Land Use Change Analysis Using Remote Sensing and Markov Modeling in Fincha Watershed, Ethiopia

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ABSTRACT

This study assessed land use and land cover change in the Fincha watershed located in Oromiya Regional State, Ethiopia, between 1985 and 2005 using the technologies of remote sensing and Markov modeling. The results indicated that agricultural land and water bodies have increased in area by 60,606 (53.59%) and 19,184 ha (93.10%), respectively. During this period, tremendous losses in forest, grazing land, swamp area and shrub lands were observed by as much as 36,225 (50.48%), 17,376 (31.23%), 19,948 (51.37%) and 6,240 ha (24.81%), respectively. During the study period, the land use and land cover change process showed no sign of being stable. The use of satellite remote sensing and Markov modeling was found to be beneficial in describing and analyzing the direction, rate and spatial pattern of land use and land cover change.

Keywords: Land use change, remote sensing, Markov modeling, Fincha, Ethiopia

INTRODUCTION

Today, land use and land cover change is perhaps the most prominent form of global environmental change since it occurs at spatial and temporal scales immediately relevant to our daily existence (Turner *et al*., 1995). This change, when coupled with climate change and variability, is likely to affect natural resources and ecosystems in complex ways. It causes a multitude of environmental impacts such as an increase in the risk of floods and landslides, changes in the hydrological balance, soil erosion, sedimentation, and soil and ground water contamination, among others.

Conversion of forest and shrub and grass lands to agricultural land is prevalent in Ethiopia due to the lack of land use planning in the country,

with the Ethiopian Forestry Action Program (EFAP, 1994) reporting that over 97% of the forest cover of the country had been lost. Bezuayehu (2006) reported that the Fincha watershed is a typical example of watersheds in the country that had undergone land use changes. The watershed had gradually been encroached by agricultural activities.

Since 1973, when a hydroelectric reservoir dam was constructed in the watershed, the backwater flow has inundated large swamp areas, grazing and agricultural lands and caused major land use changes (Bezuayehu and Strek, 2008) and evicted many people from their original settlements (Aseffa, 1994; OADB, 1996). Consequently, the displaced farmers moved to the upstream steep area and engaged in the conversion of significant amounts of forest and shrub and

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grass lands to agricultural lands that has brought about fundamental changes in the land cover patterns in the study area. In 1975, downstream of the Fincha reservoir was chosen as a state farm for the production of food and commercial crops, following which, large scale forest clearance was observed in the area.

So far, information on the spatial distribution of the dynamics of land use and land cover and its temporal behavior at the watershed level is scarce in Ethiopia in general, and in the Fincha watershed in particular. In the Fincha watershed, land use and land cover change has occurred at a faster than normal rate. The growing population, an increasing demand for cultivated land and increasing socio-economic necessities have created pressure on the land. This pressure has resulted in unplanned and uncontrolled changes in land use and land cover in the area. Knowledge of these changes, the magnitude of different land use and land cover changes, and the implications of these changes are negligible in the study area. Hence, there is an urgent need to evaluate the magnitude, pattern and type of land use and land cover changes and to project future trends in the study area.

Recently, the techniques of satellite remote sensing have been widely applied and been recognized as a powerful and effective tool in detecting land use and cover change (Ehlers *et al.*, 1990; Meaille and Wald, 1990; Treitz *et al.*, 1992; Westmoreland and Stow, 1992; Harris and Ventura, 1995; Yeh and Li, 1999; Weng, 2001).

The aims of this paper were (i) to analyze the dynamics of land use and land cover; and (ii) to derive information on the spatial distribution of change in the Fincha watershed, Ethiopia, during the period 1985 to 2005 using satellite remote sensing data, a geographic information system (GIS) and Markov modeling.

MATERIALS AND METHODS

Study area

The Fincha watershed is located in the Horro Guduru Wollegga Zone, Oromiya Regional State, Ethiopia, between 9°10′05″ N to 10°00′59″ N and 37°00′16″ E to 37°33′20″ E (Figure 1). The Fincha watershed, with an area of 3,251 km^2, is one of the sub-basins of the Nile River Basin. The topography of the watershed is rolling to hilly and ranges in elevation from 1,043 to 3,196 m above sea level (asl). Its climate is 'tropical highland monsoon' with the annual rainfall ranging from 960 mm to 1,835 mm (Figure 2) having peaks during June to August. The mean monthly minimum and maximum temperatures of the area vary from 6.0 to 16.0 °C and from 19.5 to 31.5 °C, respectively (Figure 2).

Mixed farming (integrated crop-livestock production) is the main agricultural system in the watershed. The watershed has a wide range of soil types mainly dominated by clay-loam, clay and loam soil (Bezuayehu, 2006). The largest portion of the watershed area is under intensive cultivation characterized by clay soil commonly associated with swamps and temporary wetlands on the plains with good to moderate fertility.

Data acquisition

Landsat TM (Thematic Mapper) imagery acquired on 22 November, 1985 and Landsat ETM+ (Enhanced Thematic Mapper plus) imagery acquired on 25 November, 1995 and 24 November, 2005 were used as the base data layers from which the land use and land cover maps of the study area were derived. All images were downloaded from the Global Land Cover Facility (GLCF) using an Earth Science Data Interface. All three images have a 28.5 m ground resolution and were used to map the land use and land cover patterns of the study area. The dates of the images were chosen as closely as possible to be in the same vegetation season.
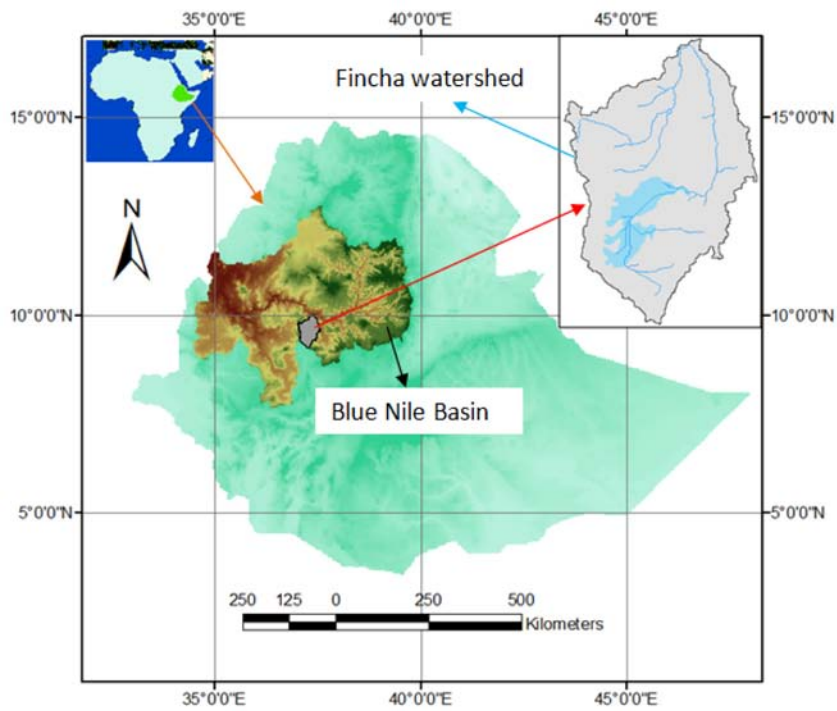
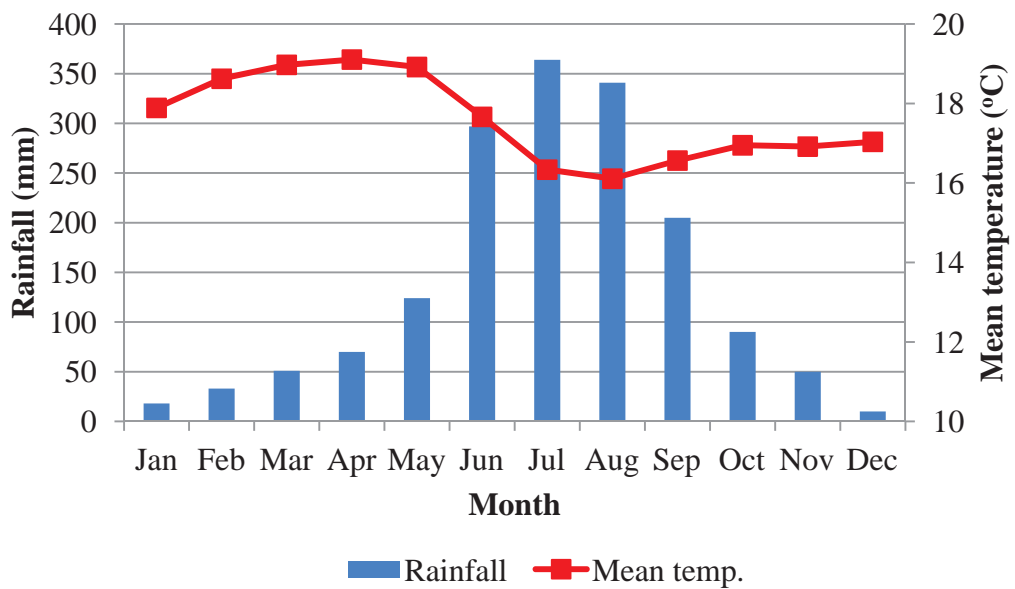**Figure 1** Location of Fincha watershed in Blue Nile basin, Ethiopia.

Figure 2 Mean monthly temperature and rainfall of Fincha watershed.

Image preprocessing

Preprocessing of the satellite imagery prior to image classification and change detection is essential; it improves the image data that suppresses undesired distortions or enhances some image features relevant for further processing and analysis tasks (Teillet, 1986). Preprocessing commonly comprises a series of sequential operations, including radiometric normalization, image registration, geometric correction, and masking of clouds, water and irrelevant features (Coppin and Bauer, 1996). The normalization of satellite imagery takes into account the combined, measurable reflectance of the atmosphere, aerosol scattering and absorption, and the earth's surface (Kim and Elman, 1990). It is the volatility of the atmosphere which can introduce variation between the reflectance values or digital numbers of satellite images acquired at different times. Geometric rectification of the imagery resamples or changes the pixel grid to fit that of a map projection or another reference image.

To conform the pixel grids and remove any geometric distortions in the imagery, the first Landsat TM 1985 image was registered and geo-referenced to the UTM, WGS84 (zone 37) coordinate system based on 1:50,000 scale topographic maps. Each of the Landsat ETM+ 1995 and ETM+ 2005 images were then registered to the 1985 image (image to image registration). To keep the original brightness values of pixels unchanged, the data were re-sampled using the nearest neighbor algorithm. This method uses the value of the closest pixel to assign to the output pixel value and thus transfers original data values without averaging them as other methods do; therefore, the extremes and subtleties of the data values are not lost (ERDAS, 1999).

Image classification and accuracy assessment

Image classification refers to the extraction or grouping of a digital image from raw, remotely sensed, digital satellite data into different classes within a particular dataset, based on attribute values. It is done to replace visual analysis of the image data with quantitative techniques. Image classification can use either supervised or unsupervised classification method. The flowchart in Figure 3 shows the procedures used to produce the land use and land cover map of the Fincha watershed.

Since the identity and location of some of the land use and land cover types such as, agricultural land, forest and shrub land, water bodies, among others were known based on the *a priori* knowledge of the study area, the author's personal experience, ground truth data and information from previous studies in the area, a supervised signature extraction with a minimum distance algorithm was used in ERDAS Imagine 9.1 (ERDAS Inc., Atlanta, Georgia, USA) and ENVI (EXELIS Visual Information Solutions, Inc., Boulder, CO, USA) to classify the images. Multi-temporal signatures were generated from all three datasets—the Landsat TM image data of 1985 and the Landsat ETM+ image data of 1995 and 2005. All visible and infrared bands of 1, 2, 3, 4, 5, and 7, but excluding band 6 (the thermal infrared), were included in the analysis.

Supervised classification processes involve the initial selection of areas (training sites) on the image which represent specific land classes to be mapped. Training sites are sets of pixels that represent what is recognized as a discernable pattern, or potential land cover class (ERDAS, 1999). Training sites for signature generation were developed from ground truth data. A total of 200 training sites were chosen for each image to ensure that all spectral classes constituting each land use and land cover category were adequately represented in the training statistics. Based on a modified version of the Anderson scheme of land use and land cover classification method (Anderson *et al*., 1976), six land use and land cover classes were established for the study area—namely, (1) agricultural land, (2) forest land,
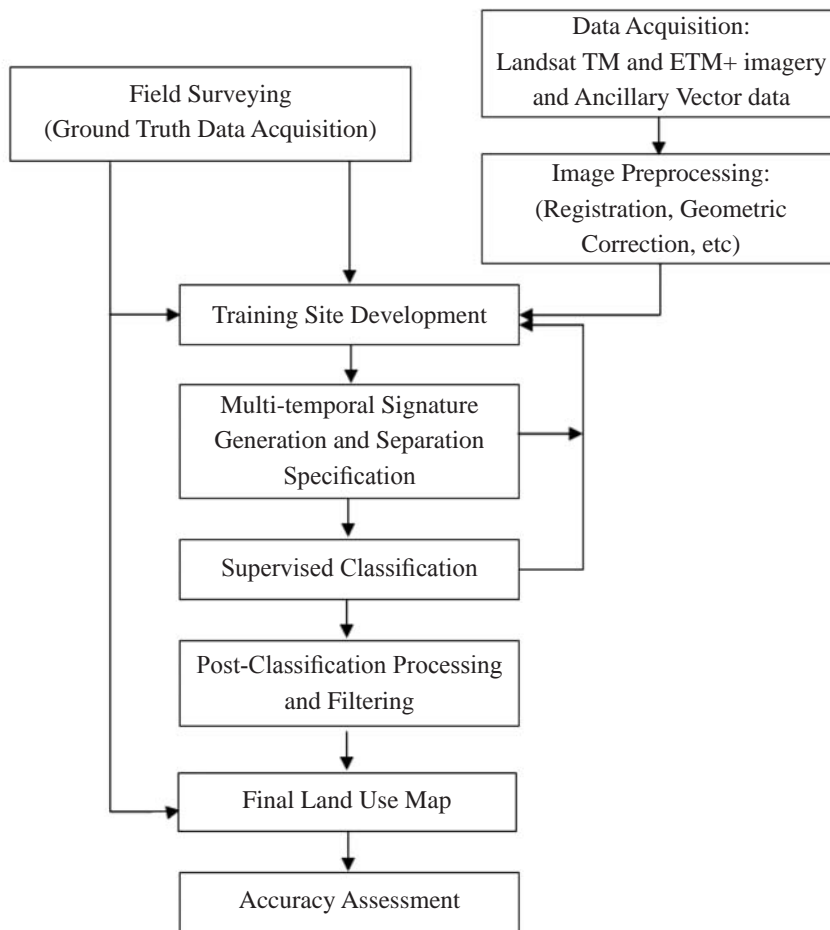
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                                                │ Landsat TM and ETM+ imagery │
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│     Field Surveying         │                 │   Image Preprocessing:      │
│ (Ground Truth Data Acquisition) │              │  (Registration, Geometric   │
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Figure 3 Flowchart showing land use and land cover mapping procedures.

(3) grazing land, (4) water bodies, (5) shrub lands, and (6) swamp areas. The land use and land cover classes for the 1985, 1995, and 2005 images are depicted on Figures 4, 5, and 6, respectively.

An error matrix was established to evaluate the accuracy of the classification. An error matrix is a square array of numbers laid out in rows and columns that expresses the number of sample units assigned to a particular category relative to the actual category as verified in the field. It is the most common and a very effective way to represent the accuracy of the classification results, as the accuracy of each category is clearly described (Fan *et al.,* 2007). The ground truth data

(reference data) used were collected from field surveys and existing land use/cover maps that had been field-checked using a stratified random sampling method, that involved a sample of 100 pixels being randomly selected for each land use and land cover category. Overall accuracy, user's and producer's accuracies, the Kappa statistics, as well as the commission and omission errors were derived from the error matrices.

The overall accuracy is computed by dividing the total correct pixels (sum of the major diagonal) by the total number of pixels in the error matrix. The user's accuracy, calculated by dividing the number of correctly classified pixels

in a class by the total number of pixels assigned to that class, is the probability that the mapped class (for example, agricultural land) correctly represents its ground distribution. The producer's accuracy, calculated by dividing the total number of correctly classified pixels in a class by the total number of reference measurements of that class, is the probability that a class identified from the reference data is correctly classified on the map. Commission errors are those that misclassify a pixel to another class, while omission errors occur when pixels are erroneously excluded from a class (Congalton and Green, 1999). Errors of commission reduce the user's accuracy while errors of omission reduce the producer's accuracy (Stehman, 1997). The Khat statistics (an estimate of Kappa), which provides a measure of how many more pixels were correctly classified than expected by chance (Congalton and Green, 1999) was also calculated.

Analytical background of Markov modeling

Markov chains have been used to model changes in land use and land cover at a variety of spatial scales. Markov analysis looks at a sequence of events and analyzes the tendency of one event to be followed by another. Using this analysis, a new sequence of random but related events can be generated, which appear similar to the original. Land use studies using Markov chain models involve both urban and nonurban areas (Bell and Hinojosa, 1977; Robinson, 1978; Jahan, 1986; Muller and Middleton, 1994). All of these studies use the first-order Markov chain models and stationarity has usually been assumed, except in a few instances (Bourne, 1971; Bell, 1974).

Markov chain models have several assumptions (Stewart, 1994). One basic assumption is to regard land use and land cover change as a stochastic process, and different categories are the states of a chain. A chain is defined as a stochastic process having the property that the value of the process at time t, X_t, depends only on its value at

time t-1, X_{t-1}, and not on the sequence of values $X_{t-2}, X_{t-3}, \ldots, X_0$ that the process passed through in arriving at X_{t-1}. In this study, the index t represents time. The process is considered discrete in time and $t = \{0, 5, 10 \ldots\}$ years approximately, which is a reasonable time unit for studying land use and land cover change phenomena. Stochastic processes generate sequences of random variables by probabilistic laws. If the stochastic process is a Markov process, then the sequence of random variables will be generated by the Markov property (Weng, 2002) as shown in Equation 1:

$$P\left\{X_t = a_j \mid X_0 = a_0, X_1 = a_1, ..., X_{t-1} = a_i\right\}$$

$$= P\left\{X_t = a_j \mid X_{t-1} = a_i\right\} \qquad (1)$$

The term $P\left\{X_t = a_j \mid X_{t-1} = a_i\right\}$, known as the one-step transitional probability, gives the probability that the process makes the transition from state a_i to state a_j in one time period. When ℓ-step is needed to implement this transition, the $P\left\{X_t = a_j \mid X_{t-1} = a_i\right\}$ is then called the ℓ-step transition probability, $P_{ij}^{(l)}$. If the $P_{ij}^{(l)}$ is independent of the times and dependent only upon the states a_i, a_j, and ℓ, then the Markov chain is said to be homogeneous. In this study, the treatment of Markov chains was limited to a first-order homogeneous process. A first-order process is a process where the transition from one class to any other does not require intermediate transitions to other states. In this event, as shown by Equation 2:

$$P\left\{X_t = a_j \mid X_{t-1} = a_i\right\} = P_{ij} \qquad (2)$$

where P_{ij} can be estimated from observed data by tabulating the number of times the observed data went from state i to j, n_{ij}, and by summing the number of times that state a_i occurred, n_i. Then Equation 3 is applicable:

$$P_{ij} = n_{ij} / n_i \qquad (3)$$

The Markov model also assumes that the future is independent of the past given the present. That means, as the Markov chain advances in time, the probability of being in state j after a sufficiently large number of steps becomes independent of the initial state of the chain. When this situation occurs, the chain is said to have reached a steady state. Then, the limit probability, P_j, is used to determine the value of $P_{ij}^{(l)}$ in Equation 4:

$$\lim_n P_{ij}^{(n)} = P_j \qquad (4)$$

where $P_j = P_i P_{ij}^{(n)}$ $j = 1; 2, \ldots m$ (state), $P_i = 1$ $P_j > 0$.

As land use and land cover change reflects the dynamics and interplay of economic, social and biophysical factors over time, it would be implausible to expect stationarity in land use and land cover data. However, it might be practical to regard land use and land cover change to be reasonably stationary through time. A stationary system is one in which the probabilities that govern the transitions from state to state remain constant with time. In other words, the probability of transition from some state i to another state j is the same regardless of the point in time that the transition occurs.

Markovian analysis of land use/cover change process

Markovian modeling is used to examine the stochastic nature of the dynamics of land use and land cover data and to project the stability of future land development in the study area. Based on the land use and land cover change data derived from satellite images, this study also establishes the validity of the Markov process for describing and projecting land use and land cover changes in the study area, by examining statistical independence, Markovian compatibility and stationarity of the data.

The testing of the statistical independence hypothesis involves a procedure for comparing the expected numbers under the Markovian hypothesis

with the actual data. If the number of land use and land cover categories is n, then the statistic to be computed is a chi-square distribution (χ^2) with $(n-1)^2$ degrees of freedom. Letting N_{ik} stand for the number of cells having category i in 1985 and k in 2005, and E_{ik} for the expected number under the Markov hypothesis, the statistic is then given by Equation 5:

$$\chi^2 = \sum_i \sum_j \left(N_{ik} - E_{ik} \right)^2 / E_{ik} \qquad (5)$$

Thus, the 0.05 critical region for $n = 6$ is any value of χ^2 greater than 37.65. Any computed value less than this critical number will lead to a conclusion that the data are compatible with the hypothesis of independence.

The computation of the expected number E_{ik} requires a direct application of the Chapman Kolmogorov equation (Stewart, 1994), which states that the transition probabilities from the years 1985 to 2005 can be calculated by multiplying the transition probabilities matrix from the years 1985 to 1995 by the transition probabilities matrix from the years 1995 to 2005. These transition probabilities can be computed with the aid of the GIS analysis function, and used in Equation 6 to calculate the expected numbers:

$$E_{ik} = \sum_j (N_{ij})(N_{jk}) / N_j \qquad (6)$$

where N_{ij}: is the number of transitions from category i to j during the period 1985 to 1995; N_{jk} is the number of transitions from category j to k during the period 1995 to 2005; and N_j: is the number of hectares in cells in category j in 1995.

To test for first-order Markovian dependence, a chi-square goodness-of-fit test is used. This statistical test judges whether or not a particular distribution adequately describes a set of observations by making a comparison between the actual number of observations and the expected number of observations. The statistic is calculated from the relationship shown in Equation 7:

$$\chi_c^2 = \sum_i \sum_j \left(O_{ik} - E_{ik}\right)^2 / E_{ik} \qquad (7)$$

where O_{ik} and E_{ik} are the observed and expected number of transition probability from 1985 to 2005, respectively. The distribution of E_{ik} is a chi-square distribution (χ_c^2) with $(n\text{-}p\text{-}1)^2$ degrees of freedom where n is the dimension of the matrices and p is the number of parameters estimated from the data. The hypothesis that the data are from the Markovian distribution is rejected if Equation 8 is true:

$$\chi^2 > \chi_c^2 \qquad (8)$$

Finally, the hypothesis of stationarity is tested. The significance of stationarity of a Markovian process is that one can project future land development based on the current transition probabilities. According to the stationarity assumption, the changes recorded over the first 10-year period (1985 to 1995) and the second 10-year period (1995 to 2005) should result from the same transition mechanism. If this holds true, both can be used to project the pattern of distribution indefinitely into the future. The resulting equilibrium, or steady state distributions, may provide an indication of the ultimate trend of the land development process.

RESULTS AND DISCUSSION

The land use and land cover maps of the Fincha watershed were produced for the years 1985, 1995, and 2005 from the Landsat images and were depicted on Figures 4, 5, and 6, respectively. The overall accuracy of each respective map was 86.18%, 86.76%, and 87.5% with KAPPA indices of 0.83, 0.84, and 0.85, respectively. These data meet the minimum standard of 85 percent stipulated by the USGS classification scheme (Anderson *et al.*, 1976). Overall, the user's and producer's accuracies were high.
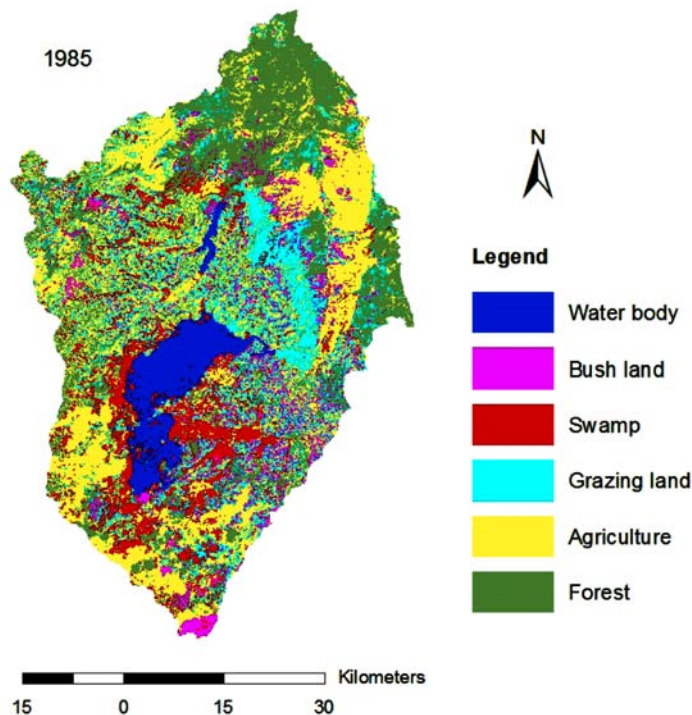

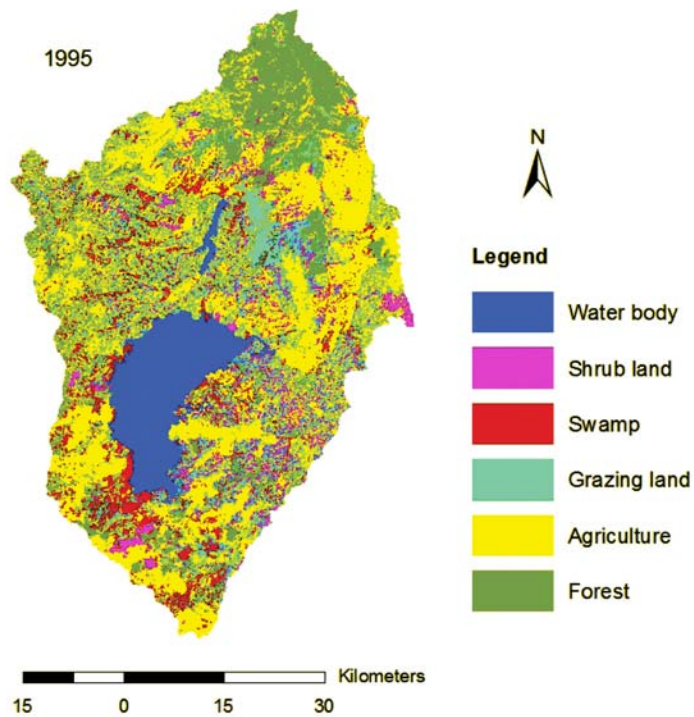**Figure 4** Land use and land cover of Fincha watershed, 1985.

Figure 5 Land use and land cover of Fincha watershed, 1995.
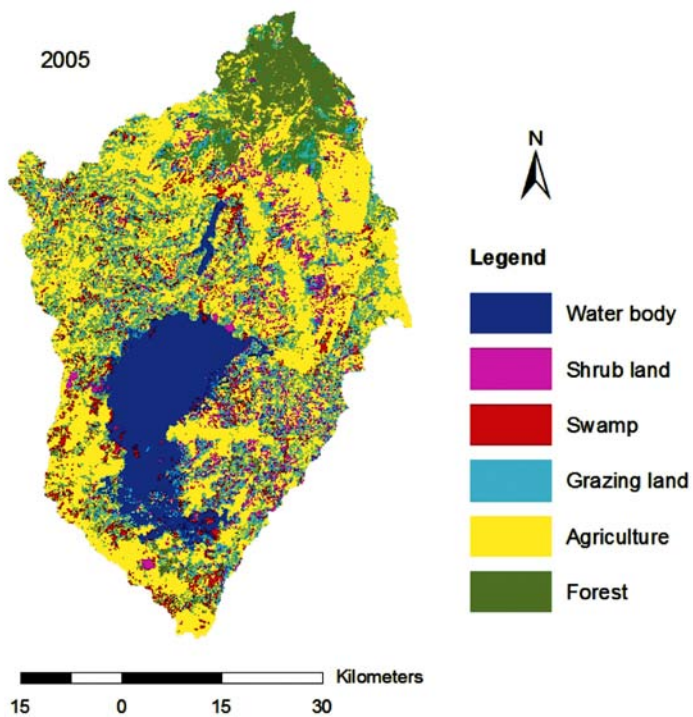

Figure 6 Land use and land cover of Fincha watershed, 2005.

Land use/cover change detection

        The land use and land cover change detection used a post-classification comparison change detection method, the most commonly used quantitative method of change detection (Jensen *et al.*, 1993). The maps were compared on a pixel-by-pixel basis using a cross-tabulation detection method (change detection matrix). The change matrix provides information on the main direction of changes (from-to information) in the

study area. Tables 1 and 2 present the land use and land cover change matrix for the two study periods from 1985 to 1995 and from 1995 to 2005, respectively. Quantitative area data of the overall land use and land cover changes in each category for the two study periods were compiled.

        Table 3 presents the extent of changes (by area and as a percentage) from one category to another during the two study periods. During both periods, there was an appreciable increase

Table 1   Land use and land cover change matrix, 1985–1995 (in ha).

1985	1995						1985 total
	Agricultural land	Forest land	Grazing land	Water body	Swamp	Shrub land	
Agricultural land	68,841	31,270	6,414	81	346	6,134	113,086
Forest land	37,094	17,152	10,302	449	935	5,823	71,755
Grazing land	28,517	1,388	15,018	8,540	449	1,731	55,644
Water body	147	0	2,095	15,893	2,157	313	20,606
Swamp	520	493	10,475	2,336	20,247	4,762	38,834
Shrub land	7,781	4,521	2,698	3,783	2,200	4,169	25,151
1995 total	142,900	54,824	47,001	31,082	26,336	22,932	325,076

Table 2   Land use and land cover change matrix, 1995-2005 (in ha).

1995	2005						1995 total
	Agricultural land	Forest land	Grazing land	Water body	Swamp	Shrub land	
Agricultural land	107,778	22,392	6,063	81	426	6,161	142,900
Forest land	29,424	9,016	9,327	449	936	5,671	54,824
Grazing land	28,525	1,550	7,691	7,728	482	1,025	47,001
Water body	204	0	1,851	26,477	2,133	417	31,082
Swamp	520	493	10,475	1,280	12,125	1,442	26,336
Shrub land	7,240	2,080	2,860	3,775	2,784	4,194	22,932
2005 total	173,692	35,531	38,267	39,790	18,885	18,911	325,076

Table 3   Extent of changes during the two study periods.

	Agricultural land	Forest land	Grazing land	Water bodies	Swamp	Shrub land
1985–1995						
Change (ha)	29,814	-16,931	-8,642	10,476	-12,498	-2,218
Change (%)	+26.36	-23.60	-15.53	+50.84	-32.18	-8.82
1995–2005						
Change (ha)	30,792	-19,293	-8,734	8,708	-7,450	-4,022
Change (%)	+21.55	-35.19	-18.58	+28.02	-28.29	-17.54

in the area of agricultural land and water bodies with a concomitant shrinkage in the area of forest, grazing land, swamp and shrub land. During the study period from 1985 to 1995, agricultural land and water bodies increased in area by 29,814 and 10,476 ha, respectively. On the other hand, forest land, grazing land, swamp areas and shrub land decreased in area by 16,931, 8,642, 12,498 and 2,218 ha, respectively.

Analysis of the remote sensing data shows that about one-third and one-quarter of the increase in the area of agricultural land during the first study period, were from forest land and grazing land, respectively. The contribution from shrub land was less than 7%. During the same period, the analysis further indicated that grazing land, swamp and shrub land contributed about 41.44 11.34 and 18.36%, respectively to the increase in the total area of water bodies in the study area.

During the second study period from 1995 to 2005 (Table 3), agricultural land and water bodies increased in area by 30,792 and 8,708 ha, respectively. However, forest land, grazing land, swamp and shrub land decreased in area by 19,293, 8,734, 7,450 and 4,022 ha, respectively. The analysis revealed that about 40% of the increase to the total area of agricultural land was from forest and grazing lands, with shrub land contributing only about 5%. During the same period, about 24.86% and 12.15% of the increase in the total area of water bodies was from grazing land and swamp areas, respectively and again, the contribution from shrub land was estimated to be less than 5%.

The increase in water bodies resulted from the diversion of the Amarti River to the Fincha reservoir through a 1.5 km tunnel in 1987 which supplies an annual runoff of 138.8 Mm^3 to the reservoir (EELPA, 1994). The increase in the total volume of water in the reservoir resulted in an increase in the area of backwater flow that inundated large areas of swamp areas, grazing, shrub and agricultural lands. Some

forest lands were also inundated by backwater. Moreover, siltation from sediment resulting from inappropriate farming practices surrounding the reservoir in the form of runoff raised the level of the reservoir, which obviously resulted in an increase in the area of the water body.

During the study period land use and land cover change from one class to another class took place throughout the watershed. However, compared to other areas, much change was observed near the periphery and downstream of the Fincha reservoir. The land use change surrounding the reservoir was due to the backwater flow that inundated large areas of swamp, grazing, agricultural and shrub lands and evicted many people from these areas. The displaced farmers opened up new farmland by clearing marginal areas that resulted in much greater change. The loss in the area of forest, grazing and shrub lands downstream of the Fincha reservoir was related to the establishment of a sugar factory because the area under sugar cane production increased at the expense of forest land, grazing land and shrub land.

Stability of the land use/cover change process

The transition probabilities governing the periods 1985–1995, 1995–2005, and 1985–2005 are presented in Tables 4, 5, and 6, respectively. Table 6 presents the transitional probability (TP) values from 1985 to 2005. For instance, the TP from forest land, grazing land, and shrub land to agricultural land was 0.0236, 0.0271, and 0.0155, respectively. The computation is based on the actual number of observations in land use and land cover change during the same study period.

The expected TP values from 1985 to 2005 under the Markov hypothesis are presented in Table 7. From the table, it can be noted that if the land use and land cover change process was Markovian, the TP to agricultural land from forest land, grazing land and shrub land would have been 0.101, 0.1065, and 0.0608, respectively.

Table 4 Land use and land cover transition probabilities, 1985–1995.

1985	1995					
	Agricultural land	Forest land	Grazing land	Water body	Swamp	Shrub land
Agricultural land	96.09	2.77	0.57	0.01	0.03	0.54
Forest land	5.17	92.39	1.44	0.06	0.13	0.81
Grazing land	5.12	0.25	92.70	1.53	0.08	0.31
Water body	0.07	0.00	1.02	97.71	1.05	0.15
Swamp	0.13	0.13	2.70	0.60	95.21	1.23
Shrub land	3.09	1.80	1.07	1.50	0.87	91.66

Table 5 Land use and land cover transition probabilities, 1995–2005.

1995	2005					
	Agricultural land	Forest land	Grazing land	Water body	Swamp	Shrub land
Agricultural land	97.54	1.57	0.42	0.01	0.03	0.43
Forest land	5.37	91.64	1.70	0.08	0.17	1.03
Grazing land	6.07	0.33	91.64	1.64	0.10	0.22
Water body	0.07	0.00	0.60	98.52	0.69	0.13
Swamp	0.20	0.19	3.98	0.49	94.60	0.55
Shrub land	3.16	0.91	1.25	1.65	1.21	91.83

Table 6 Land use and land cover transition probabilities, 1985–2005.

1985	2005					
	Agricultural land	Forest land	Grazing land	Water body	Swamp	Shrub land
Agricultural land	99.47	0.06	0.25	0.04	0.02	0.16
Forest land	2.36	96.99	0.15	0.03	0.07	0.41
Grazing land	2.71	0.12	96.42	0.69	0.04	0.01
Water body	0.09	0.00	0.53	99.18	0.13	0.08
Swamp	0.07	0.06	1.26	1.14	96.84	0.62
Shrub land	1.55	0.74	0.54	0.91	0.44	95.83

Table 7 Expected values of land use transition probabilities under Markov hypothesis, 1985–2005.

1985	2005					
	Agricultural land	Forest land	Grazing land	Water body	Swamp	Shrub land
Agricultural land	93.93	4.05	0.98	0.03	0.07	0.94
Forest land	10.11	84.76	2.93	0.18	0.29	1.73
Grazing land	10.65	0.62	84.99	3.04	0.19	0.52
Water body	0.20	0.01	1.56	96.29	1.66	0.28
Swamp	0.53	0.32	6.28	1.12	90.10	1.66
Shrub land	6.08	2.53	2.21	3.01	1.96	84.21

The computed value of the statistic χ^2 was 1.31×10^5, which is much greater than 37.65 (the χ^2 value from tables at $\alpha = 0.05$ with 25 degrees of freedom). The hypothesis of statistical independence is therefore rejected. The land use and land cover change data are statistically dependent, but the question is whether this dependence can be characterized by a first-order Markov dependence, or by a higher order dependence.

Whether the land use and land cover change process in the area has been stabilized is a more critical issue relating to land development policies. To answer this question, steady state probabilities in the three different periods were computed and compared (Table 8). These values show the probabilities that a cell (parcel of land) will be in different categories at a sufficiently distant point in time. An inspection of this table indicates that the three distributions are distinctly different, implying differences in the transition mechanism. As a result, the idea that the process is stationary may be rejected although this assumption has not been thoroughly tested as a hypothesis. However, if the three transition mechanisms are to continue in a stationary manner, the distribution of land use and land cover categories can be projected for a remote future (Table 8): 66.96% of the land will be agriculture, 2.64% will be forest land, 8.35% will be grazing land, 16.88% will be water bodies, 1.73% will be swamp area and 3.44% will be shrub land.

CONCLUSION

This paper described an integrated approach using satellite remote sensing, GIS and stochastic modeling techniques to address land use and land cover changes in the Fincha watershed, Ethiopia, during the period 1985–2005. The ability of GIS to integrate spatial data from different sources is especially useful in land use and land cover studies.

It was found that during the study period, agricultural land and water bodies have notably increased in the study area by as much as 60,606 (53.59%) and 19,184 ha (93.10%), respectively. On the other hand, forest land, grazing land, swamp area and shrub lands have decreased in area by 36,225 (50.48%), 17,376 (31.23%), 19,948 (51.37%), and 6,240 ha (24.81%), respectively.

Landsat data have been generally successful in the detection of land use and land cover changes. The digital image classification coupled with GIS technology demonstrated its ability to provide comprehensive information on the direction, nature, rate and location of land use and land cover changes. The Markov chain models were capable of descriptive power and simple trend projection for land use and land cover change. The analysis can serve as an indicator of the direction and magnitude of change in the future as well as a quantitative description of change in the past.

The application of stochastic models to simulate dynamic systems such as land use and land cover changes in a developing nation is rare. Clearly, much work needs to be done in order to develop an operational procedure that integrates the techniques of satellite remote sensing, GIS, and Markov modeling for monitoring and modeling land use and land cover changes.

Table 8 Comparison of steady state probabilities.

Year	Agricultural land	Forest land	Grazing land	Water bodies	Swamp	Brush land
1985–1995	0.4478	0.1819	0.1180	0.1395	0.0515	0.0613
1995–2005	0.5325	0.1098	0.0893	0.1765	0.0418	0.0501
1985–2005	0.6696	0.0264	0.0835	0.1688	0.0173	0.0344

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