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A Fuzzy approach to modelling land cover changes in north-eastern Nigeria

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ABSTRACT

This project has explored the use of GIS and Remote Sensing techniques to model and provide a better conceptualization of land cover changes using a Fuzzy approach in the north-eastern part of Nigeria (Kukawa town bordering Lake Chad), The maps shows the spatial extent of the land cover changes. The ability and the capacity of GIS to provide answers to questions on where the changes have occurred will help the environmentalist and the policymakers in solving environmental related problems and in the management of the existing natural resources since the locations of the changes were identified. Fuzzy supervised classification using normalized sigmoidal fuzzy membership function was performed on the Landsat images of three dates and the classified maps inputted into GIS and the land cover changes modelled. The results shows that the dry soil was more intensive in 1992, whilst vegetation and moist soil were more intensive in 1984 and the water body was more intensive in 2000. The dry soil covers an area of 39.02% (1984), 48.27% (1992) and 39.98% (2000), whilst the moist soil occupied 46.37% (1984), 35.1% (1992) and 45.52% (2000), Vegetation on the other hand showed a continuous decrease from 19.23% (1984), 15.37% (1992) to 14.47% (2000) whilst water body continues to increase from 3.77% (1984), 6.67% (1992) to 7.27% (2000).

Keywords: Fuzzy classification, land cover modelling, change detection, remote sensing, GIS, North eastern Nigeria.

1. Introduction

The physical surface of the earth is in constant change due to man's activities as well as natural phenomena. Knowing that our landscape is changing is not enough, but knowing the locations and the intensity of changes will be of more benefit to the society for planning purposes and other applications. Land cover is the physical material at the surface of the earth; it includes trees, grass, woodland, water, and bare areas (Khmag, 2012), whose classes are usually defined by their biophysical properties, such as bio-geographic location and landscape context (Comber et al., 2005).

Remote sensing without GIS may not effectively model land cover changes. The ability and the capacity of GIS to provide answers to questions on where the changes have occurred will help the environmentalist and the policymakers in solving environmental related problems and in the management of our resources since the locations of the changes can be identified. Recently, Remote Sensing and Geographic Information System (GIS) techniques have been the most successful approaches for detecting the long-term land cover changes (Kundu and

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Dutta, 2011). Remote Sensing provides information about the earth's surface at regional and global scale over a large extent of land (Csaplovics, 1998; Foody, 2002), therefore making it an ideal tool and source of data for land cover change detection and modelling (Rogana and Chen, 2004). GIS involves processing, interpreting or transforming data to derive some sort of interpretation (Comber et al., 2005). GIS uses information provided by remote sensing to provide answer to various questions relating to land cover changes; it is able to model the various changes across a particular landscape and revealing a wealth of information.

Various classification approaches are used for land cover change detection and modelling using satellite images depending on the nature of feature or objects to be classified and modelled. Whilst some landscape have well defined boundaries, others do not have i.e. vaguely defined due to mixed pixel. Modeling of vague concepts is possible using fuzzy set theory (Zadeh, 1965). The fuzzy approach of land cover modelling is able to measure the degree of vagueness in a particular land cover class which may result from a mixed pixel - a pixel not completely occupied by a single, homogeneous category (Zhang, 1998). In order to describe natural phenomena more precisely, the fuzziness in these natural phenomena should be considered and represented in a GIS to allow the derivation of better results, and a better understanding of the real world to be achieved (Tang, 2004). This is important to the policy makers who want to know the spatio-temporal and degree of changes that have occurred to enable adequate planning since the change can't be the same spatially and in intensity. The choice of a fuzzy approach to model the land cover change is due to the nature (vagueness) of the land cover types - a semi-arid region (North-Eastern Nigeria) with known incidence of desertification. Land cover change detection and desertification are poorly defined phenomena; hence, fuzzy approach is suitable for modelling them (Foody and Boyd, 1999).

In this paper an attempt has been made to model the land cover changes in the study area using Fuzzy approach and representing them in GIS to enable both quantitative and qualitative analysis to be carried out to assess the land cover changes in a complex land scape of North-Eastern Nigeria which is known to have incident of desertification by determining the magnitude of change (MC) and the nature of change (NC).

2. Literature review

2.1 Lake Chad

Although the study area does not cover all of Lake Chad, the fact that the study area borders Lake Chad and is part of the image of the study area which means it will have a great influence on the study area. Lake Chad is the largest lake in West Africa and the fourth largest lake in the African continent; it lies 281meters above sea level in the Sahel (Schneider et al., 1985). Lake Chad is a very shallow lake and is not often more than 7meters (m) deep. It provides fresh water and other resources to more than 20 million people living in about 30 shore-line communities in the five riparian countries of Chad, Cameroon, Nigeria, Niger and the Central African Republic, which make up the conventional Lake Chad Basin Commission (Onuoha, 2008b). This lake has been susceptible to increasing climatic variability and human impacts over the past 40 years, which has resulted in it shrinking (Coe and Foley, 2001), and as such it has lost about 90% of its original size (Masari, 2006), which has resulted in a more arid climate for the region, leading to water scarcity, harvest losses, cattle dying, fishing activities being abandoned, soil salination and poverty.

2.2 Fuzzy Logic

The complexity in land cover has made it difficult to visually represent a geographical object that has no well-defined boundaries. Humans are able to perceive the vagueness in land cover classes without well-defined boundaries, but representing vagueness in the form of maps is a difficult task since computers do not perceive and understand vagueness as humans do. To solve this problem, a notion of partial truth was formulated mathematically by Zadeh in 1965 and processed by computers, in order to apply a more human-like way of thinking in the programming of computers, which is an alternative to the traditional notion of set membership and logic, which originated from the ancient Greek philosophy called fuzzy logic (Hellmann, 2002),In essence, fuzzy logic is the logic of perceptions in which everything and especially truth and possibility is, or is allowed to be, a matter of degree, whilst probability logic is the logic of measurements where only likelihood is a matter of degree (Zadeh, 2009), Fuzzy logic has also emerged as a profitable tool for the classification of remotely sensed data (Hellmann, 2002) without a well-defined boundary such as desertification.

2.3 Remote sensing/land cover mapping

Remote sensing is gaining more popularity in land cover change detection, with desertification monitoring being one of the areas of application over the years. Remote sensing has proved to be a valuable data source for the efficient extraction of land-use/land-cover change information which helps in analysing dynamic changes associated with the earth's resources, such as land and water (Ramachandra and Kumar, 2004), In the past two decades, there has been a growing trend for the development of change detection techniques using remote sensing data (Chen et al., 2003), Satellite remote sensing offers huge advantages in monitoring the expansion and process of land cover change and desertification to determine it causes and consequences (El Hassan, 2004; Kundu and Dutta, 2011; Lacaze et al., 1996), Abbasova (2010) used remote sensing to discover land degradation in the countries in the Caspian Region. Nevertheless, if these observations are not coupled with GIS-based modelling concepts, they may not develop their full capacity for use in modifying and adapting environmental management principles and mitigation strategies (Hill et al., 2006),

2.4 Classification

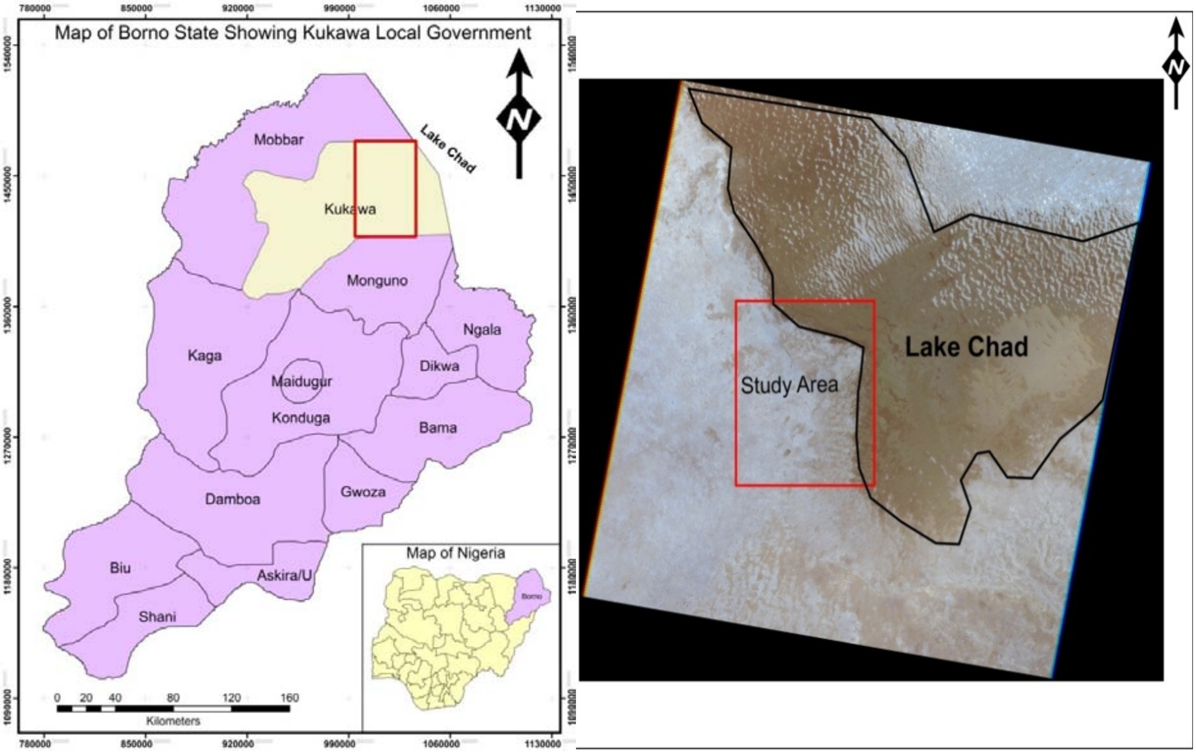
Classification is an automated computer assisted grouping of pixels of remotely sensed images into land cover classes. Basically, there are two types of classification; supervised and unsupervised, and it is usually performed to produce land cover maps from remote sensing data (Saha et al., 2005), The choice of the classification approach depends on the purpose, need and how knowledgeable the analyst is about the scene, the accuracy required, etc. The multi-spectral mapping of landscapes consists of drawing boundaries around geographically located classes and their various attributes and relations in a consistent logical manner (Robinove, 1981), The objective of classification is to classify each pixel into only one class or to associate the pixel with many classes (Arora, 2004), Classifiers are broadly divided into hard (Boolean) and soft (fuzzy) classifiers, with each having its own merit depending on the landscape on which they are used. The hard traditional (crips) classification is use when the objects/features have well-defined boundaries (homogeneous), It assumes that a pixel can only belong to a particular class; hence it is not suitable for modelling heterogeneous landscapes. The soft classifier, unlike the hard classifier, is used when the land cover classes have no well-defined boundaries; a pixel could belong to more than one class at a time and have a degree of membership in each class. Its ability to represent vaguely defined geographical phenomena makes fuzzy supervised classification the preferred approach.

2.5 Change detection/land cover modelling

Change detection has to do with the apprehension of change in the world around us (Rensink, 2002) by observing it at different times (Oune, 2006) using GIS and Remote Sensing, along with digital image processing techniques (Ramachandra and Kumar, 2004), Many techniques exist for land cover change detection using remote sensing data; traditionally, pre-classification and post-classification (Metternicht, 1999), The post-classification comparison is the most commonly used quantitative method (Jerson, 1996), which involves comparison of two or more classified images of the same scene taken at different dates to determine the amount of change that has occurred. In recognition of the fact that land cover classes are vague phenomena, a number of researchers have advocated modelling of land cover as fuzzy sets, as opposed to Boolean sets (Fisher, 2010), He recommended a type 2 fuzzy set recognising the existence of higher order vagueness to reveal the depth of the uncertainty, and allows the analyst to be specific about minimum, maximum, and average extents of land cover types, and even to report the fuzzy area itself as a fuzzy number. Hester et al. (2010) integrated several fuzzy techniques into an approach for transforming map uncertainty into accurate and practical change analysis. To overcome the problem of vagueness in boundary of land cover classes, Hegde (2003) uses a fuzzy approach to model land cover change in Simla, the capital of Himachal Pradesh state using fuzzy operators to identify the nature and direction of changes occurring in land cover.

2.6 Study area

Kukawa is a town and local government area in Borno, a north-eastern state in Nigeria, bordering Lake Chad on the east/north east side. It shares boundaries with both Cameroun and the Republic of Chad in the east, and three Local Government Areas: Mobba the North West, Kaga and Madukur in the south west and Munguno in the south, which are all in Nigeria. Kukawa is located between latitudes 12° 20’ 00”N and 13° 20’ 36”N and longitudes 12° 20’ 00”E and 13° 15’ 34”E; it has an estimated population of 3,576 people and is 111.5 miles away from Maiduguri, Borno’s state capital. The temperatures are high all the year round, ranging between 39°C and 40°C with a vast open plain of Sudan Savannah vegetation, which is flat or gently undulating with fluvial and Aeolian landforms such as fossil sand dunes, beach ridges, inter-dunes areas with no prominent hill with an average elevation of about 300m above sea level and slopes towards Lake Chad. 85% of the population are farmers, herdsmen and fishermen. The farm produce in the region include; groundnuts, cotton, cowpeas and gum Arabic. Others crops are; millet, rice, cassava, date palms, fruit, vegetables, sorghum, wheat, sweet potatoes, maize, sugar cane and also irrigation activities. (http://en.wikipedia.org/wiki/Kukawa).



A B

Figure 1: Location of the study area in red, A) in relation to the map of Borno State and B) in relation to a Landsat satellite image of 2000

3. Methodology

3.1 Satellite images

Three Landsat images acquired on three dates were used: Landsat5 TM 1984 l, Landsat 4TM 1992 and Landsat7 ETM+2000. The images were downloaded from the USGS website and geometrically corrected and projected to WGS 84 Universal Traverse Mercator Projection Zone 33.The Landsat ETM+2000 of a 15m pixel was resampled to a 30m pixel size so that the three images would be of the same pixel size to effectively carry out pixel-to-pixel change detection. Due to the nature of the landscape and also to make the application of the methodology easier, three band combinations were used in satellite images 2, 3 and 4 for the classification, whilst also bearing in mind the land cover responses to various Landsat spectral bands.

Table 1: Landsat image spectral band specifications

Bands	Wavelength(m)	Region
2	0.52 - 0.60 m	Near infrared
3	0.63 - 0.69 m	Red
4	0.76 - 0.90 m	Near infrared

Table 2: Landsat sensors platforms, paths/rows and pixel sizes

Sensor	Date	Platform	Path/Row	Pixel size(m)
TM	06/ 11/ 1984	Landsat 5	185/051	30
TM	22/ 12/ 1992	Landsat 4	185/051	30
ETM+	28/ 02/ 2000	Landsat 7	185/051	15

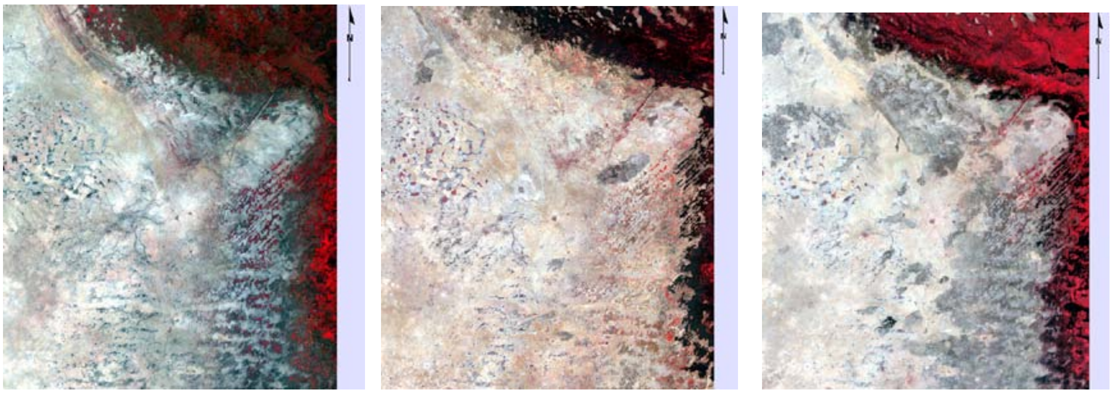

A B C

Figure 2: 30m pixel 1984 Landsat5 TM 234 band composite of the study area A), 30m pixel 1992 Landsat4 TM 234 band composite of the study area B), and 15m pixel 2000 Landsat5 TM 234 band composite of the study area C).

3.2 Methods

Landsat TM5, TM4 and ETM+ images were used as images 1, 2 and 3, as shown in figures 2, 3 and 4. For classification purposes, three bands of Landsat images were considered for classification, as stated in section 3.1. Three satellite images of the same scene acquired at different dates were sub-setted to carve out the area of interest, thereby, removing the less useful part since the focus was on a particular scene rather than the entire Landsat scene. The 2000 15m pixel size image was resampled to enable it have the same pixel size as the 1984 and 1992 images, which are 30m pixels in size. The images were classified to produce the land cover maps by applying the fuzzy membership function and the maps used as input in GIS to enable modelling the land cover changes: the magnitude of change (MC) and the nature of change (NC).

3.3 Fuzzy classification

Fuzzy image classification for this research is summarized into four parts: the development of the classification scheme, training site development, spectral signature development and fuzzy supervised classification. Four land cover classes were identified: dry soil, moist soil, vegetation and water body. Google earth/maps were used to aid the development of the classification scheme since site visitation was not possible. Lo (1986) suggested that the classification scheme should have no ambiguity and should be simple in terms of defining each land cover class. There are various fuzzy membership functions used for fuzzy classification in Idrisi Taiga 16.0: the sigmoidal, j-shaped, linear and user-defined functions. The sigmoidal membership function which is conceivably the most commonly used function in fuzzy set theory produced using the cosine function is used since it is good for a continuous surface. A total of four maps were produced from each image: one for each land cover class making it a total of twelve fuzzy land cover maps from three images.

Magnitude of Change (MC) was calculated using the spectral change vector analysis principle (Hegde, 2003), This is a GIS operation which was explored in IDRISI Taiga 16 GIS analysis, in which fuzzy operator is used to compute the difference between two fuzzy classified images through the summation of the absolute difference of the membership function of each class between two different dates.

$$MC_{(1)}=[\mu^1c(i)\ \ -\mu^2c(i)]/k\text{----------------------------------}\ 1$$

$\mu^1c(i)$=Pixel i of class k at date 1 membership function

$\mu^2c(i)$=Pixel i of class k at date 2 membership function

Nature of Change (NC) was obtained by comparison each pixel of two fuzzy classified images with a particular class of interests using a fuzzy operator in GIS environment. The comparison is one of inter classes rather than the same class at different dates. For instance, the following question could be asked: which pixels of class dry soil *D* in time t1 have changed to class water *W* at time t2, etc., that is, pixel *I*, which belongs to class *D* at time t1 to the extent $\mu^1 D$ (i)? Moreover, at time t2, it belongs to class *W* to the extent of $\mu^2 W$ (i), The membership value of change between class D and W can be mathematically depicted as NC (See Equation 2)

$$NC=\min\ [\mu^1 D(i),\ \mu^2 W(i)]\ \text{--------------------------------------}\ 2$$

This operation utilizes the operator that gives the least upper bound of a class of interest. This is archived by taking the minimum of two fuzzy membership values (Zadeh, 1965) since the operator provides the highest estimate for the membership of a particular change in a class, that is, from class *D* to *W* (Deer and Eklund, 2001), We can see that these elements can be interpreted as being the intersection of the two cover types (Peter et al., 2006) called fuzzy ***AND*** operator.

4. Results

4.1 Fuzzy maps of various types of land cover

Figure 3 shows the fuzzy maps of various land cover classes of the study area in 1984, 1992 and 2000. The columns represent the years, whilst the rows represent the fuzzy land covers. For example, row 1 is for dry soil for the periods 1984, 1992 and 2000, whilst row 2 is moist soil, row 3 is vegetation and, lastly, row 4 is for water. Column 1 is for the classes of land cover in 1984, column 2 is for 1992 and, lastly, column 3 is for 2000. The legend indicates the degree of fuzzy membership function of each class; that is, black (0) indicates areas without fuzzy membership, whilst red (1) shows areas with full fuzzy membership rising from above 0.

Looking at row 1, for dry soil, the maps reveal that the north-eastern and south-eastern regions are dark. This is because the study area is bordered by Lake Chad and the areas are mostly water and vegetation. Rows 3 and 4, on the other hand, show the occurrence of vegetation and water on that part of the map (north-eastern and south-eastern). It is possible to determine, in the three fuzzy dry soil maps, that the spatial extent of dry soil was the largest in 1992, having increased from 1984, and it reduced in 2000. Moreover, the second row shows that the largest extent of moist soil occurs in 2000. In addition, vegetation is less extensive during this year. Water, however, may be more extensive in this year, although it is hard to be certain of this from the map. The result shows how fuzzy classification modelled vagueness in land cover.

Table 3 shows the fuzzy areas covered by all the land cover classes for the periods under investigation, in both square kilometres and as a proportional percentage of the total area of the study, which is 3,572.986 square kilometres (km^2)

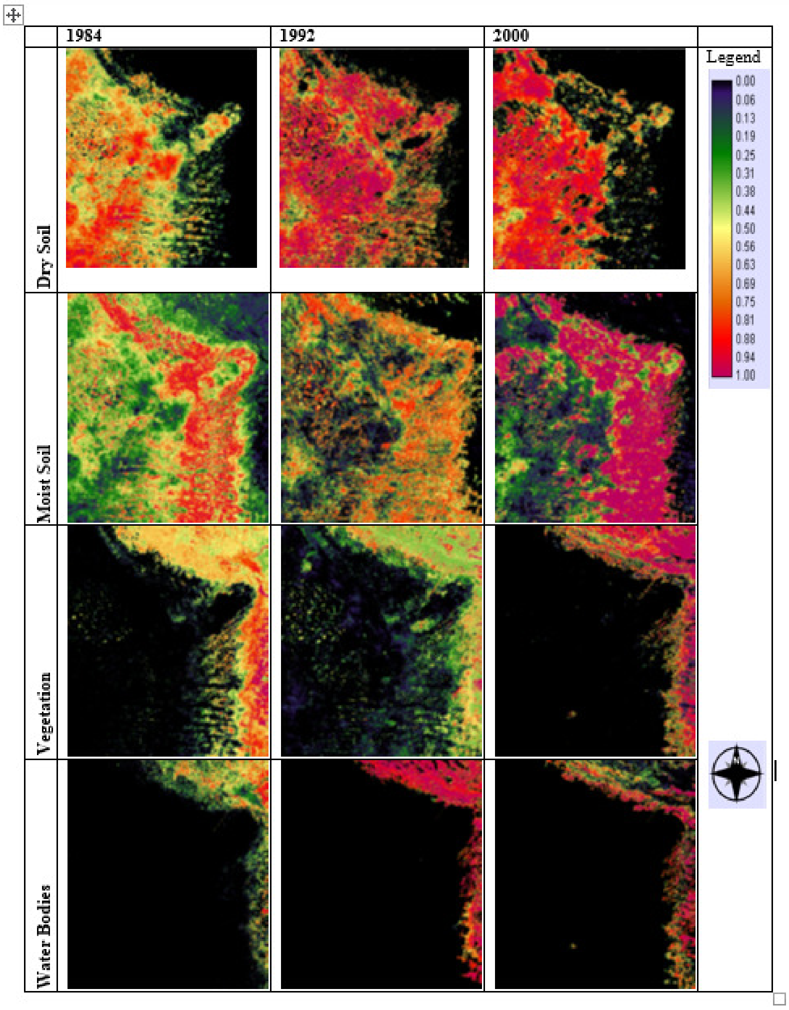


Figure 3: Maps of fuzzy land cover types for 1984, 1992 and 2000

Table 3: Fuzzy areas of land cover classes in 1984, 1992 and 2000

Land cover class	Area in square kilometres			Area as percentage		
	1984	1992	2000	1984	1992	2000
Dry Soil	1394.826	1724.60	1428.34	39.02	48.27	39.98
Moist Soil	1656.78	1325.53	1626.46	46.37	37.10	45.52
Vegetation	686.94	549.51	516.90	19.23	15.37	14.47
Water	134.66	238.25	259.69	3.77	6.67	7.27

4.2 Fuzzy magnitude of change in land covers: gains and losses

The full spatial pattern of gains and losses for 1984 to 1992 are shown in Figure 4(A) and for 1992 to 2000 in Figure 4(B). This type of results was archived because GIS was used; it has the ability to show the locations of where each land cover has gained or lost which will serve as a source of information to the environmentalist and policy makers. The rows show land cover classes whilst the columns show land cover gains (column 1) and losses (column 2). For example, row 1, column 1 and 2, shows the gain and loss in terms of dry soil in both 1992 and 2000 (figure 4B). The legend ranges from 0 to 1, which indicates the degree of gain and loss for the land cover types. In terms of gain in column 1, black (0) indicates areas without fuzzy membership (no gain), whilst anything above 0 to 1 shows areas with fuzzy membership (gain).

Table 4: Gains and losses of fuzzy land cover from 1984 to 1992.

Land cover class	Area in square kilometres		Area as percentage	
	Gain	Loss	Gain	Loss
Dry soil	578.55	189.07	41.48	13.56
Moist soil	328.40	650.41	19.82	39.26
Vegetation	110.31	264.41	16.05	38.49
Water	148.88	43.82	110	32.54

With regard to loss in column 2, black (0) indicates areas without fuzzy membership (no loss), whilst anything above 0 to 1 shows areas with fuzzy membership (loss), GIS operation where used to generate this maps whilst fuzzy approach made it possible to know area that gain or loss more. Tables 4 and 5 show the amount of gain and loss for the land cover types for 1984 to 1992 and 1992 to 2000 respectively. Dry soil, for example, gains 578.55km^2 and loses 189.07km^2 in 1992 whilst it gains 295.00km^2 and loses 584.59 km^2 in 2000.

Table 5: Gains and losses of fuzzy land cover from 1992 to 2000**.**

Land cover class	Area in square kilometres		Area as percentage	
	Gain	Loss	Gain	Loss
Dry Soil	295.00	584.59	`17.11	33.90
Moist soil	709.61	417.82	53.53	31.52
Vegetation	224.12	240.96	40.79	43.85
Water	167.96	140.87	70.49	59.13

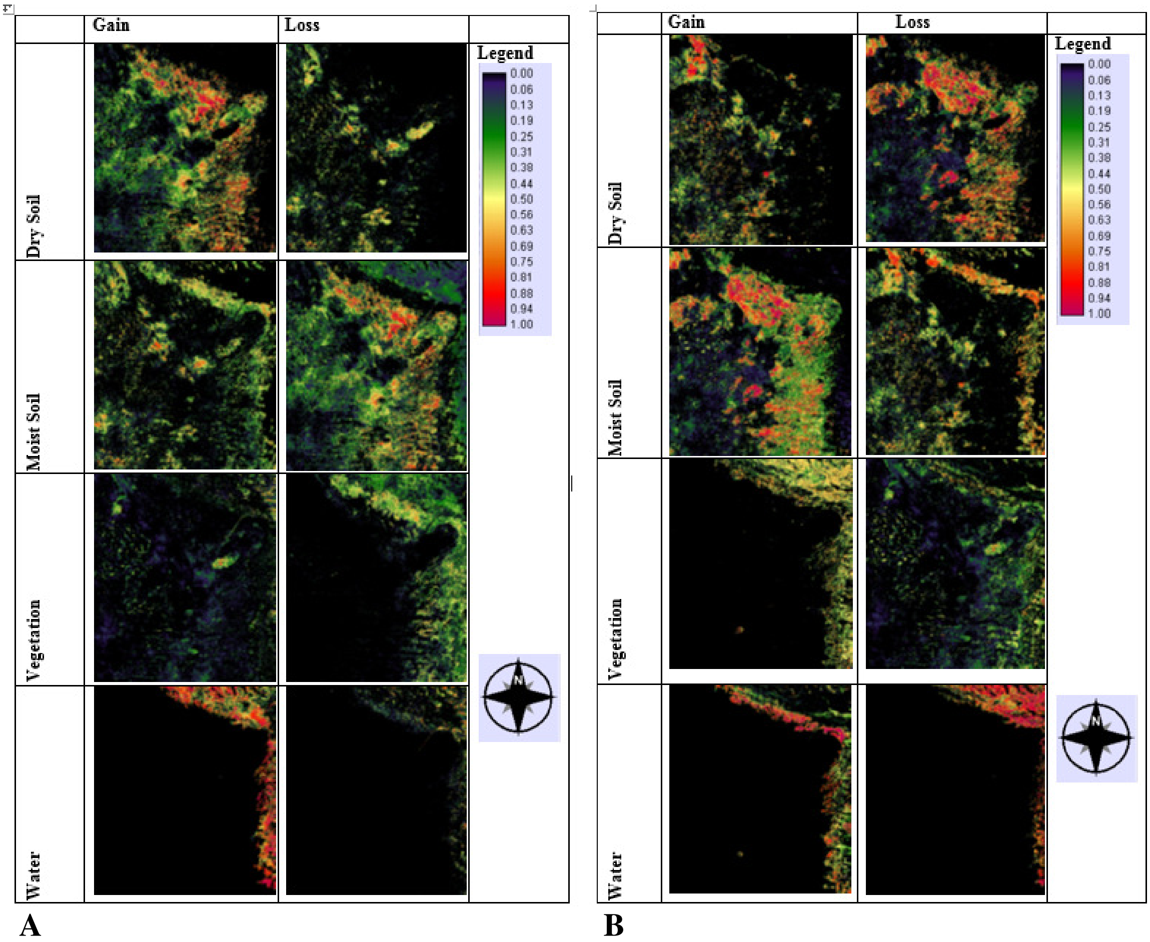


Figure 4: Fuzzy MC maps: gains and losses between 1992 and 2000 (A), between 1984 and 1992 (B).

4.3 Nature of changes

The NC entails comparing each land cover type with the others to determine which is taking from which using GIS techniques. A loss in any particular land cover type could lead to a gain by more than one land cover type. The rows represent changes (conversion) from all the classes to a single class, whilst the columns represent conversion from a single class to all the classes (many to one, rows and one to many, columns), as shown in figures 5 and 6 for the periods 1984 to 1992 and 1992 to 2000 respectively. These types of queries was made possible using GIS and are important when information is needed about the extent to which a particular land cover is changing; for example, a pixel belonging to the moist soil class in 1984 to the extent of $(m)\mu^1$ belonged to forest and water, etc., to the extent of $(f)\mu^2$ and$(w)\mu^3$,in 1992. Also, the fuzzy maps generated from GIS operations is able to graphically show where the conversion are taking place as well as their magnitude

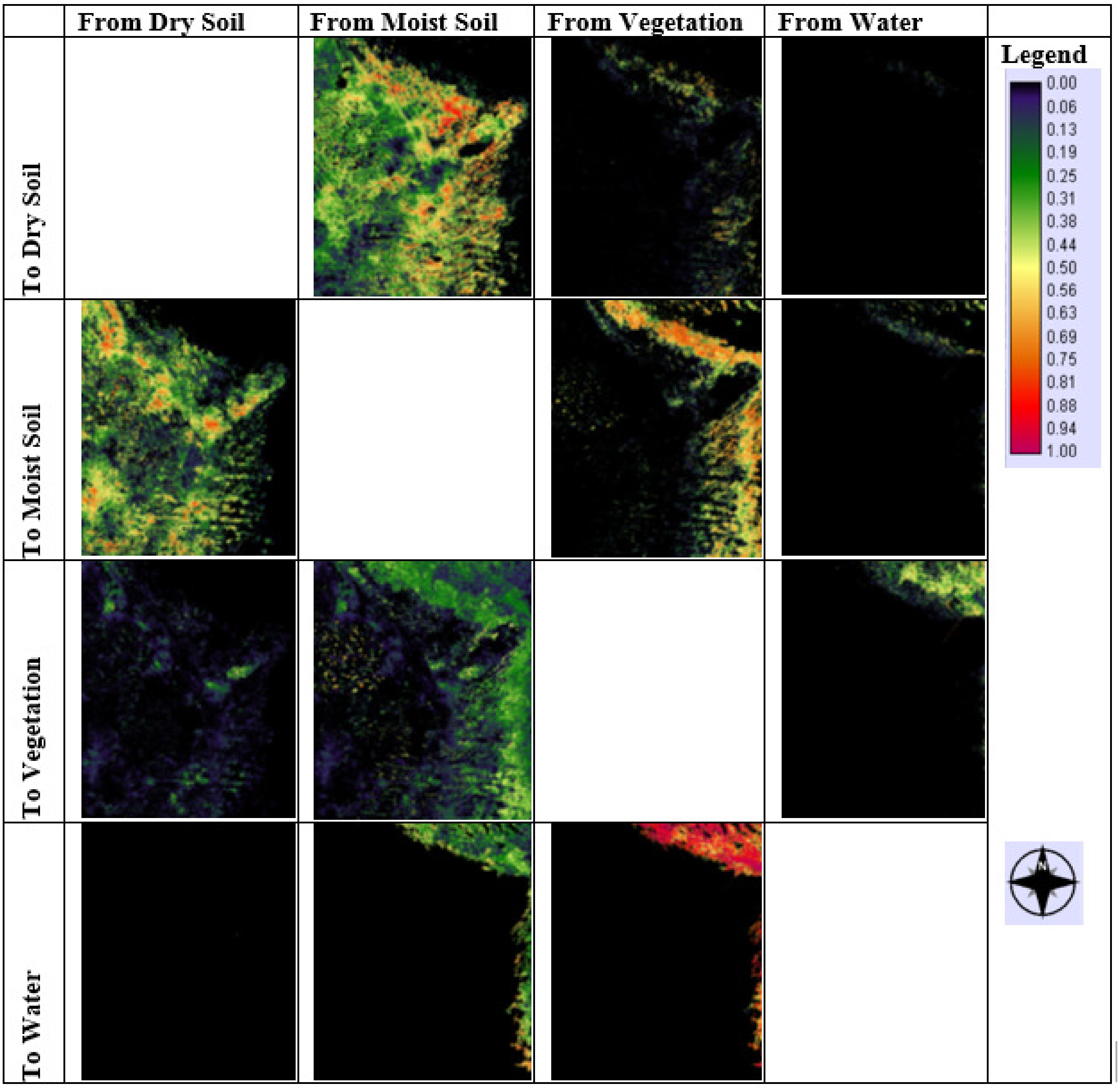


Figure 5: Fuzzy maps of the NC between the land cover types from 1984 to 1992

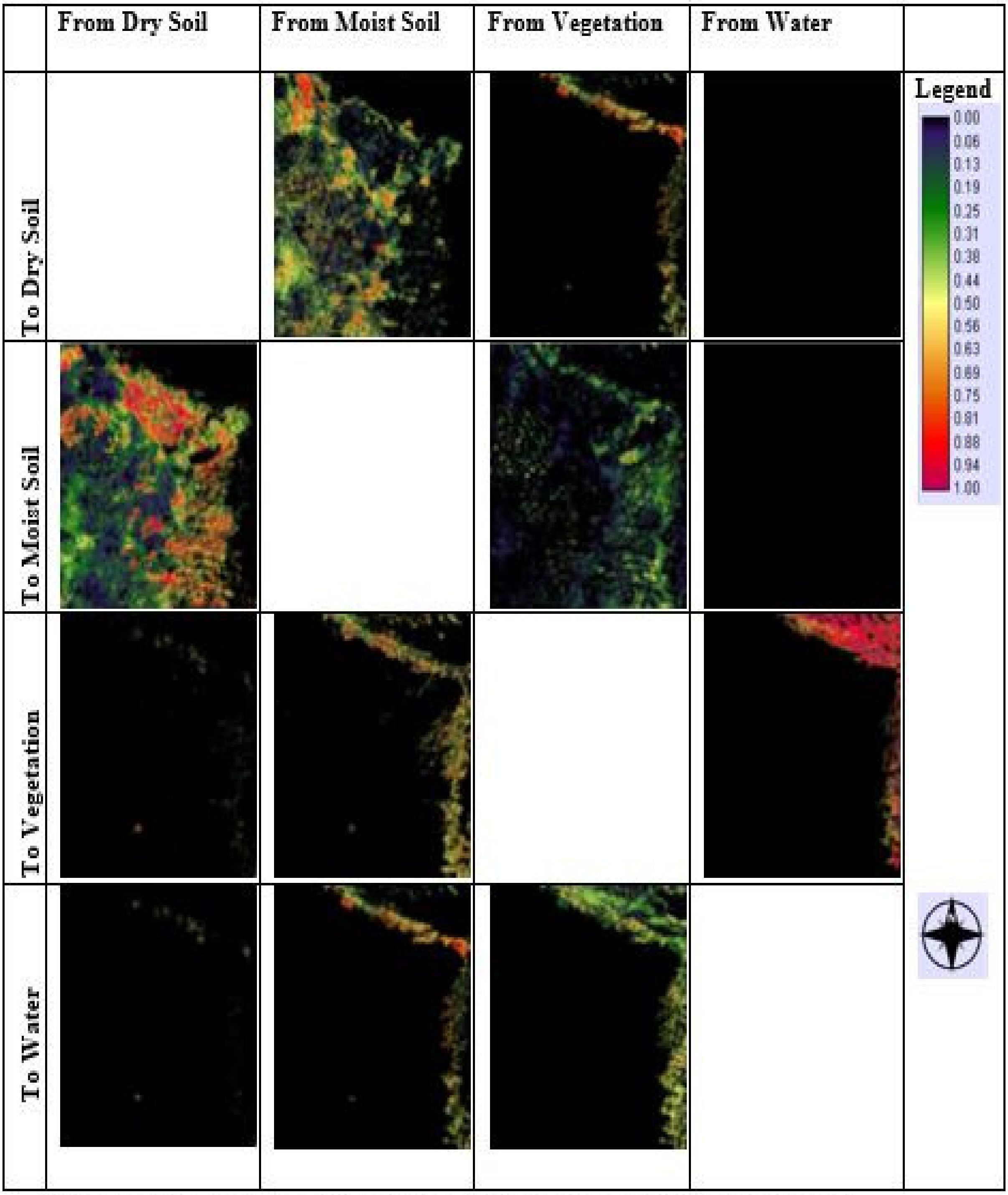


Figure 6: Fuzzy maps of the NC between the land cover types from 1992 to 2000

5. Discussion

This work has modelled the land cover changes in North-Eastern Nigeria using GIS techniques combined with Fuzzy approach of land cover modelling to reveal the depth of the uncertainty and also reported the fuzzy area itself as a fuzzy number (Fisher, 2010), The advent of GIS has really brought about new invention in the field of land cover modelling; whilst fuzzy is able to reveal the amount of uncertainties in land cover, GIS is able to show (maped) the uncertainties. Post-classification comparison method is used for quantitative analysis (Jerson, 1996) which involves the comparison of two or more fuzzy classified images of the same scene taken at different dates to determine the amount of changes that have occurred (The magnitude and the nature), The maps produced are significant as they will help the policy makers and the environmentalist as well as the Federal Government of Nigeria and other agencies to know where to focus their scarce resources in taking measures that would help in solving environment problem in this region with known incident of desertification.

5.1 Extent of Fuzzy Land Covers Classes

The results in Figure 3 shows the spatial extent of various fuzzy land cover classes in the study area for the periods of 1984, 1992 and 2000 which shows a subtle variation (Fisher et al, 2006). It is observed that dry soil increases in spatial extent and fuzzy membership (degree of belonging) by 1992 compared with 1984 but that it decreases again by 2000, although it remains higher than 1984 in fuzzy membership but smaller in spatial extent. However, moist soil did not show much difference between 1984 and 1992. It extended spatially but also decreased in fuzzy membership compared with 1984, which indicates some level of loss. There was a noticeable increase in spatial extent and fuzzy membership by 2000 in areas close to Lake Chad, i.e., towards the eastern part of the map, which indicates gains. The vegetation shows a larger spatial extent and fuzzy membership on the 1984 map compared with the 1992 and 2000 map. This shows a decrease in both the extent and the fuzzy membership of the vegetation in 1992. The 2000 map shows a higher fuzzy membership of vegetation than in both 1984 and 1992, especially around Lake Chad, although it has a smaller area coverage, which indicates continued loss. This could be as a result of the vegetation mainly comprising of ***Typhaaustralis*** (*Aligeti 2011),* which grows on the waters of Lake Chad. There was increase in the water body in 1992, which could also explain why there is less vegetation that year. The water body has a smaller spatial extent but with the highest fuzzy membership in 1992 compared with 1984 and 2000, which has a higher spatial extent. Unlike the hard classification, the fuzzy maps are able to shows the vagueness and the intensity in the land cover maps. This types of maps are important in taking decision by policy makers or environmentalist e.g. if the government want to choose a site for irrigation scheme, the map will not only tell where water is, but places with more water to grow crop based on the water content in the soil i.e. for moist soil, there are different level of moisture. Some crop requires high level of moisture whilsts some do not. This could only be possible using fuzzy approach of image classification with GIS.

Figure 7 (derived from Table 3) show the land cover areas in percentage. Dry soil covers 39.02% in 1984, 48.27% in 1992 and 39.98, which shows a decrease in 2000. However, the area covered in 2000 is still higher than that in 1984, i.e., 39.02% in 1984 and 39.98% in 2000.Figure 8, moist soil occupied 46.37% (1984), 35.1% (1992) and 45.52% (2000), which shows a decrease in 1992 from 1984 and an increase in 2000. However, it occupied less space in 2000 than in 1984. Vegetation on the other hand showed a continuous decrease from 19.23% (1984), 15.37% (1992) to 14.47% (2000). The reason why this is so, may be due to the human activities (Abubakar, 2002) e.g. over grazing. This is what happens when demand exceeds supply. Within the study area, water body continues to increase from 3.77% (1984), 6.67% (1992) to 7.27% (2000) as shown in Figure 7

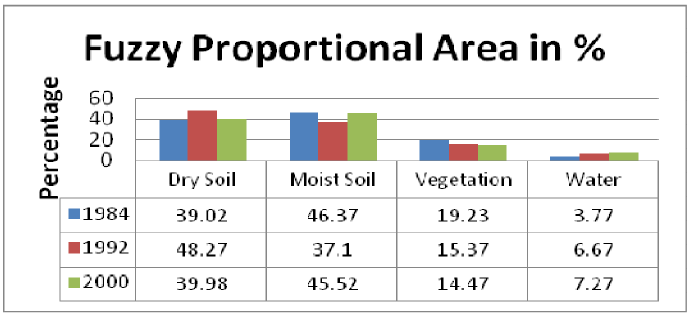


Figure 7: Fuzzy proportional land cover areas from 1984, 1992 and 2000 derived from Table 3

5.2 Magnitude of change: fuzzy land cover gains and losses

Figures 4A and 4B show the spatial extent of gains and losses in 1992 and 2000, respectively, this was made possible using GIS. It is not just enough to know that the land cover types have changed, but more interesting is' which type of change is it, is the changes positive or negative and where are the changes occurring? The use of GIS made it possible for these questions to be answered whilst fuzzy classification is able to give answer to the degree (intensity) of gain and loss in particular location. Figure 8 (derived from Table 4 and 5), shows that the dry soil gained 41.48% and lost13.56% in 1992, whilst it lost 33.9% and gained 17.11% in 2000. This shows that dry soil did not lose more than it gained in 1992; it suffered a reduction but not below its initial quantity in 1984, i.e., it gained three times what it lost in 1992 and lost only two times what it gained in 2000. Moist soil gained 19.82% and lost 39.26% in 1992, whilst it gained 53.53% and lost 31.51% in 2000. Moist soil did not gain in 2000 as much as one half of what it lost in1992, whilst in 2000 it gained about one half of what is lost in that same year. Vegetation has been losing continuously, although it gained more in 2000 and as well lost more. It gained 16.05% and lost 38.49% in 1992, whilst it gained 40.79% and lost 43.85% in 2000. Its losses are always more than the gains. The water body has gained continuously from 1992 to 2000, it gained 110% and lost 32.25% (three times what it lost) in 1992, whilst it gained 70.49% and lost 59.13% in 2000. This shows that water is the highest gainer, followed by dry soil, moist soil and lastly vegetation, whilst moist soil is the highest loser in 1992. The full list of gains and losses is shown in Figure 8

5.3 Nature of change

The maps in Figures 5 and 6 shows the spatial extent and the degree (intensity) of land cover changes in 1992 and 2000. Figure 6 column 1 shows a noticeable change from dry soil to moist soil and vegetation, whilst any change from dry soil to water is not noticeable. The change from dry soil to moist soil is more prominent, followed by the change to vegetation. Moist soil changes to all the three other classes: dry soil, vegetation and water with the dry soil having the largest portion (column 2). Vegetation also changes to all the other classes with water and moist soil taking the largest portions (column3), whilst dry soil takes the least. There was no change from water to dry soil (column4) but there was change from water to moist soil and vegetation, the latter taking the larger portion. In 1992, moist soil and vegetation changed to all classes, whereas dry soil and water did not. In addition, all classes changed to moist soil and vegetation in 1992, whereas water and dry soil did not get changes from all the others. The maps show that dry soil and water get more from the changes in1992.

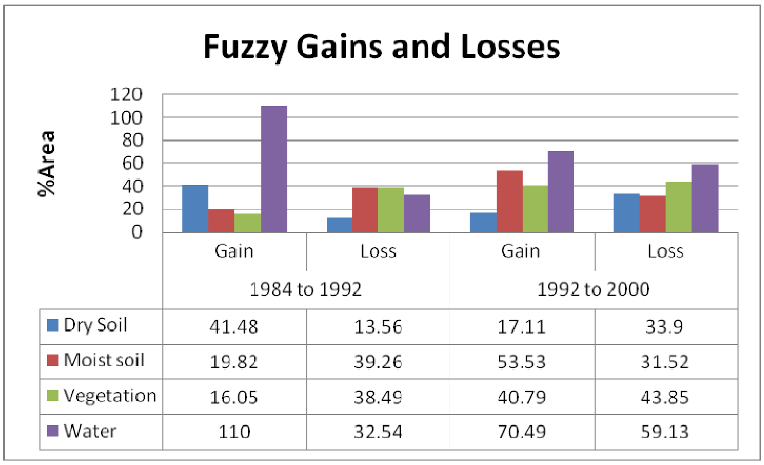


Figure 8: Fuzzy gain and losses areas as percentages

In 2000 (Figure 6), there were changes from dry soil, moist soil and vegetation to all classes except from water. Moist soil took the largest portion from dry soil, whilst vegetation and water have almost the same extent (column 1). The water changes only to vegetation in 2000 but gets changes from all (column 4, row 4). Whilst the dry soil, moist soil and vegetation changes to all classes (column 1, 2 and 3). This shows the patterns on how the areas of land cover changes i.e. which changes from what and what is changing to which. This could help the policy makers in making decisions since the pattern of change is known.

5.4 Conclusions

This research has explored the use of GIS combined with fuzzy classification to model the land cover changes in the North-Estern Nigeria using remote sensing data. Fuzzy Supervised classification was used, using normalized sigmoidal fuzzy membership function. The result will go along way in helping the United Nation as well as the Federal Government of Nigeria in solving enviromental problems in the region. The maps did not only model the changes, but the degree (intensity) of the changes. These maps will help the policy makers in determining places that need more urgent attention since the intensity of land cover changes are not the same across the spatial extent therefore increasing efficiency. The fuzzy approach to change detection conbine with GIS techniques has proved effective in modelling vague landscapes i.e areas with incidences of desertification.

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