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An object oriented classification approach for mapping land cover from Landsat and Sentinel image data in the north of Ivory Coast

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Abstract

Monitoring and analyzing land cover changes help to provide relevant information for the establishment of diagnostics and the preparation of environmental forecasts. The objective of this work is to apply an "object-oriented" classification method to three satellite images for monitoring and detecting land cover changes in the North of Ivory Coast. The landscape complexity of this environment and the low resolution of the images (30 m and 20 m) constitute an important limitation for conventional classification methods using the "pixel by pixel" approach. Two Land sat images TM/ ETM + (1986; 2002) and a Sentinel-2 image (2019) were used in this study. The method developed for monitoring and detecting changes in land cover is carried out through 1) a classification of land cover using the «object-oriented» method based on fuzzy logic and 2) detecting changes of land cover by the post-classification method followed by the integration within a GIS of the three land cover maps obtained. The Kappa coefficients of the classified land cover maps were 86, 88, and 84.55% at the level of the 1986 images; 2002 and 2019, respectively. For the period of interest (33 years), we mapped and quantified land-use changes in this complex environmental context. Our study shows that the study area is undergoing major changes in land cover. The modifications identified in the study area concern all the topics of interest.

Keywords: Land cover, North of Ivory Coast, Object-oriented approach, Post classification method.

1. Introduction

Environmental management and the preservation of biodiversity are now considered a priority in the context of the acceleration of global changes that affect the physical and biological resources of the earth. Further amplified by the inappropriate modes and systems of exploitation of the available resources, these changes raise fears of a «Desertification of landscape and flora» in the northern region of Ivory Coast (8 ° and 10 ° North latitude and 3 ° and 6 ° West longitude). The study area located northwest of the Ivory Coast is the savannah formations' domain. Agro-pastoral activities' growth endangers and increases the risks of degradation in this fragile environment (Geerling and Diakité, 1988).To study the degradation phenomenon of natural resources, numerous works based on optical remote sensing exist (Vägen et al., 2013; Mouissa et al., 2018). These studies generally use conventional classification methods (Maximum likelihood) which have recourse to the "pixel by pixel" approach (Podest and Saatchi, 2002; Mouissa and Fournier, 2013). However, the landscape complexity of the areas of interest and the great spectral heterogeneity of the images reduces the statistical dispersal of the classes, inducing an imprecision of the cartographic results (Chust et al., 2004). Also, several studies in optical remote sensing have used textural image information on the one hand and classification by object-oriented method on the other to improve the quality of the purely spectral classification (He et al., 1994). Thus, Galletti and Myint (2014) compared classifications by the "object-oriented" approach to the classic classification methods which use the "pixel by pixel approach". From an ASTER image, the authors proceeded to an "object-oriented" segmentation and classification of the Arizona "Sun Corridor" following six thematic classes of interest. With respectively 93.71% of overall processing precision and 0.92 of Kappa coefficient, Galletti and Myint (2014) concluded the contribution of textural information is essential if we want to improve qualitatively the results obtained from the purely spectral classification. Moran (2010), explored different classification methods from a QuickBird image taken on June 20, 2008, on the Lucas do Rio Verde (Mato Grosso, Brazil) to improve the mapping of occupation and land use in the urban area. Ultimately, Moran (2010) concludes that the integration of textural and spectral images improves the overall classification accuracy by 11.7% and the Kappa coefficient by a score of 0.14. Also, the use of the "object-oriented" classification method based on segmentation constitutes an effective approach to considerably improve the mapping of land cover. Johansen et al. (2007) explored from the "object-oriented" method, the potential of using textural information from a QuickBird image with very high spatial resolution from June 2005 for discrimination and mapping of the structural stages of vegetation in adjacent forest and riparian ecosystems on Vancouver Island. Following a geostatistical study using semivariograms, the authors concluded that the contribution of textural parameters (dissimilarity; contrast

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and homogeneity) to the spectral data greatly improves, on the one hand, the discrimination of the structural classes of vegetation (between 2 -19%) and on the other hand, the overall accuracy of the cartographic results with 78.95%. Herold et al. (2002) evaluate the use of the "object-oriented" approach for land cover mapping in the Santa Barbara area (California). To do this, a set of treatments is carried out: geometric and atmospheric corrections, a segmentation of seven IKONOS images and then their classification using their spectral and textural properties. With a map with an overall accuracy of 79%, Herold et al. (2002) concluded that the object-oriented approach has enormous potential to report detailed and precise information on the physical structure of urban areas. Ultimately, though many studies in optical remote sensing use textural parameters and segmentation, few use principal component analysis (PCA) and an "object-oriented" approach to execute classifications based on fuzzy logic. In this context, the objectives of this work are twofold: 1) to use on three satellite images an object-oriented classification approach and 2) to detect changes in land use.

2. Literature review

The landscape's complexity and the relatively low resolution of the images used in this study (30 m and 20 m) constitute an important limitation for conventional classification methods which proceed "pixel by pixel" (Jukka and Aristide, 1998). Unlike these classifiers, the "object-oriented" classification does not treat the pixel in isolation but its context, by grouping pixels within objects whose spectral value, size, shape and context constitute the key to interpretation (Dell'acqua and Gamba 2006). Otherwise, the semantic information necessary for the interpretation of the image is not represented in isolated pixels, but rather in objects having a particular meaning, as well as in their mutual relationships (Schwarzer et al., 2009). The "object-oriented" classification is organized in two main stages (Stow et al., 2008): 1) a multi-resolution segmentation whose purpose is the establishment of a hierarchical network of objects representing different levels of reality on the ground (Wemmert et al., 2009); 2) a supervised classification based on different algorithms (Maximum likelihood, Fuzzy logic, etc.).

The assessment of cartographic accuracy is very important for understanding the results obtained. The success of change mapping and the GLCM method through the use of remote sensing data also necessitates the careful choice of textural parameters to use as neo-channels in the subsequent classification process. In this perspective, the approach by the co-occurrence matrix of the grey levels is retained (Kayitakire et al., 2002) and applied to the eight textural parameters calculated respectively on the 7x7 and 17x17 windows and generated from each of the images available for this study. Two textural parameters, the mean and the correlation are chosen because of their weak correlations with the other six and added as neo-channels to the main components 1 (CP1) of the images of interest to drive and improve the "oriented" classification object" (Cruse et al., 1984). The most common elements include the assessment of overall accuracy, producer accuracy, user accuracy and the Kappa coefficient (White et al., 2007). The literature provides detailed information on the methods for calculating these elements (Congalton et al., 1983; Congalton, 1991; Congalton and Green, 1999).

In the field of land cover mapping, textural information of satellite images is of the first importance. It is established that the contribution of textural information improves the quality of the purely spectral classification (He and Wang, 2010). To do this, Haralick et al. (1973) proposed for the calculation of textural parameters, the method of grey level co-occurrence matrices (GLCM) mostly used in the analysis of remote sensing data (Del Frate et al., 2008). The success of this method requires the prior determination of three parameters: 1) the appropriate distance between pixels; 2) the appropriate direction between pixels; 3) the optimal window for calculating the textural parameters on the study area. In this study, the first two parameters are chosen according to the indications in Haralick (1979) and Safia and He (2015): an interpixel distance of 1 is used and the textural parameters used correspond to the average values in the four directions (0°; 45°; 90° and 135°) likely to carry all the textural information derivable from the Gray Level Co-occurrence Matrices (GLCM). The choice of the optimal window is more sensitive because it depends on the satellite data used and on the study objectives. It is achieved through the calculation of the coefficient of variation (standard deviation/average) of any textural parameter in the image (Puissant et al., 2005). Ultimately, the window for which the coefficient of variation is stable and lower for the majority of land use classes is chosen (Puissant et al., 2005).

3. Materials and Methods

3.1. Study area

The study area [9 ° 27'to 9° 57' N; 5° 39'to 5° 58' W] is located in the northwest of Ivory Coast (Figure 1).

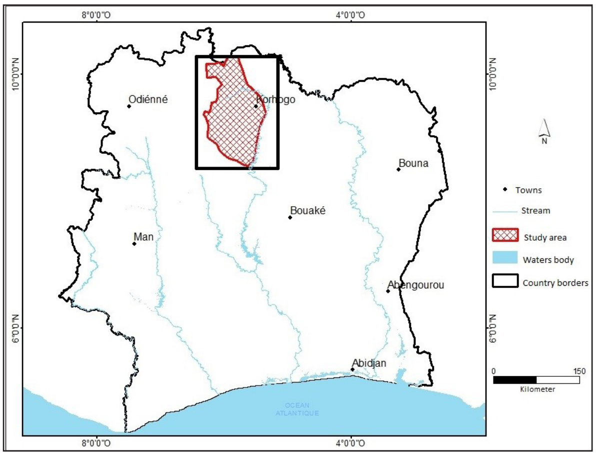

Figure 1. Study area located at (9 ° 27' to 9° 57' N; 5° 39' to 5° 58' W) in the northwest of Ivory Coast.

Here, the relief is a vast peneplain of 300 to 500 m altitudes interspersed with buttes, armoured plateaus and isolated inselbergs like Mount Korhogo. The region has a tropical Sudano-Guinean climate characterized by the existence of two very contrasting seasons (Géomines, 1982): a rainy season which lasts from May to October, with maximum rainfall in July-August and a dry season, well-marked from November to April. In terms of land cover, plant formations of the savannah, tree or shrub type are more widespread in the Center with a grassier tendency in the North and clear forest in the South and the West. Forest galleries highlight certain rivers and classified forest islands and "sacred woods" are found on the outskirts of villages. The demography of the department of Korhogo is one of the most dynamic in the Ivory Coast with 763,852 inhabitants in 2014 (INS, 2014). This population (Sénoufo, Malinké) is mainly rural and cultivates corn, sorghum, yam, rainfed or irrigated rice, cotton and cashew. Land tenure in the Senoufo country is democratic as all individuals have access to land. This status of the land leads to competition in its access and appropriation. As a result, people cultivate large areas and would not hesitate to migrate to new cropland at the first signs of soil degradation.

3.2. Satellite images and Data

Three satellite images, including two Landsat TM / ETM + images (Scene 197-53 acquired from http://earthexplorer.usgs.gov/) taken in the dry season, on January 16, 1986, and January 21, 2002, respectively and a Sentinel-2 (Acquired from (https://scihub.copernicus.eu/dhus/#/home) image which was acquired February 12, 2019, were used to perform this study. In addition to these images, there are also field data relating to 69 ground control points (GCPs). The Landsat TM / ETM + and Sentinel-2 images have a spatial resolution of 30 m and 20 m respectively. In this study, the GCPs would help to learn and validate the method of mapping and detecting changes in land cover. Also, 50% of the GCPs are integrated as learning points for conducting the images classification and 50% of the points as validation for accuracy assessment.

4. Methodological approach

A preliminary step consists of processing the images of interest (radiometric and geometric correction, generation of different indices, resampling, etc.) by ENVI 5.3 software. The method of mapping and detecting changes in land use are developed and carried out through 1) a Principal Component Analysis (PCA) transformation applied to the three satellite images; 2) classification and detection of land-use changes from Landsat TM/ETM+ and Sentinel-2 images using i) textural information of the images and ii) the «object-oriented» method based on the fuzzy logic according to the land use classes (open forest; wooded savannah; humanized areas and ponds or water).

Figure 2 presents the methodological flowchart of this project. Details of the different methodological aspects of monitoring and detecting land-use changes are presented in the following subsections.

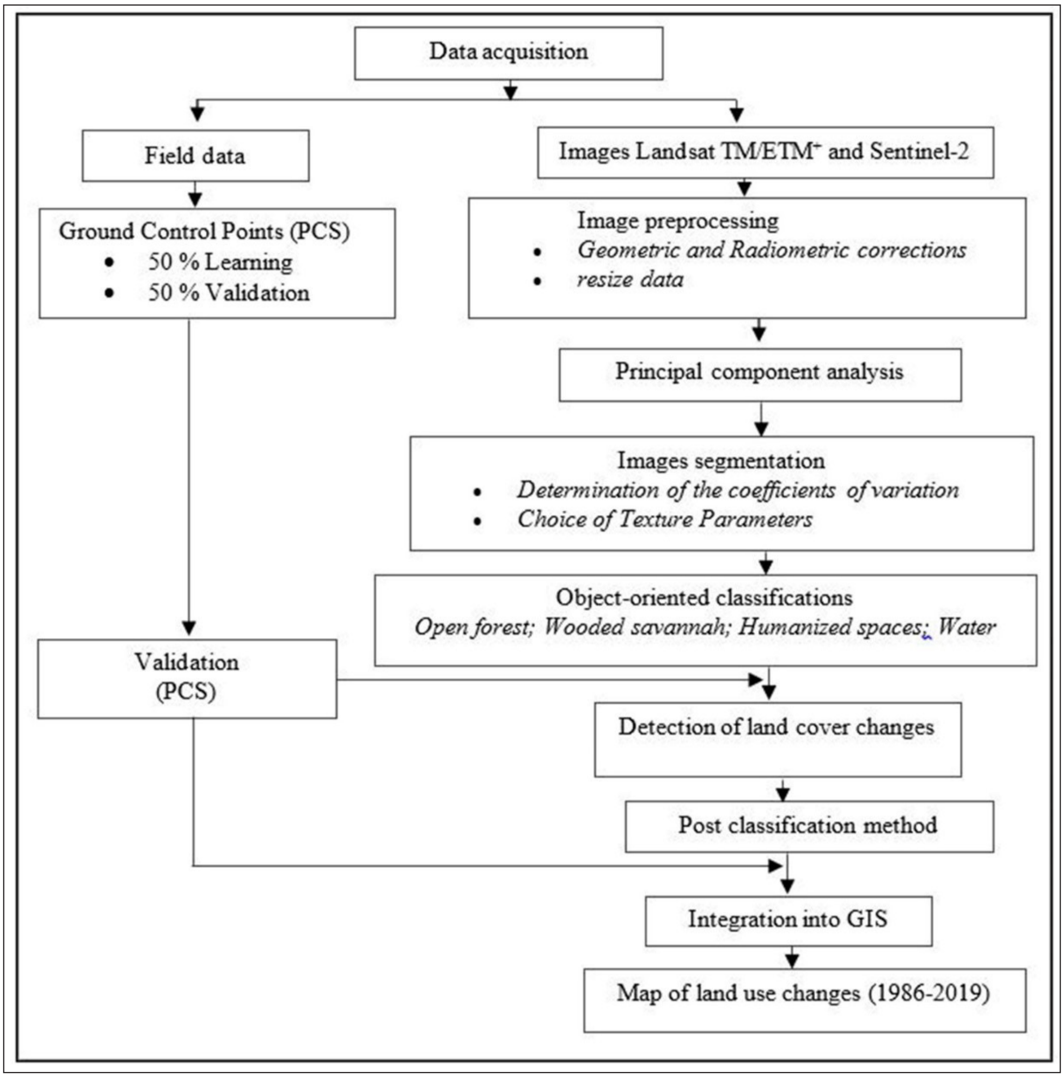

Figure 2. Methodological flowchart of monitoring and detecting land-use changes in the department of Korhogo.

4.1. Principal Component Analysis (PCA)

Satellite images of the same scene recorded according to the different spectral bands of a multispectral sensor (Landsat TM / ETM +; Sentinel-2) are generally strongly correlated. In this study, PCA is therefore used to eliminate redundancy in information and to retain for each image, the only components with significant information content (greater than 85%) and therefore optimal for mapping and fine detection of changes in land use (Jensen, 2005). Indeed, PCA makes it possible to synthesize a set of data initially expressed by highly correlated variables into a reduced number of new «uncorrelated» variables which express the maximum variance in the raw data (Carvalho and Gherardi, 2008).

4.2. Land cover mapping

4.2.1. Textural information of satellite images

To determine the optimal window size (size from 3 to 21) for each satellite image in this study, the second angular momentum and contrast parameters are chosen from the eight textural parameters (homogeneity; contrast; dissimilarity; mean; standard deviation; entropy; second angular momentum and correlation). These parameters are the least correlated and the most used in remote sensing (Solberg, 1999). The evolution of the coefficient of variation of these parameters on the different windows for the four lands' types allows identifying the windows' size of 7x7 and 17x17 as optimal for calculating the textural parameters. Figure 3 presents the evolution of the coefficient of variation for the Sentinel-2 image of February 12, 2019.

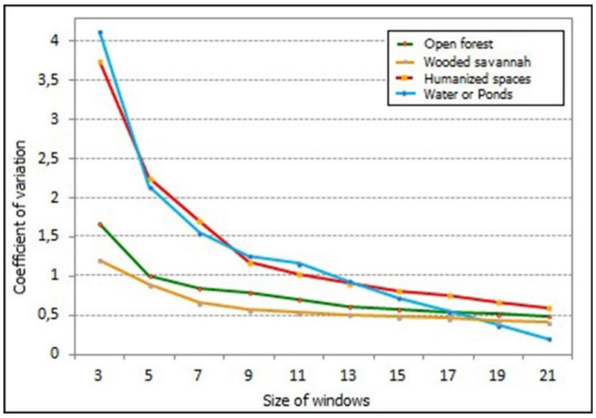

Figure 3. Coefficient of variation of the contrast parameter (Sentinel-2 of February 12, 2019).

When using the sizes 3 and 5 as windows, the coefficients of variation were low for three out of four land use. Thus, on the 7x7 window, they stabilize and reach low values for two classes of land cover. Beyond the 7x7 window, the coefficients of variation, although small, become divergent. Regarding the image of February 12, 2019, we observe that for window sizes less than 17x17 (Figure 2), the coefficients of variation of the four land cover classes are high and dependent on the window size. On the 17x17 window, they stabilize and reach very low values. Beyond the 17x17 window, the coefficients of variation are small and divergent (Figure 3).

4.2.2. Object-oriented image classification

For the present study, different thresholds are respectively tested on the 1986 image sets; 2002 and 2019 (CP1 and the two textural images selected). These thresholds identified the segmentation parameters (scale from 500 to 25 and heterogeneity criteria: shape and compactness from 1 to 0) adapted to the study area. In the present context, this approach is well suited because it calls on membership functions taking into account the notion of uncertainty through the formulation of a certain number of knowledge rules defined for each type of object to be classified (Jensen, 2005). These membership functions are obtained from the two textural neo-channels (Average and Correlation) or combinations of these neo-channels with the CP1s of the two images of interest (Castaneda and Ducrot, 2009).

4.3. Detection of changes in land cover and accuracy assessment

The post-classification approach is carried out by superimposing two or more multi-temporal images of the same scene, classified independently and then comparing the thematic classes of interest on a "pixel" basis. It generates a complete matrix of change information and indicates both the nature of the change and its magnitude (Jensen, 2005).

In this study, we limit the process of assessing overall accuracy to the Kappa index. And as already indicated, 50% of the ground control points (GCPs) were used for this validation purpose.

5. Results and Discussion

5.1. Principal component analysis

The multispectral bands of the Landsat TM / ETM + and Sentinel-2 images used in this study have strong correlations. Also, these spectral bands are subjected to an ACP transformation. The first main components (CP1) concentrate 88.08%, 84.76% and 78.14% variance for the satellite images of 1986, 2002 and 2019, respectively. Therefore these components (Figure 4a (1986) and 4b (2019)) are used for the implementation of multi-resolution segmentation.

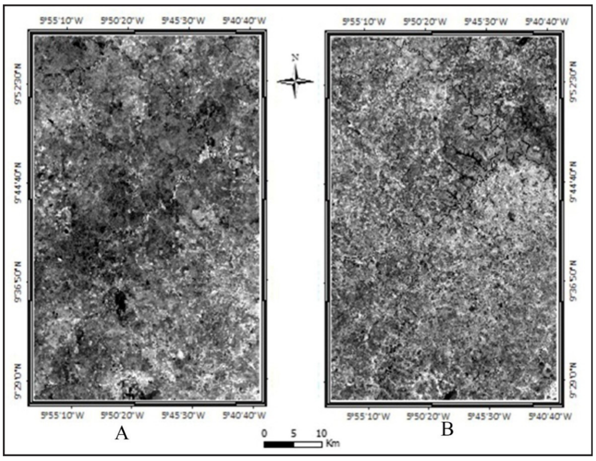

Figure 4. Result of the ACP transformation. A) Main component1 (Landsat TM, January 16, 1986); B) Main component1 (Sentinel-2, February 12, 1919).

5.2. Classification and validation of land cover

Fine mapping of land use according to the four classes of interest was obtained using a segmentation which let to identify fairly precise geographic objects on the three satellite images. This mapping of land use reached Kappa coefficients of 86, 88 and 84.55% for the maps of 1986, 2002 and 2019 respectively (Figure 5, Figure 6, Figure 7 and Table 1). These statistics represent a very acceptable overall precision as reported by Chalifoux et al. 2006). As to confirm the effectiveness of the segmentation and membership functions chosen, we note for the image sets (CP1 and textural images) of 1986; 2002 and 2019 that the segmentation is efficient with an overall scale factor of 125 and shape and compactness values of 0.4 and 0.9 respectively. The geographic objects thus identified are precise enough to discriminate between the four land cover classes. Regarding the supervised classification, fuzzy logic (Sparfel et al., 2008) is applied to the study site characterized by land use classes with fuzzy semantic and spatial limits.

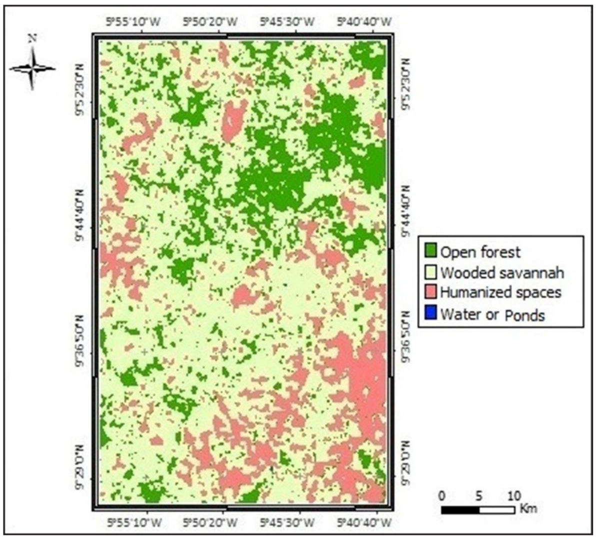

Figure 6. Result of the classification of the land cover of the study area in 2002.

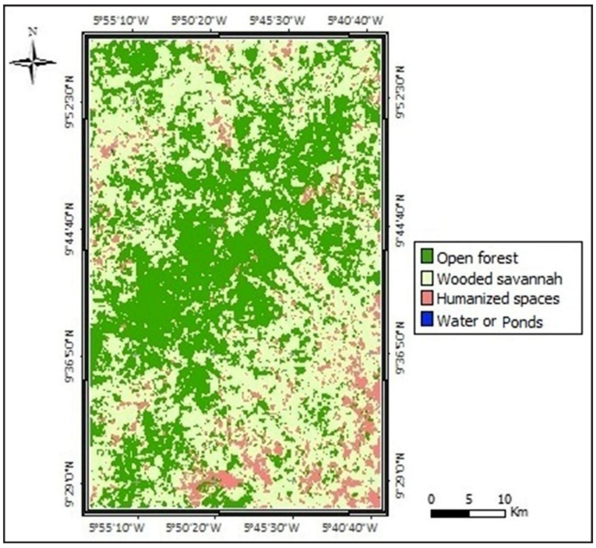

Figure 5. Result of the classification of the land cover of the study area in 1986.

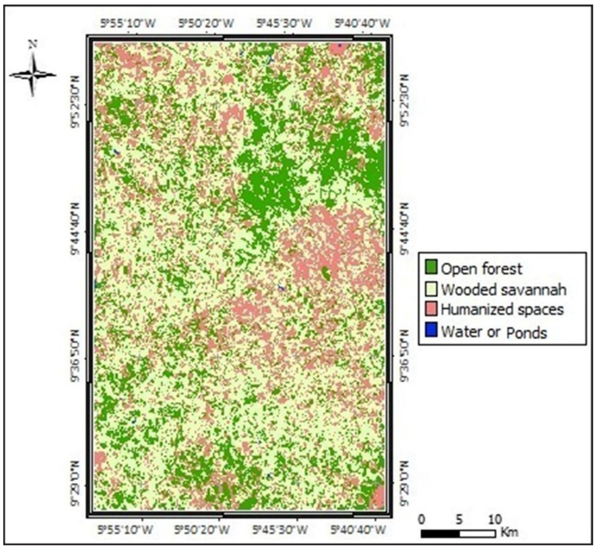

Figure 7. Result of the classification of the land cover of the study area in 2019.

Table 1. Land cover and areas mobilized in 1986, 2002 and 2019.

Land cover	Area of 1986 (ha)	(%)	Area of 2002 (ha)	(%)	Area of 2019 (ha)	(%)
Water or ponds	18	0.01	35	0.02	105	0.06
Humanized areas	13782	7.86	31755	18.11	36385	20.75
Open forest	72892	41.57	34456	19.65	46397	26.46
Wooded savannah	88656	50.56	109102	62.22	92461	52.73
Total	**175348**	**100**	**175348**	**100**	**175348**	**100**

The Analysis of maps (Figures 5, 6 and 7 and Table 1) shows that the study area is undergoing major changes in land cover. These findings are corroborated by Agouale et al. (2017).The modifications identified in the study area concern all the topics of interest. However, a more detailed thematic analysis makes it possible to detect certain specificities. These include the open forest experienced a reduction of more than half of its area from 1986 to 2002 (- 52.73%). Between the intermediate analysis period (2002) and the year 2019, the open forest increased (+ 36.56%). Wooded savannah was subjected to significant mutations (Wendpouiré, 2020). Between 1986 and 2002, it experienced a 23.06% increase in its surface areas. But since 2002, a decreasing trend was observed and the wooded savannah areas decreased to 92 461 ha. An extension of the floodable or marshy areas was observed. Indeed, the Water (dams-ponds-ponds) and floods and/or swampy areas complex which mobilized in 1986 only 0.01% of the area or 18 ha increased in 2019 and now covers 0.06% of the area is 105 ha.

Overall, from the change detection approach used in this study it noted that a significant part of the study area (+ 79%) is covered with plant formations (Clear forest and/or wooded savannah and wooded savannah and/or shrubby). This situation is certainly the result of a change in peasant land management practices and the strengthening of measures to protect and conserve classified areas (Korhogo and Badénou classified forests). In fact, due to the increase in the purchase price of cashew nuts, the favourable land of open forest and wooded savannah were transformed into cashew and mango plantations (Gansaonré, 2018).

5.3. Detection of changes in land cover

The detection of land cover changes by the post-classification method is carried out by superimposing the three previously obtained maps (Figures 5-7). Analysis of the global map of land cover changes (Figure 8) shows that the proportions of the different rights-of-way reflect those from the maps of 1986 2002 and 2019. It is thus noted that more than 2/3 of the study area (72.18%) is affected by modifications in land use (Table 2).

Table 2. Global change Statistics map (1986-2019).

Land cover	Area (ha)	Area (%)
Water or ponds	53	0.03
Humanized areas	2122	1.21
Open forest	12134	6.92
Wooded savannah	34473	19.66
Changes	*126566*	*72.18*
Total	**175348**	**100**

This area of 126,566 ha mostly coincides with the southern and central part of the study area where the agricultural plots are mainly established (Figure 8).

On these portions of the area, the interannual changes (1986-2019) of land use make their identification and recognition by remote sensing difficult and complex. In addition, the methodological approach (post-classification method) implemented in this study for the detection of changes has as a corollary, the generation of a class of changes grouping all the geographic objects having an interannual movement. However, these objects cannot be immediately assigned to a type of land cover without further analysis (Sylla, 2012). Also, the complex nature of the study area and the state of the available data require that the notions of uncertainty and imprecision be taken into account for the monitoring and detection of changes in land use. The Dempster-Shafer theory, an expert-type model, could help in the identification and better detection of land-use changes (Sylla, 2012). Indeed, the Dempster-Shafer probabilistic fusion rule makes it possible to combine different sources of data with a view to better decision-making (Corgne, 2004; Mora, 2009). Also, we are considering the use of specific spectral indices such as the three decorrelated indices (brightness, greenness and wetness) from the Tasseled Cap transformation. These indices allow the characterization of agricultural areas in numerous studies (Mora, 2009; Mouissa et al., 2018).

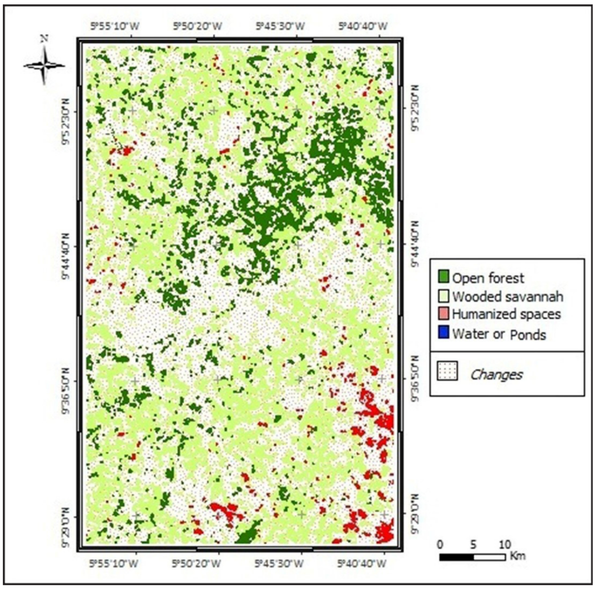

Figure 8. Global map of changes (1986-2019).

6. Conclusions

The study area is a complex environment. Monitoring and detecting land cover changes in such an environment was a real challenge. With the «object-oriented» method, we monitored and detected land cover changes from three satellite images (Landsat TM / ETM + and Sentinel-2 images). For the period of interest, the methodology developed in this study reached a fine detection of changes in land cover. The final map of land cover changes is intended to serve as a decision-making tool for planning agricultural activities. Dempster-Shafer's probabilistic combination rule is well suited for this purpose.

References

Agouale, Y. J., Vei, K. N., Affro, M. J. (2017). Anthropic pressures and dynamics of land cover in Katiola sub-prefecture. Ivorian. Journal of Savannah Geography 1: 78-86.

Carvalho, M., and Gherardi, D. F. M. (2008). Mapping the environmental sensitivity to the oil spill and land use/land cover using spectrally transformed Landsat 7 ETM data. Brazilian Journal of Aquatic Science and Technology 2: 1-9.

Castaneda, C., and Ducrot, D. (2009). Land cover mapping of wetland areas in an agricultural landscape using SAR and Landsat imagery. Journal of Environmental Management 7: 2270-2277.

Chalifoux, S., Nastev, M., Lamontagne, C., Latifovic, R., Fernandes, R. (2006). Land cover and land use mapping using Landsat imagery in hydrogeology. Télédétection 1: 9-17.

Chust, G., Ducrot, D., Pretus, J. LL. (2004). Land cover discrimination potential of radar multitemporal series and optical multispectral images in a Mediterranean cultural landscape. International Journal of Remote Sensing 17: 3513-3528.

Congalton, R. G., Oderwald, R. G., Mead, R. A. (1983). Assessing Landsat classification accuracy using discrete multivariate analysis statistical techniques. Photogrammetric Engineering and Remote Sensing 12: 1671-1678.

Congalton, R. G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. Remote Sensing of Environment 1: 35- 46.

Congalton, R. G., and Green, K. (1999). Assessing the Accuracy of Remotely Sensed Data: Principles and Practices. Boca Raton, FL, USA: CRC/Lewis Press, USA.

Corgne, S. (2004). Predictive modelling of land use in an intensive agricultural context: application to winter soil cover in Brittany. PhD. Dissertation, University of Rennes 2-Haute-Bretagne (France).

Cruse, D., Oddy, C. J., Wright, A. (1984). A Segmented Image Data Base (SID) for Image Analysis. In: 7th International Conference on Pattern Recognition (ICPR). Montreal, Canada July, Institute of Electrical and Electronics Engineers: 493-496.

Del Frate, F., Pacifici, F., Solimini, D. (2008). Monitoring Urban Land Cover in Rome, Italy, and Its Changes by Single-Polarization Multitemporal SAR Images. Institute of Electrical and Electronics Engineers Journal of Selected Topics in Applied Earth Observations and Remote Sensing 2: 87-97.

Dell'acqua, F., and Gamba, P. (2006). Discriminating urban environments using multiscale textural and multiple SAR images. International Journal of Remote Sensing 18: 3797-3812.

Galletti, C. S., and Myint, S. W. (2014), Land-Use Mapping in a Mixed Urban-Agricultural Arid Landscape Using Object-Based Image Analysis: A Case Study from Maricopa, Arizona. Remote Sensing 7: 6089-6110.

Gansaonré, R.N. (2018). Dynamique du couvert végétal et implications socio-environnementales à la périphérie du parc W/Burkina Faso. VertigO La revue électronique en sciences de l'environnement 18 (1): 1-19.

Geerling, C., and Diakité, M. D. (1988). Final report of the Research project for the rational use of prey in the Sahel (RURGS). Department of Nature Planning, Wageningen Agronomic University, Wageningen, 93 p.

Géomines, (1982). Hydrogeological inventory of Ivory Coast applied to village hydraulics. Ministry of Public Works and Transport.Central Directorate of Hydraulics.The Republic of Ivory Coast.Map of Gagnoa. Cahier n° 24, 31 p.

Haralick, R. M. (1979). Statistical and Structural Approaches to Texture. Proceedings of the Institute of Electrical and Electronics Engineers 67 (5): 786-804.

Haralick, R. M., Shanmugam, K., Dinstein, I. (1973), Textural Features for Image Classification. Institute of Electrical and Electronics Engineers Transactions on Systems, Man, and Cybernetics 6: 610-621.

He, D.-C.; Wang, L.; Baulu, T.; Morin, D.; Bannari, A. (1994). Classification spectrale et texturale des données d'images SPOT en milieu urbain. International Journal of Remote Sensing 15(10): 2145-2152.

He, D. C., and Wang, L. (2010). Simplified texture spectrum for texture analysis. Journal of Communication and Computer 8: 44-53.

Herold, M., Scepan, J., Müller, A., Günther, S. (2002). Object-oriented mapping and analysis of urban land use/cover using IKONOS data. Proceedings of 22nd EARSel Symposium Geoinformation for European-wide integration, 8 p. Prague, Czech Republic, June 4-6.

INS, (2014). General Population and Housing Census in 2014. Global results, Permanent Technical Secretariat of the GPHC, Technical Committee of GPHC, 26 p.

Jensen, J. R. (2005). Introductory digital image processing: A remote sensing perspective, (3rdEd). Pearson Prentice Hall Upper Saddle River, USA.

Johansen, K., Coops, N. C., Gergel, S. E., Stange, Y. (2007). Application of high spatial resolution satellite imagery for riparian and forest ecosystem classification. Remote Sensing of Environment 1: 29-44.

Jukka, H., and Aristide, V. (1998). Land cover/land use classification of urban areas: a remote sensing approach. International Journal of Pattern Recognition and Artificial Intelligence 4: 475-489.

Kayitakire, F., Giot, P., Defourny, P. (2002). Automated delineation of the forest stands using digital colour orthophotos: A case study in Belgium. Canadian Journal of Remote Sensing 5: 629-640.

Mora, B. (2009). Mapping of forest parameters by obvious fusion of multi-source geospatial data; application to regenerating forest stands and mature hardwoods in southern Quebec. PhD. Dissertation, University of Sherbrooke, Canada.

Moran, E. F. (2010). Land Cover Classification in a Complex Urban-Rural Landscape with Quickbird Imagery. Photogrammetric Engineering and Remote Sensing 10: 1159-1168.

Mouissa, H., and Fournier, R. A. (2013). Mapping stand volumes of Pinus halepensis Mill in a semi-arid region using satellite imagery of the Sénalba Chergui forest in north-central Algeria. Journal of Arid Environments 92: 63-75.

Mouissa, H., Fournier, R.A., Oldache, E.H., Bellatreche, M. (2018).Detection of changes in forest cover in a semi-arid environment from 1984 to 2009: Case of the Senalba Chergui forest in Djelfa (Algeria). Canadian Journal of Remote Sensing 2: 113-130.

Podest, E., and Saatchi, S. (2002). Application of multiscale texture in classifying JERS-1 radar data over tropical vegetation. International Journal of Remote Sensing 7: 1487-1506.

Puissant, A., Hirsch, J., Weber, C. (2005). The utility of texture analysis to improve per-pixel classification for high to very high spatial resolution imagery. International Journal of Remote Sensing 4: 733-745.

Schwarzer, S., Allenbach,K., Jaquet, J.M. (2009). Semi-automated, multi-source cartography of land cover. Archives des Sciences 62: 107-124.

Solberg, A. S. (1999). Contextual data fusion applied to forest map revision. IEEE Transactions on Geoscience and Remote Sensing 3: 1234-1243.

Sparfel, L., Gourmelon, F. Le Berre, I. (2008). Object-oriented approach of coastal land cover. Revue Télédétection 4: 237-256.

Stow, D., Hamada, H., Coulter, L., Anguelova, Z. (2008). Monitoring shrubland habitat changes through object-based change identification with airborne multispectral imagery. Remote Sensing of Environment 3: 1051-1061.

Safia, A., He, D-c. (2015). Multiband compact texture unit descriptor for intra-band and inter-band texture analysis. ISPRS Journal of Photogrammetry and Remote Sensing 105: 169-185.

Sylla, D. (2012). Spatio-temporal modelling of environmental vulnerability to soil degradation in the semi-arid area from radar data. PhD. Dissertation, University of Sherbrooke, Canada.

Vägen, T. G., Winowiecki, L. A., Abegaz, A., Hadgu, K. M. (2013). Landsat-based approaches for mapping of land degradation prevalence and soil functional properties in Ethiopia. Remote Sensing of Environment 134: 266-275.

Wemmert, C., Puissant, A., Forestier, G., Gançarski, P. (2009). Multiresolution remote sensing image clustering. IEEE Geoscience and Remote Sensing Letters 3: 533-537.

Wendpouiré, A. Z. (2020). Dynamics of forest coverage of Sahelian agrosystems of northern Burkina Faso after the droughts of 1970-1980: implication of land management practices. PhD. Dissertation, University of Québec at Montréal, Canada.

White, J. C., Wulder, M. A., Grills, D. (2007). Assessing the accuracy of mountain pine beetle red attack damage maps generated from satellite remotely sensed data. Canadian Forest Service Publications 36: 1- 4.