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Detection and predictive modeling of land use changes by CA-Markov in the northern part of the Southern rivers: From Lower Casamance to Gêba river (Guinea Bissau)

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The northern part of the Southern rivers, which is the subject of this study, lies between 18° 54’ and 14° 48’ north latitude and 11° 30’ and 12° 54’ west longitude. It is characterized by a dense hydrographic network dominated by maritime marshes and expanses of salty lands and mangrove mudflats that have developed on a vast coastal plain. The objective of this study is to analyze spatio-temporal changes of the geomorphological units and to simulate their spatial behavior in 2035. The methodology is based on the processing of Landsat TM and Landsat OLI satellite images acquired in 1986 and 2018, respectively. Change detection is performed by post-classification comparison of the two previously validated land cover states with overall accuracies of 91% for the 1986 image and 97% for the 2018 image. The prediction made using the CA-Markov model yielded a result with 88% agreement. This made it possible to understand the spatio-temporal evolution of land use and changes in the near future (2035). The results of the land use prediction in 2035 show that bare land will have the highest gain with 93% probability while tans will decrease by 60% to other land use categories. Vegetation and mangroves will lose 47 and 44% of their areas respectively to bare soil and mudflats. A strong degradation of vegetation cover is predicted by the Markov chain by 2035. The probability of change in the area covered by water is the lowest during this period.

Key words: CA-Markov, landsat, land use change, predictive modeling, Southern rivers.

INTRODUCTION

Land, which is not elastic is definitely one of the most important natural resources, since life and developmental activities are based on it. Land use and land cover is an important component in understanding the interactions of
the human activities with the environment and thus it is necessary to be able to simulate changes (Baboo et al., 2017; Padalia et al., 2018; Karki et al., 2021a,b). Land use refers to the type of utilization to which man has put the land. It also refers to the evaluation of the land with respect to various natural characteristics. Land use and land cover data are essential for planners, decision makers and those concerned with land resource management (Pande et al., 2002; Bargali et al., 2019). The variations of the vegetation in an area constitute an important parameter affecting the slope failures, as slope stability is very sensitive to changes in vegetation (Rozos et al., 2011; Bargali et al., 2018; Manral et al., 2020).

Poverty, population pressure, agricultural expansion and intensification and development of infrastructure have been are the major activities to change the land use pattern and land cover which adversely affect the nutrient status of soil and biodiversity (Bargali et al., 1993, 2015; Davidar et al., 2010; Vibhuti et al., 2018, Padalia et al., 2022).

Studies of land use land cover change are of an importance because they allow us to know the current trends in the processes of deforestation, degradation, desertification and loss of biodiversity in a given region (Lambin et al., 2001). The detection of land cover changes allows to estimate the nature of the natural and anthropogenic processes that is involved and to evaluate the risks and the issues of natural resources and territories management (Serradj, 2007). In sub-Saharan Africa, the majority of the population depends on natural resources to satisfy its basic needs. Thus, it is essential to preserve them in order to ensure resilience sustainable development. Land use and land cover changes can affect regional and global climates in terms of car emission or sequestration and can alter the global reflection properties of the Earth's surface (Fedema et al., 2005; Pan et al., 2011 in FAO, 2012). They are the result of anthropogenic phenomena and impact environmental quality, availability and use of natural resources (Serradj, 2007). The Intergovernmental Panel on Climate Change (IPCC) reports of 2007 and 2014 predict an increase of temperature between 2 and 6°C by 2035-2100, climate variability and rising sea levels. These climate changes impact coastal environments and control ecosystem dynamics. These effects make coastal areas dynamic entities with regard to coastal erosion that affect the world's coastal regions (Leclerc, 2010).

Thus it is essential to monitor the dynamics of current surface conditions to better understand its future evolution, for a sustainable management of the environment. Indeed, the rational management of natural resources become an imperative, especially with climate change which is causing profound changes and may be severe in the coming decades. However, resource management requires better knowledge, and if possible, accurate measurements, of the natural resources used, usable, degraded or disappearing on the surface of the globe (Kpedenou, 2016). It is therefore necessary to have sufficient information about the factors that govern its dynamics evolution, whether natural or anthropogenic. In this sense spatial remote sensing, which offers a global and diachronic vision of the environment, has become today, an essential tool in environmental management.

Predictive or prospective modeling provides information on the future of spatial behavior of land use units. It is not intended to predict reality but can help us to better understand complex environmental and/or social spatio-temporal changes. Land use modeling means a simulation of what reality might be, a reasoned and quantifiable scenario in the context of decision support (Paegelow et al., 2004). However, the literature has shown that the models for predicting land use and land cover changes are numerous and varied. Among others we can mention the Markov chain (CA-Markov), Cellular Automata that model spatial interrelationships between different land use typology (Debolini, 2014), Land Change Modeller (LCM) that allows to study land cover changes and to predict their future evolution that is one of the models frequently used to predict surface states. The objective of this study is not to test all of these models but to model future land cover changes in a context of climate change in the Southern rivers region using Markov chain. The choice of CA-Markov is based on its flexibility to develop customized models whose changes are based on the proximity effect (areas near the sites of a land use category are more likely to change towards it).

Study area

The study area (Figure 1) is located in the northern part of the Southern rivers, particularly from the lower Casamance to the Géba river. The name “Southern rivers” refers to the south trading posts of Gorée which depended on its administration in colonial times. The northern part of the Southern rivers, which is the subject of this study, lies between 18° 54’ and 14° 48’ north latitude and 11° 30’ and 12° 54’ west longitude. It is characterized by a dense hydrographic network dominated by maritime marshes and expanses of salty lands and mangrove mudflats that have developed on a vast coastal plain. This coastal fringe is characterized, from a geological point of view, by the Senegalese-Mauritanian sedimentary basin of Meso-Cenozoic age that extends from Cap Blanc in Mauritania to Cap Roxo in Guinea Bissau and the Bowé basin that occupies the...
south and southeast of the Gêba river. It is a transitional area between the maritime and continental domains with a relatively low topography along the coastal zone. This relief is dominated by a littoral plain constituted in its natural state by mangrove mudflats, composed essentially of *Rhizophora mangle* and *Avicennia africana* in particular (Diop, 1990). At the limits of the mangrove mudflats, there are expanses of tans that are flooded in places during the rainy season due to the flatness of the relief. The area studied is marked by the density of the hydrographic network composed of rivers constantly invaded by the tides. From a climatic point of view, the area belongs to the Libero-Guinean domain (Leroux, 1983) which is a sub-division of the tropical climate. The region is characterized by two seasons due to the alternating circulation of the trade winds and the monsoon. A dry season from November to April and a rainy season from May to October. Rainfall is relatively abundant (over 1000 mm per year). This abundance is mainly related to the high potential advected rainfall and the relief that conditions the summer translation of the intertropical convergence zone (Pennober, 2009).

**MATERIALS AND METHODS**

The Landsat images selected for this study were chosen on the basis of their availability, their free and open access, and their age, covering a period from 1972 to the present. The dry season images (February and April) are selected to better discriminate the vegetation cover from the grass cover whose reflectance are confused when the images are acquired in the rainy season or just at the end of it. A series of corrections is applied to these images in order to increase the quality of the information and minimize the uncertainty in the data, which is often linked to atmospheric disturbances.

The satellite images (Table 1) were obtained from the Google Earth Engine (GEE) platform and Climat Engine. The GEE platform allows the analysis and visualization of satellite images of our planet. This cloud platform groups an archive of more than 40 years of satellite imagery, as well as tools with the computational power to analyze and exploit this huge geospatial data warehouse or big data. It also stores a set of geospatial data such as land use, vegetation cover etc. Change detection is done by post-classification comparison which involves using two previous land cover states to produce change information. The results describe the transition from one morphological unit to another depending on the characteristics of the environment.

**CA-Markov Model**

The Markov chain model is used to simulate temporal changes in land use. The spatial dimension is taken into account by cellular automata models that simulate spatial distributions. The principle of the cellular automaton consists in taking into account the state of the neighboring cells in the definition of the future state of the considered cell (Ladet et al., 2004). The CA-Markov model then simulates the spatio-temporal changes of the landscape based on the principle that the future state of a cell depends on the state of its
neighbors and at the same time on its previous state. A Markov chain corresponds to "a process whose transition probabilities are conditional on the past" (Berchtold, 1998).

Validation of the model

The statistical approach was chosen, at the expense of the visual comparison of land cover states. The Kappa index was chosen for this purpose to compare predicted data with observed data (references) using the CROSSTAB module of IDRISI software. For all Kappa statistics, 0% indicates that the level of agreement is equal to the agreement due to chance and 100% indicates perfect agreement. If the Kappa index is less than or equal to 0.4 (40%), then the land cover has changed significantly and with poor consistency between the two images. If the Kappa index is between 0.4 (40%) and 0.75 (75%), there are general consistencies and obvious changes between the two images otherwise there is high consistency between two images (Yousheng, 2011). The composite rule was chosen because of its many attractive features such as the identity matrix with a 5x5 adjacency filter.

Treatment procedure with IDRISI software

Several predicting models of spatio-temporal behavior of land use units are implemented in the IDRISI software. However, their use is not easy because of the complexity of IDRISI software. The procedure of change detection and prediction is described in Figure 2, which consists of producing two land cover maps (1986 and 2018) and detecting changes. Then, use the 2018 land use as a benchmark for the Markov chain simulation and validate it before predicting the 2035 land use. The results of this processing are composed of a transition matrix, a transition probability matrix, a change image, an inter-class change images and a change trend images.

RESULTS

Reflectance analysis of coastal morphological units

The reflectance of geomorphic units depends on their intrinsic characteristics as well as their surface condition. Moisture, roughness and other time-varying elements influence the reflectance of land cover features. In the coastal environment, difficulties often noted in the evaluation of geomorphological units are related to confusions due to reflected mixing signal, spatial and radiometric resolution.

Estimating and mapping salted lands is a real problem related to their typology, degree of salinity and reflectance. Salted lands reflect differently depending on the season and surface conditions. In the dry season, under the effect of strong evaporation, salt tends to be concentrated in the soil surface layers. Depending on their salinity degree, some saline soils are generally covered with herbaceous or shrubby vegetation, so their signal is mixed with that of the vegetation and this causes confusion with sparsely wooded land on images acquired in the dry season. Only bare saline soils, commonly referred to as light Salty lands, are identifiable in the visible and near-infrared spectral bands. The mapping of light Salty lands by remote sensing does not pose any difficulties. In contrast, sodic horizon soils, little salted soils or in the process of salinization without specific surface manifestations, are poorly identified and their surface areas underestimated (Mougenot et al., 1990).

Figure 3 shows that the water contained in the salts, reflects the short wavelengths of blue and is at the origin of the absorption peaks observed at the level of the green wavelengths and the near infrared.

The appearance of spectral signatures in the visible range justifies the confusion noted in the classifications. These curves have the same appearance in the visible and separate from the near infrared, hence the choice of these one in the false color compositions. The water content of mudflats sometimes gives them a spectral signature identical to that of water. The differentiation of these land use units is in the shortwave infrared (SWIR 1) where Salty lands and lightly wooded land reflect strongly.

Table 1. Characteristics of the Landsat image that used.

| Sensors | Bands | Wavelengths (µm) | Resolution | Date of acquisition |
|---------|-------|-----------------|------------|---------------------|
| TM      | 1-Blue| 0.45-0.52       | 30 m       | April-May 1986      |
|         | 2-Green| 0.52-0.6        |            |                     |
|         | 3-Reed| 0.63-0.69       |            |                     |
|         | 4- NIR| 0.76-0.9        |            |                     |
|         | 5-SWIR 1| 1.55-1.75    |            |                     |
|         | 7- SWIR 2| 2.08-2.35     |            |                     |
| OLI     | 2- Bleu| 0.45-0.52       | 30 m       | April-May 2018      |
|         | 3- Vert| 0.53-0.60       |            |                     |
|         | 4- Rouge| 0.63-0.68      |            |                     |
|         | 5- PIR| 0.85-0.89       |            |                     |
|         | 6- SWIR 1| 1.56-1.66    |            |                     |
|         | 7- SWIR 2| 2.10-2.30     |            |                     |
Oceanic waters and turbid waters (those of the bolongs) are separated in order to observe the variation of reflectance in the visible and near infrared spectrum (Figure 3). The variation of the reflectance of the two entities is due to the content of suspended solids (SS) in the continental waters. Mudflats and mangroves have a strong signal in the blue channel due to the water content. Vegetation always shows a peak in the near infrared, which is also the appropriate channel for estimating vegetation cover. The mixing of signals between sandy strips and salty lands may be related to their white color which is difficult to discriminate by photo-interpretation. This color is found in some places in lightly wooded land, hence the confusion noted with Salty lands. In the near-infrared, the reflectance of lightly wooded land, salty lands and vegetation is somewhat similar, which can impact the accuracy of classifications and lead to an underestimation of these units. The use of short-wave infrared allows, in this case, to better discriminate the land use units except for mudflats which are mixed but with a small shift in the near infrared.

**Land use dynamics**

The change detection operations are based on a prior mapping of the land cover (Figure 4). The accuracy of the two land cover states is evaluated by a confusion matrix from which the performance of the classifications is evaluated and results in a Kappa coefficient of 91% for
the 1986 image and 97% for 2018. Bare soil and sparsely forested areas were grouped into a single class (bare soil) since they are difficult to separate. Oceanic, estuarine and rivers are also grouped in one class (water) because of the complexity of their identification. The spatial and radiometric resolution of the images used does not provide sufficient information on the nature of the water.

**Land use status**

Land use has undergone a slight evolution compared to the 1970s, which justifies the fact that we are so far in the periods of drought that West Africa has experienced. The mangrove and the salty lands, whose extension is dependent on the rainfall conditions, have experienced a slight change from respectively 6.93 and 2.89% in 1986 to 7.06 and 4.37% in 2018. These changes correspond to an extension of 20107.26 ha for the mangrove or 0.13% and 59409.63 ha for the salt land or 1.48% compared to their areas in 1986. The vegetation has increased by 5.28% of the total area which represents a total of 211982.22 ha. The increase in mangrove area can be linked to the rainfall conditions that characterize this part of the Southern rivers. The annual rainfall totals exceed on average 1200 mm of precipitation. This positive evolution of the mangrove and the vegetation cover can also be due to the numerous reforestation campaigns that the region has experienced, especially in Lower Casamance.

Salted area was more developed in Lower Casamance but is beginning to occupy large areas in the Guinean region (Figure 5). This is explained by climatic variability.
Table 2. Land use statistics between 1986 and 2018.

| Classes     | 1986          | 2018          |
|-------------|---------------|---------------|
|             | Area (ha)     | Proportion (%)| Area (ha)     | Proportion (%)|
| Water       | 2097997.11    | 52.25         | 2044990.98    | 50.93         |
| Vegetation  | 266606.91     | 6.64          | 478589.13     | 11.92         |
| Mangrove    | 263563.38     | 6.56          | 283670.64     | 7.06          |
| Salty lands | 116171.73     | 2.89          | 175581.36     | 4.37          |
| Mudflats    | 202976.91     | 5.05          | 192737.88     | 4.80          |
| Bare soil   | 1061448.03    | 26.43         | 807552.27     | 20.11         |

Figure 6. Gains and losses of land use units between 1986 and 2018.

along a south-north gradient that results in a decrease in precipitation and an increase in temperatures that can reach 38°C in the dry season. This situation induces strong evaporation that contributes to the increase in salt content in marine and estuarine waters and to the effervescence of salt at the surface level of the soil. In Lower Casamance, many rice fields have been lost in recent decades due to the expansion of saline lands. They represent 4.4% of the total area or 175581.36 ha in 2018 (Table 2). These areas are lost because so far, no sufficiently effective method has been developed to restore the salt lands. To these extents are added 192737.88 ha of mudflats in 2018, or 4.8% of the studied area. These are constantly flooded salt lands that in some places harbor mangrove formations.

Detection of land use changes

Analysis of the morphological units changes between these two dates shows that the landscape of the area studied has undergone changes often linked to the variation in climatic conditions and the influences of marine hydrodynamic actions. The tides and the regular submergence of the low-lying areas such as salty lands, mudflats and mangrove areas influence the hydrological regime. The rise of the saltwater wedge, the low freshwater input, the increase in temperature and evaporation, and the capillary rise of the saltwater constitute a dynamic system that generates changes (progression or regression) in land use units. The post classification comparison provides in terms of gains and losses (Figure 6), the evolution of land cover between 1986 and 2018. The analysis of Figure 6 shows that only the water class remained almost stable during the whole period studied (from 1986 to 2018). Mangrove and vegetation appear stable as well if losses are subtracted from gains. An expansion of mudflats is observed while salt land has experienced a regression although it is spatially developed in some places in the region.

Spatialization of changes (Figure 7) revealed a north-south gradient of vegetation cover and mangroves. These two land use units remain sparse in the lower Casamance, leaving place to bare soil and mudflats. In the Guinean region, which seems to be a very dynamic environment, vegetation has strongly gained space. This situation can be explained by the good rainfall conditions noted in this region. However, some pockets of bare soil appear, particularly north of the Gêba river. The extension of mudflats is noted in estuarine environments and their immediate edges and can be linked to marine dynamics.
Figure 7. Spatial analysis of land use changes between 1986 and 2018.

Table 3. Transition probability matrix in % obtained from observed and simulated land use in 2018.

| Observation 2018 | Water   | Vegetation | Mangrove | Salty lands | Mudflats | Bare soil |
|------------------|---------|------------|----------|-------------|----------|-----------|
| Water            | 0.9901  | 0.0000     | 0.0028   | 0.0003      | 0.0058   | 0.0010    |
| Vegetation       | 0.0003  | 0.5259     | 0.1829   | 0.0020      | 0.0013   | 0.2877    |
| Mangrove         | 0.0041  | 0.1098     | 0.5604   | 0.0111      | 0.1430   | 0.1817    |
| Salty lands      | 0.0144  | 0.0023     | 0.0210   | 0.4043      | 0.1532   | 0.4048    |
| Mudflats         | 0.0415  | 0.0002     | 0.0606   | 0.231       | 0.8215   | 0.0532    |
| Bare soil        | 0.0115  | 0.1184     | 0.0917   | 0.0251      | 0.0631   | 0.6901    |

Predictive land use modeling

Predictive land use in 2018

The transition matrix from the CA-Markov model shows in percentage the dynamics of each land use unit between 1986 and 2018. Table 3 shows a remarkable stability of the spaces covered by water followed by mudflats and bare soil. However, more pronounced transition probabilities are observed for salted land, mangrove and vegetation. The transition matrix shows that there is a higher probability (45%) that salty lands become bare soil or that they become mudflats (14%). This means that salty lands still remain as saline soils but their reflectance may change depending on their surface condition to the point of being confused with bare soil. The transition from mangrove to vegetation occurs with a probability of 13%, which may be related to signal confusions, but also to mudflats (13%) and bare soil (30%). For vegetation, the probability of changing to other categories is 49%. It is 17% to change to mangrove and 32% to bare soil. This shows a considerable loss of forest and mangrove vegetation. It is followed by a change in salted land which may be the cause of the degradation of the vegetation.
Table 4. Transition matrix of areas (in ha) calculated from observed and simulated land use in 2018.

| Observation 2018 | Simulation 2018 |
|------------------|-----------------|
|                  | Water | Vegetation | Mangrove | Salty lands | Mudflats | Bare soil |
| Water            | 16801440 | 649 | 48258 | 5108 | 97581 | 17044 |
| Vegetation       | 1030 | 2062803 | 717575 | 7706 | 4929 | 1128514 |
| Mangrove         | 17884 | 479092 | 2444861 | 4609 | 623748 | 792861 |
| Salty lands      | 9740 | 1577 | 14196 | 273495 | 103615 | 273820 |
| Mudflats         | 95283 | 358 | 139307 | 53016 | 1887943 | 122300 |
| Bare soil        | 112771 | 1158782 | 897515 | 245719 | 617498 | 6750934 |

Figure 8. Spatial comparison between observed and predicted changes in 2018.

cover. All these probable changes can be linked to climate variability and its effects on coastal environments in particular.

**Area transition matrix analysis (in ha)**

The area transition matrix (Table 4) shows, in terms of hectares, which land use categories have changed to which ones. The matrix shows a strong transformation of land use units between 1986 and 2018. 53016 ha of Mudflats have migrated to Salty lands while the amount of salted land converted to mudflats is estimated at 103615 ha. The change between these two land use units is dependent on climatic conditions and tidal intensity. A significant regression of forest vegetation is observed between these two dates. These losses amount to 1.2% of its actual area and converted to salted land, 358 ha that became mudflats and 1158782 ha that leaves place to bare soil. There are 479092 ha of mangroves that became vegetation. However, these changes noted between the two classes may be due to the temporal variation of chlorophyll which strongly influences the reflected signal.

**Comparison between observed and predicted changes in 2018 and model validation**

The simulated and observed 2018 land use maps are presented in Figure 8. A visual interpretation shows a great similarity between land cover categories except for mangrove which appears denser in the prediction. A progression of mangrove is noted in the estuaries, along
the bolongs and south of the Gêba river while bare soil is much more developed in the north of the Casamance River. The spatial distribution of morphological units is correctly simulated.

Comparison of the statistics of predicted and observed changes (Figure 9) shows a slight difference between some categories. The observed and simulated changes show almost the same areas in the water category while vegetation, mangrove, salty lands, mudflats and bare soil show slight difference. The simulated mangrove shows an increase while the vegetation, mudflats and tans show a slight regression compared to the observed model. A small difference is also observed in the bare soil category. This difference in water occupied area represents a gain of 0.4% of occupied space.

Markov chain validation

The Kappa index from the cross between the predicted land cover condition and the observed one in 2018 is 0.88, which is greater than 0.75 and therefore the results are reliable. There is a high consistency between the observed reality and the predicted results. This agreement shows that the land cover changes in 2035 can, for this scenario, be simulated.

Residual analysis

The residuals represent the part of mismatches between simulated and observed land use categories. The bold diagonal (Table 5) represents the match between reality and simulation. The rest of the matrix is the residuals. Water and Salty lands show complete agreement with reality. 61% of observed water areas agree with the simulation while Salty lands were observed and simulated at 1%. Of the 7% vegetation and 8% mangrove simulated, 5% agree with observations. Bare soil represents 14% of consistent in the 17% observed while mudflats are 4% consistent in the 6% observed.

Status of land use in 2035

The land cover prediction for 2035 was performed using the CA-Markov model on the basis of ten iterations, which is sufficient for this study. The probability of land cover change between 2018 and 2035 was analyzed using the Markov transition estimator. Table 6 shows the probability of change matrix of land use classes in 2035. Bare soil will get the highest gain with 93% probability while Salty lands will decrease by 60% to the benefit of other classes like bare soil and mudflats. Vegetation and mangrove will lose 47 and 44% of their areas respectively to bare soil and mudflats. A strong degradation of vegetation cover is predicted by the Markov chain by 2035. The probability of change in the area covered by water is the lowest during this period.

The areas of the different land use categories are also estimated by the Markov transition estimator. The changes between 2018 and 2035 are shown in Table 7 and Figure 10. Although the vegetation statistically loses a large part of its area (3.37%), it is very dense in the estuaries of Cacheu, Mansoa river and in the Quinara region in the south of Gêba river. The mangrove will experience an increase of 2.46% compared to the year 2018. This increase will be observed along the bolongs.
and at the estuarine limits in lower Casamance. The increase of the mudflats is estimated at 78542.32 ha, that is, 1.96% of their area in 2018. Their spatial extension will be more accentuated in the Casamance estuary and its borders, where tidal flats are formed.

**Impacts of land use change on the Sustainable Development Goals (SDGs)**

Climate change is significantly influencing the spatio-temporal dynamics of land use. Its impact on the physical environment has resulted in the regression of continental vegetation cover and a slowing of the increase in the world's freshwater supply. Preserving and restoring ecosystems to mitigate the effects of climate change is an integral part of the Sustainable Development Goals (SDGs). From 1998 to 2013, nearly one-eighth of the Earth's vegetated surface showed strong downward trends in productivity. Soil and land degradation undermines food security and development in all countries (ODD, 2017). The results of this study showed a regression of vegetation cover and an increase in mudflats and salty lands as a consequence of sea level rise. In the face of these situations, knowledge of changing trends of the surface conditions and natural resources is essential to facilitate the achievement of goals 13 and 15 of the 2030 Agenda for Sustainable Development. The severity of future impacts of climate change on natural resources can be understood through

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**Table 5. Comparison of observed and simulated land use (2018).**

| Observation 2018 | Water | Vegetation | Mangrove | Salty lands | Mudflats | Bare soil | Total Observed |
|------------------|-------|------------|----------|-------------|----------|-----------|----------------|
| Water            | 0.60  | 0.00       | 0.00     | 0.00        | 0.00     | 0.00      | 0.61           |
| Vegetation       | 0.00  | 0.05       | 0.01     | 0.00        | 0.00     | 0.02      | 0.07           |
| Mangrove         | 0.00  | 0.01       | 0.05     | 0.00        | 0.01     | 0.01      | 0.08           |
| Salty lands      | 0.00  | 0.00       | 0.00     | 0.01        | 0.00     | 0.00      | 0.01           |
| Mudflats         | 0.00  | 0.00       | 0.00     | 0.00        | 0.04     | 0.00      | 0.04           |
| Bare soil        | 0.00  | 0.02       | 0.01     | 0.00        | 0.01     | 0.14      | 0.18           |
| Total Observed   | 0.61  | 0.07       | 0.08     | 0.01        | 0.06     | 0.17      | 1.00           |

**Table 6. Transition probability matrix between 2018 and 2035.**

| 2018          | Water | Vegetation | Mangrove | Salty lands | Mudflats | Bare soil | Lost |
|---------------|-------|------------|----------|-------------|----------|-----------|------|
| Water         | 0.990 | 0.000      | 0.003    | 0.000       | 0.006    | 0.001     | 0.010|
| Vegetation    | 0.000 | 0.526      | 0.183    | 0.002       | 0.001    | 0.288     | 0.474|
| Mangrove      | 0.004 | 0.110      | 0.560    | 0.001       | 0.143    | 0.182     | 0.440|
| Salty lands   | 0.014 | 0.002      | 0.021    | 0.404       | 0.153    | 0.405     | 0.596|
| Mudflats      | 0.042 | 0.000      | 0.061    | 0.023       | 0.822    | 0.053     | 0.179|
| Bare soil     | 0.012 | 0.118      | 0.092    | 0.025       | 0.063    | 0.690     | 0.310|
| Gaine         | 0.072 | 0.231      | 0.359    | 0.052       | 0.366    | 0.928     |      |

**Table 7. Land use statistics between 2018 and 2035.**

| Classes       | 2018     | 2035     |
|---------------|----------|----------|
|               | Superficie (ha) | Proportion (%) | Superficie (ha) | Proportion (%) |
| Water         | 2044990.98 | 50.93    | 2124807.54 | 52.92 |
| Vegetation    | 478589.13 | 11.92    | 343155.59 | 8.55  |
| Mangrove      | 283670.64 | 7.06     | 382396.43 | 9.52  |
| Salty lands   | 175581.36 | 4.37     | 54780.52  | 1.36  |
| Mudflats      | 192737.88 | 4.80     | 271280.2  | 6.76  |
| Bare soil     | 807552.27 | 20.11    | 839075.97 | 20.90 |
the prediction of their spatio-temporal behavior. This is a key source of information for the evaluation of the program. At the rate of land use change observed, the objectives of sustainable development could be compromised in this area.

DISCUSSION

The detection of land use changes in the northern part of the Southern rivers between 1986 and 2018 is made on the basis of prior land use mapping. The classifications are found to be acceptable and allow for the assessment of land use changes from 1986 to 2018, a 33-year period. Confusion errors are noted in the salty lands, mudflats, bare soil classes. The difficulty in visually discriminating these classes may be due to similar spectral signatures, as mudflats are constantly flooded salty lands. The confusion between salty lands and bare soil is that salty lands without salted surface concentration and sometimes grasslands are inseparable from the visual observation (Tine et al., 2020). The change detection results show an increasing trend of mudflats, a regression of salty lands and bare soil, and a slight stability of vegetation and mangrove. The method of comparing classifications demonstrated the utility of a simple approach to detecting land cover change and the ease of creating change maps (Hoang, 2007). The overall accuracies of the classifications give satisfactory results with 91% for 1986 and 97% for 2018.

The validation of the prediction with the 2018 reference image showed a satisfactory result with a Kappa of 88%. These results corroborate with those of Yirsaw et al. (2017) who further assert that Markov chain is an appropriate model for predicting land cover changes. The reliability of the model in predicting land cover changes is confirmed by the work of Maestripieri and Paegelow (2013) who have an accuracy of 86% between observed and simulated changes.

The Markov chain is not too complex to use with IDRISI software. However, problems related to the execution of the model can occur when the reference images, which are used for prediction, are processed by other software. It is often an imbalance related to the size of the images (number of rows over number of columns). Another limitation of predictive models is related to their spatial and statistical validation. Only the opinion of experts constitutes an element of judgment of the simulation. In this work, the results were submitted to the appreciation of several experts. However, the supervised approach (CA-Markov) generates more realistic maps (Maestripieri and Paegelow, 2013). The comparative analysis between
the observations and simulation of 2018 showed a similarity of 88%. This accuracy was deemed acceptable and allowed to simulate land cover for 2035. Slight changes in land cover categories will be observed in 2035. Most notable is the 3% regression of saline land from its 2018 footprint. Conversion of salty lands to other categories is possible only if they are mudflats, water and mangroves. Bare soil that encompasses cropland as well as vegetative cover cannot gain space on salty lands due to salinity. This means that saline lands can be modified but remain unsuitable for agriculture. This regression could also be related to model simulation error.

**Conclusion**

The prediction of land use changes showed an increase of 1.99% in water surfaces, a decrease in continental vegetation from 11.92% in 2018 to 8.55% in 2035. A degradation of the vegetation cover will be observed in 2035 if no preservation measures are taken. Mangrove will occupy more than 2.46% of new space, while 3.01% of the saline land will be converted to other land use categories. Mudflats and bare land will increase slightly in area, with 1.96% and 0.79% respectively by 2035. However, the detection of land use changes and the prediction of their areas is not a perfect representation of the reality on the field. The numerous experiences capitalized in the framework of this work have proven that the temporal horizon should not exceed thirty years. The absence of external data such as population growth, climatic and geomorphological data are the limitations in predicting the state of land cover. However, the Markov chain allows quantifying and mapping the spatial dynamics of future land use changes. The simulation of land use patterns allows the evaluation of actions undertaken within the framework of programs to combat environmental degradation and to adopt sustainable ecosystem management strategies. Despite the methodological problems often encountered in land use simulation, predictive models provide reliable results that are very useful for decision making. A better prediction of morphological units requires taking into account climatic and anthropogenic factors which not considered in this work. The contribution of new sources of information such as urban areas, geology, geomorphology, etc., can improve the quality of the prediction.

**CONFLICT OF INTERESTS**

The authors have not declared any conflict of interests.

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