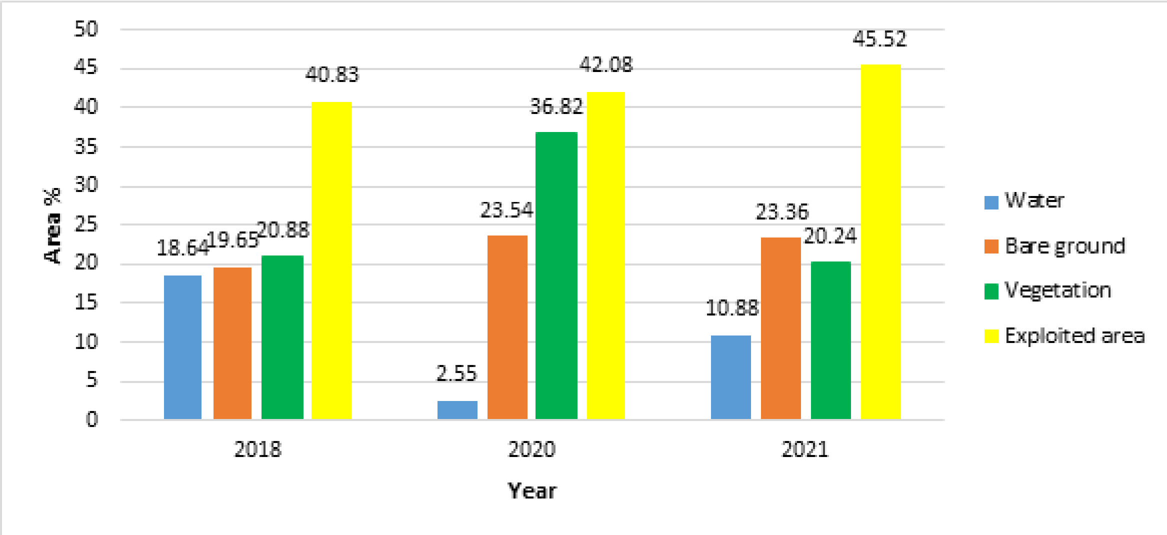
Figure 4 Woloni Land Use Unit Statistics 2018, 2020 and 2021



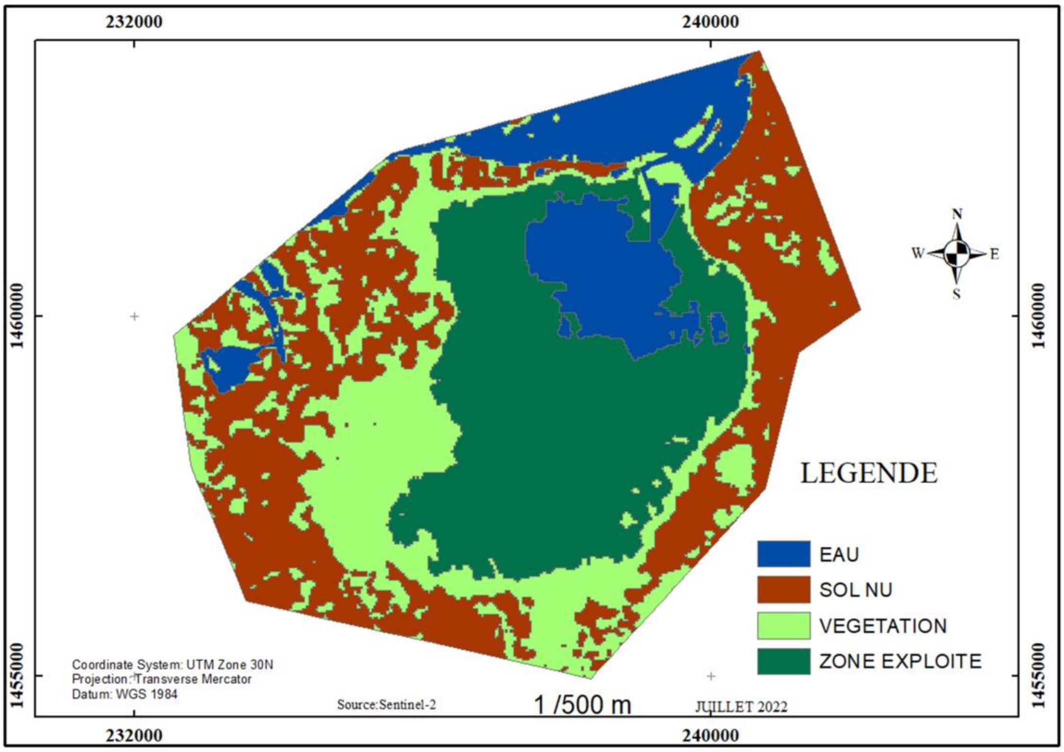
Source: Group Production

Table 5 Land use units of Woloni 2018,2020 and 2021

Occupancy units	**2018**		**2020**		**2021**	
	Area	**Percentage**	**Area (ha)**	**Percentage**	**Area**	**Percentage**
Water	1022.86	18.64	140.12	2.55	597.04	10.88
Bare ground	1078.23	19.65	1017.57	23.54	1282.01	23.36
Vegetation	1146	20.88	2020.78	36.82	1110.9	20.24
Exploited area	2240.93	40.83	2309.55	42.08	2498.08	45.52
Total	5488.03	100	5488.03	100	5488.03	100

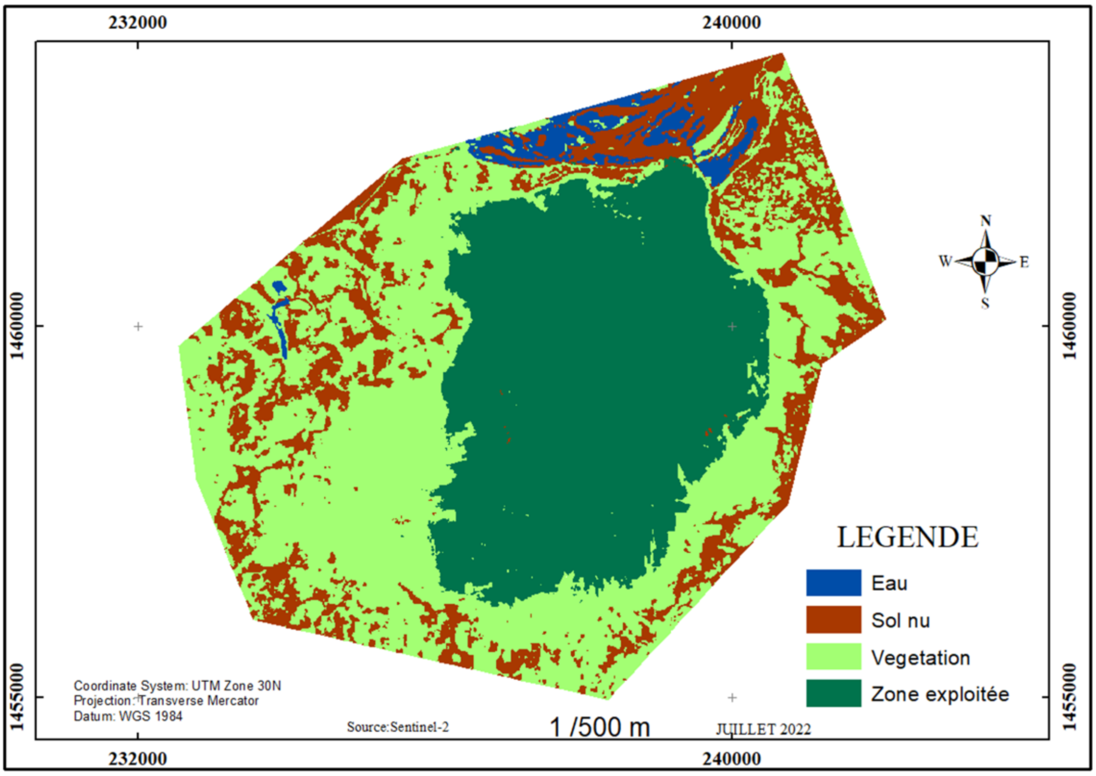
Source: Group Production

Figure 4 Land use map of Woloni 2018



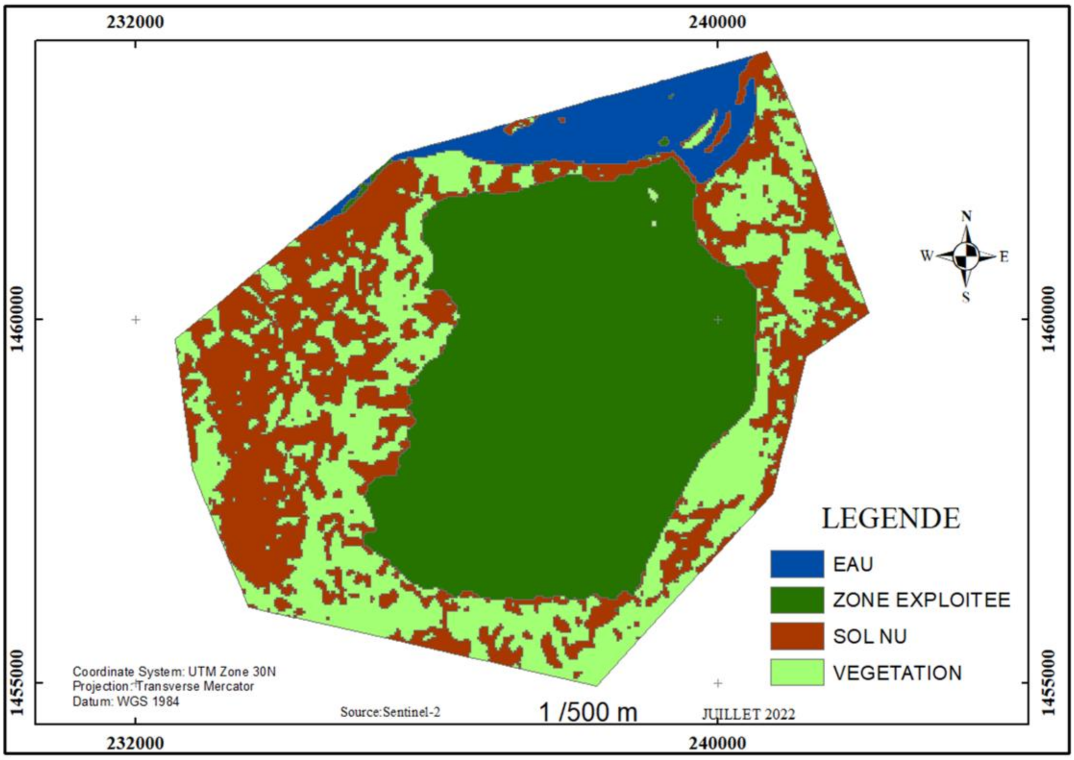
Source: Group Production

Figure 5 Land use map of Woloni 2020



Source: Group Production

Figure 6 Land use map of Woloni 2021



Source: Group Production

Analysis of the land use dynamics of the Tounga plain 2018, 2020 and 2021

The Tounga plain, with a surface area of 27126.30ha, is made up of four (4) classes: water, bare soil, vegetation and exploited area. The statistics and maps of Tounga's occupation of the three years are shown below.

Table 5 and Figure 8 show for the year 2018 that the largest land use class is vegetation with 10605.84ha or 39.10%. The other classes have the following proportions: 35.91% for logged area, 20.96 for bare soil and 4.03% for water.

From the 2020 It turned out that the vegetation still occupies the largest area of the zone, 39.10%. The next largest areas are the exploited area and bare soil, which represent 38.42% and 17.67% respectively. Finally, water has the smallest area of 2.76%.

In 2021, the same trend is noticed, vegetation still occupies the largest area with 39.21%, followed by the exploited area with 39.18% of the total area. The bare soil surface is 18.92% and finally, there is a low water content of 2.69% in the area.

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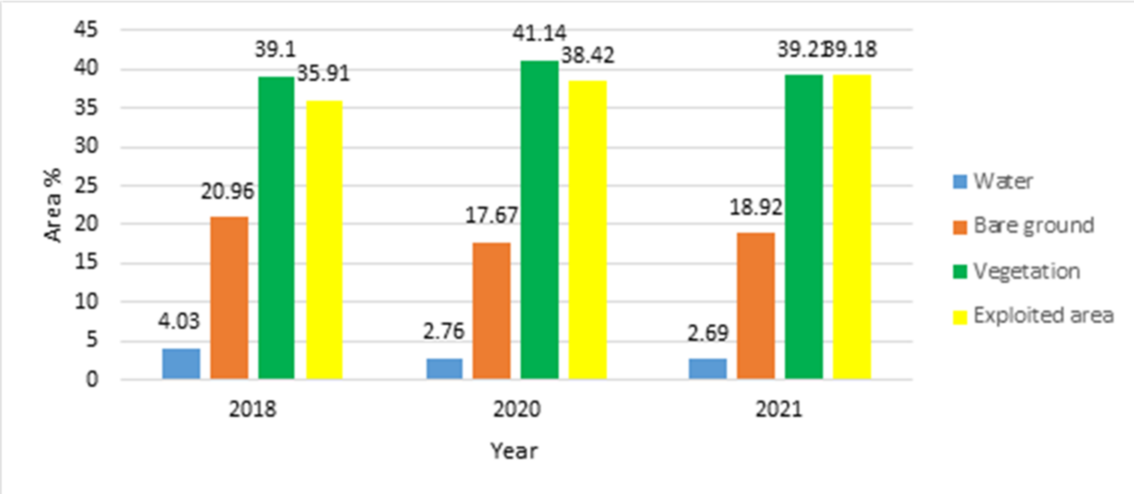
Figure 7 Tounga Land Use Unit Statistics 2018, 2020 and 2021



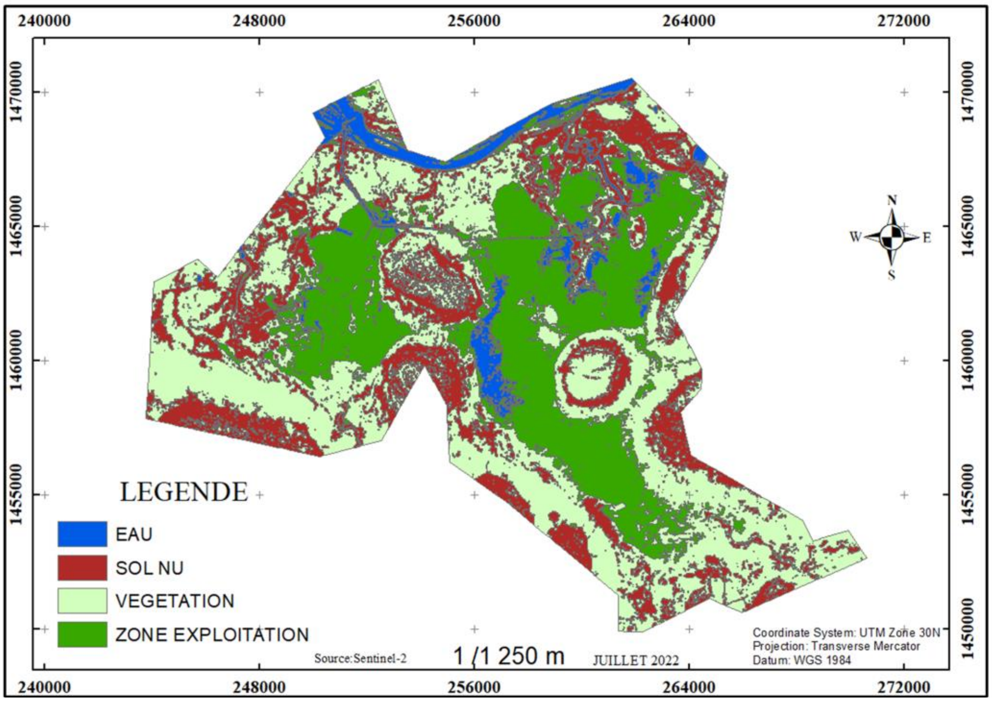
Source: Group Production

Table 6 Occupancy units in Tounga 2018. 2020 and 2021

Source: Group Production

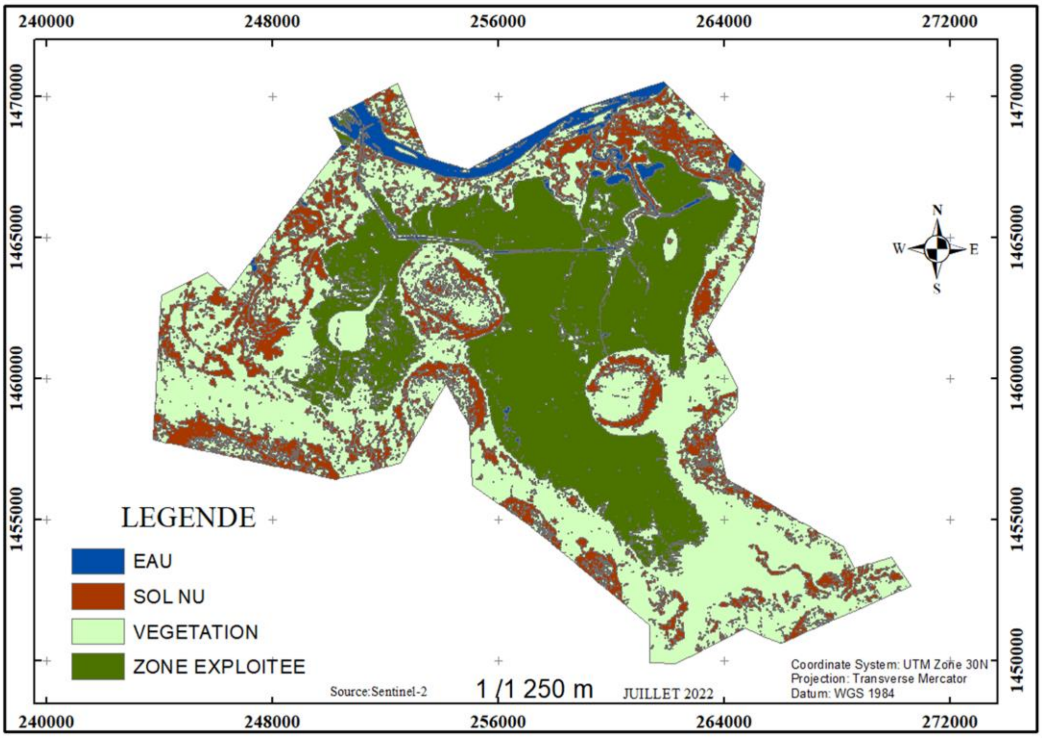
Occupancy units	**2018**		**2020**		**2021**	
	Area	**Percentage**	**Area (ha)**	**Percentage**	**Area**	**Percentage**
Water	1093.84	4.03	749.1	2.76	732.78	2.69
Bare ground	5686.8	20.96	4793.91	17.67	5149.56	18.92
Vegetation	10605.84	39.1	11160.08	41.14	10670.7	39.21
Exploited area	9739.82	35.91	10423.2	38.42	10663.26	39.18
Total	27126.3	100	27126.3	100	27216.3	100

Figure 8 Land use map of Tounga 2018



Source: Group Production

Figure 9 Land use map of Tounga 2020



Source: Group Production

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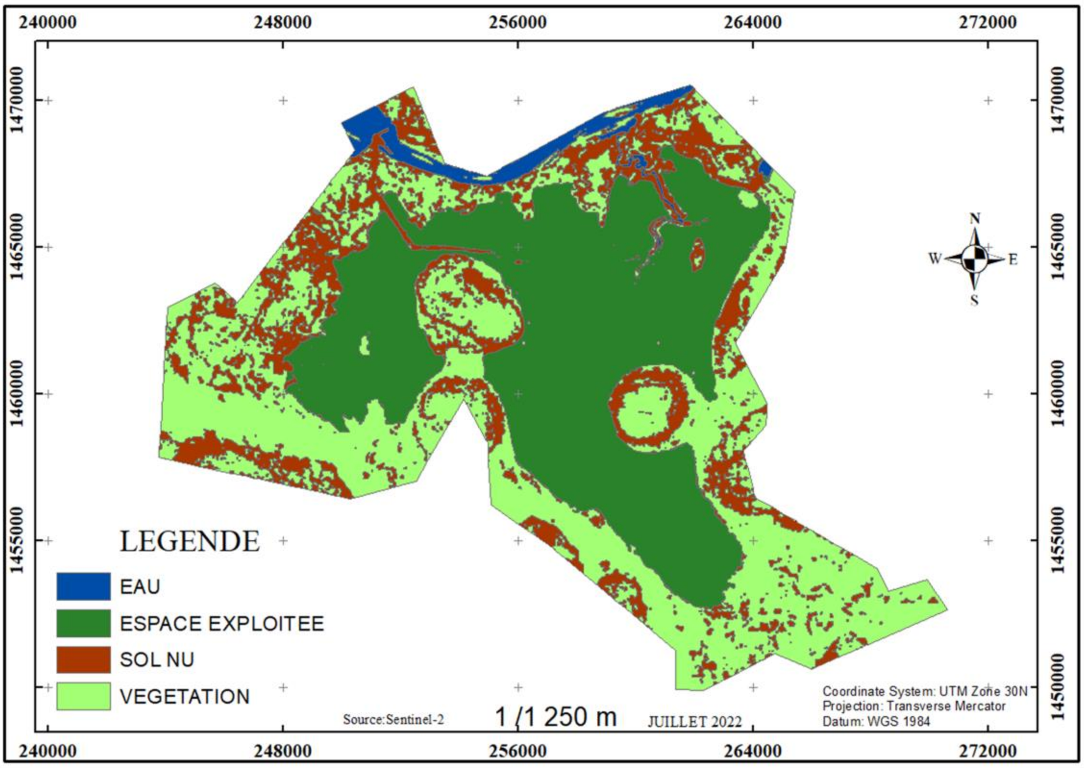
Figure 10 Land use map of Tounga 2021



Source: Group Production

3.3 Assessment of the area of the plains

The method of assessing the area of the plains consisted of processing the Sentinel-2 images using the maximum likelihood supervised classification method to highlight the different land use units in the area. After processing, statistical analyses were used to deduce the area of each occupation class.

The statistics provided us with the total area harvested on the plains for the three years. These results are shown in the following Table 7.

Table 7 Result of the exploited areas of the plains

Plains	Years	Area farmed (ha)
Woloni	2018	2240.93
	2020	2309.55
	2021	2498.08
Tounga	2018	9739.82
	2020	10423.20
	2021	10663.26

Source: Group Production

3.4 Analysis of evaluation results

The analysis of the results consists in verifying the accuracy of the exploited areas obtained from remote sensing methods. In order to confirm the area of our plains, we carried out a comparative study between the value obtained and the value obtained from other studies, specifically the 2018 surveys carried out by the OMB. Table 8 shows the results of the comparison.

Table 8 Results of the comparative study

Plain	**2018 Sentinel-2 image area (ha)**	**Area of the 2018 OMB report (ha)**	**Difference (ha)**
Woloni	2240.93	2276	35.07
Tounga	9739.82	9975	55.20

Source: Group Production

Table 8 shows a difference of 35.07 ha in the Woloni plain and 55.20 ha in the Tounga plain. We estimate that our results have an error of :

* For the Woloni plain

$$\text{Erreur} = \frac{\text{Difference}}{\text{total area covered by remote sensing method of Woloni}}$$

$$\text{Erreur} = \frac{35.07}{2240.93} = 0.02$$

Error on Woloni = 2%.

* For the Tounga plain

$$\text{Erreur} = \frac{\text{Difference}}{\text{total area covered by remote sensing method of Tounga}}$$

$$Erreur = \frac{55.20}{9739.82} = 0.01$$

Error on Tounga = 1%

3.5 Study of the annual evolution of the plains

Evolution of the Woloni plain

The results of the diachronic analysis of the Woloni Plain from 2018 to 2021 are shown in Table 9. They show a regression in the area of water and vegetation in favour of bare soil and exploited area. Between 2021 and 2018, vegetation decreased by –0.63% and water by -7.75% . Which means an annual rate of regression of -0.21% and -2.58%. respectively for the vegetation and

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for the water. Thus for the bare soil and the exploited area, we note a progression rate by year of 1.23% and 1.56% per year.

Table 9 Rate of progression of the units in the Woloni plain between 2018 and 2021

Occupancy units	2018-2020 (%)	2020-2021(%)	2021-2018 (%)	Balance sheet
Water	-16.08	8.32	-7.75	Regression
Bare ground	3.89	-0.18	3.71	Progression
Vegetation	15.93	-16.57	-0.63	Regression
Exploited area	1.25	3.43	4.68	Progression

Source: Group Production

Evolution of the Tounga plain

In Table 10, we can see that the surface area of water and bare soil has decreased in favour of the exploited area and vegetation. Between 2021 and 2018, vegetation increased by. by 0.11%, and the exploited area by 3.27%. As for water and bare soil, we observe an annual regression rate of -0.44% and -0.68% respectively.

Table 10 Rate of progression of the units in the Tounga plain between 2018 and 2021

Occupancy units	2018-2020 (%)	2020-2021(%)	2021-2018 (%)	Balance sheet
Water	-1.27	-0.07	-1.34	Regressions
Bare ground	-3.29	1.25	-2.04	Regressions
Vegetation	2.04	-1.93	0.11	Progression
Exploited area	2.51	0.76	3.27	Progression

Source: Group Production

Assessment of the evolution of the exploited area in the plains

Looking at the data in Table 9 and Table 10, we see an increase in the amount of land used on the two plains at an annual rate of 1.56% in Woloni and 1.09% in Tounga.

3.6 Prediction for 2030, 2040 and 2050

After calculating the different parameters of the equations for predictions in the future, we observe for the woloni area that the linear correlation coefficient r of the class "exploited area" which constitutes the center of interest of the study is strong with 0.899, and the with 0.931 (

Table 11). Concerning the unit classes "water" and "vegetation" the linear correlation coefficients *r* are very low. Therefore, we considered necessary to make a forecast for the classes "exploited area" and "bare ground". In Table 12 are represented the percentage rates of the surfaces that will be occupied by the classes "exploited area" and "bare ground".

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Table 11 Coefficients of the forecast's equations for Woloni

Class	β_0	β_1	r
Water	2021	-0.1213	0.639
Bare ground	2005.3	0.6475	**0.931**
Vegetation	2019	0.0253	0.156
Exploited area	1995.5	0.5654	**0.899**

Source: Group Production

Table 12 Coefficients of the forecast's equations for Woloni

Class	**2030**	**2040**	**2050**
Bare ground %	38.147	53.591	69.031
Exploited area %	61.019	78.705	96.392

Source: Group Production

In the same way as Woloni, from the calculated parameters (Table 13), we projected into the future the surface of the "exploited area" class (Table 14) which is the only one to have an r greater than 0.8 and positive.

Table 13 Coefficients of the forecast's equations for Woloni

Class	β_0	β_1	r
Water	2025.8	-1.9423	-0.959
Bare ground	2032.9	-0.6919	-0.752
Vegetation	2007.2	0.314	0.236
Exploited area	1986.1	0.8873	**0.994**

Source: Group Production

Table 14 Coefficients of the forecast's equations for Woloni

Class	**2030**	**2040**	**2050**
Exploited area %	49.476	60.747	72.016

Source: Group Production

Conclusion and Future Perspectives

The estimation of the quantities of the different class units existing on the two sites (Woloni and Tounga) were successfully determined. The effectiveness of the study was made possible by the new technology methods of remote sensing and GIS. Sentinel-2 images from different dates were classified by the method of supervised classification and underwent statistical analysis in order to extract the values of exploited areas and visualize their evolution over time. Compared to the areas surveyed by the field agents in 2018, we note a variation of about 2%. This is very acceptable for large-scale operations. Then we made a forecast for the exploited area. In light of these results, we can conclude that the remote sensing method is an alternative that can reduce the amount of field work to an acceptable accuracy.

In addition to the assessment of farmed area, remote sensing data offers a number of advantages in the field of agriculture, such as: mapping of different types of crops, identification of factors that influence crop health, assessment of damage caused by disasters, monitoring of agricultural activities, to name a few. Therefore, we unequivocally state that remote sensing methods can serve well to the management organizations of irrigated perimeters in order to reduce the volume of field work and to avoid human errors that can often be very detrimental to the results provided.

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APPENDICES

Occupancy unit	X(m)	Y(m)	Z(m)	Occupancy unit	X(m)	Y(m)	Z(m)
Water	240289.54	1462505.39	275.42		255506.78	1463145.83	276.21
	239902.76	1462186.05	275.49		255506.87	1463247.26	275.56
	240103.21	1462312.75	274.83		263334.56	1463158.91	274.92
	240103.21	1462312.75	274.83		263334.30	1463360.86	274.06
	240103.40	1462412.39	276.59		263539.69	1463456.72	275.63
	240103.40	1462412.39	276.59		263329.73	1462554.66	277.76
	251111.43	1466816.23	275.09		262931.51	1462561.67	273.81
	251765.64	1468367.46	267.00		262930.91	1462458.47	274.05
	251850.98	1468401.54	266.00		246074.83	1460228.80	275.45
	251899.74	1468428.32	267.00		246080.09	1460128.10	275.49
	259319.74	1468056.37	275.20		246268.11	1460225.65	275.12
	259520.20	1468383.46	268.46		246273.36	1460130.20	275.47
	259520.38	1467726.03	273.48		246273.50	1460530.12	274.89
	259719.14	1467696.27	274.17		246271.27	1460429.80	274.97
	259722.59	1467771.98	276.11		246373.96	1460128.28	275.50
	260732.34	1467270.64	274.64		246479.41	1460130.49	275.32
	260732.93	1467172.85	273.96		249091.93	1462826.70	276.16
	260946.33	1466727.55	274.94		249091.78	1462732.66	275.91
	260950.54	1466674.41	274.88	Vegetation			
	261143.92	1466502.66	273.78		257915.00	1455294.81	278.64
Exploited area					257915.00	1455294.81	278.64
	237395.98	1461098.19	275.10		257915.00	1455294.81	278.64
	237390.72	1460895.16	275.09		257915.00	1455294.81	278.64
	237790.30	1461089.08	274.99		257915.00	1455294.81	278.64
	237790.04	1460889.03	274.87		257915.10	1455342.99	278.42
	238616.48	1459137.55	274.99		257915.10	1455342.99	278.42
	238612.63	1459245.01	274.97		257915.10	1455342.99	278.42
	238827.66	1459126.66	274.79		257915.10	1455342.99	278.42
	238827.66	1459126.66	274.79		257915.10	1455342.99	278.42
	238827.66	1459126.66	274.79		263332.48	1460369.36	0.00
	238827.66	1459126.66	274.79		263332.48	1460369.36	0.00
	238829.53	1459229.44	274.78		263332.48	1460369.36	0.00
	257904.22	1463552.76	272.33		263334.28	1460267.80	0.00
	258301.81	1463552.38	272.44		263334.28	1460267.80	0.00
	258300.38	1463342.16	272.43		263334.28	1460267.80	0.00
	257901.43	1463349.46	272.32		263335.08	1460167.13	276.81
	259115.99	1457573.10	272.89		263335.08	1460167.13	276.81
	258723.35	1457571.04	272.81		263335.08	1460167.13	276.81
	259115.90	1457771.49	272.82				
	258722.68	1457770.43	272.76				
Bare	255301.91	1463543.26	276.25				
	255302.92	1463445.65	276.27				

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