Application of Earth Remote Sensing and GIS in Mapping Land Cover Patterns in Kinangop Division, Kenya

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Abstract: Land cover is a fundamental variable that links many facets of the natural environment and a key driver of global environmental change. Alterations in its status can have significant ramifications at local, regional and global levels. Hence, it is imperative to map land cover at a range of spatial and temporal scales with a view to understanding the inherent patterns for effective characterization, prediction and management of the potential environmental impacts. This paper presents the results of an effort to map land cover patterns in Kinangop division, Kenya, using geospatial tools. This is a geographic locality that has experienced rapid land use transformations since Kenya's independence culminating in uncontrolled land cover changes and loss of biodiversity. The changes in land use/ cover constrain the natural resource base and presuppose availability of quantitative and spatially explicit land cover data for understanding the inherent patterns and facilitating specific and multi-purpose land use planning and management. As such, the study had two objectives viz. (i) mapping the spatial patterns of land cover in Kinangop using remote sensing and GIS and; (ii) evaluating the quality of the resultant land cover map. ASTER satellite imagery acquired in January 23, 2007 was procured and field data gathered between September 10 and October 16, 2007. The latter were used for training the maximum likelihood classifier and validating the resultant land cover map. The land cover classification yielded 5 classes, overall accuracy of 83.5 % and kappa statistic of 0.79, which conforms to the acceptable standards of land cover mapping. This qualifies its application in environmental decision-making and manifests the utility of geospatial techniques in mapping land resources.

Key words: mapping, land cover, validation, remote sensing, GIS, Kinangop, Kenya

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1 INTRODUCTION

Land cover, which alludes to the conspicuous biophysical attributes of land, is an important variable that links many facets of the natural environment and a key driver of global environmental change. Alterations in its status, hence, land surface processes are inherently dynamic and spatial and, can impact the natural environment in ways that parallel the effects of climate change (Aspinall and Hill, 2008, Foody, 2002 and Rembold *et al.*, 2000). The escalating human population has occasioned alteration of the earth surface at unprecedented pace, magnitude and spatial extent (Lunetta and Elvidge, 1999 and Lambin *et al.*, 2001), thus, making it difficult to find pristine lands anymore. Conversions of land cover for agricultural, residential, industrial and urban development concomitant to population growth affects the proper functioning of terrestrial ecosystems in the long run. For instance, the conversions can impact on the bio-geochemical cycling leading to modifications in land-atmosphere energy exchanges, carbon and water cycling, soil quality, biodiversity, ability of biological systems to support human needs and, ultimately, climate at all scales (Foody, 2002, Lambin *et al.*, 2003, Loveland *et al.*, 1999 and Overmars and Verburg, 2005). This provides rationale for recognition of land cover changes as a fundamental agent of global environmental change and great challenge in the domain of environmental sciences (Aspinall and Hill, 2008 and Bottomley, 1998). Consequently, monitoring, assessment, modelling and mapping of land cover changes have gained currency as a means of comprehending the relationships and interactions between human beings and global earth systems in order to foster sustainability in the management of natural resources and environmental change as well as appraisal of sustainable development (Carpenter *et al.*, 2001, Bottomley, 1998 and Lu *et al.*, 2004).

Kinangop division in central Kenya is one geographic locality that has experienced dramatic land use and demographic changes since Kenya's independence culminating in uncontrolled land cover changes and biodiversity loss. The land cover changes are inimical to the sustainability and integrity of the

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First author biography: Kennedy Okello WERE (1979—), Kenyan. He holds of BA degree in Geography from Moi University (Kenya) and a joint MSc degree in Geo-information Science and Earth Observation from University of Southampton (UK), Lund University (Sweden), Warsaw University (Poland) and ITC (The Netherlands). He is interested in geospatial and natural resources management research. E-mail: kenwerez@yahoo.com natural resource base, which underpins economic growth and development in the area. Therefore, deliberate decision-making and planning should be undertaken with a view to mitigating the repercussions of the cover changes. This presupposes availability of detailed, accurate, timely, consistent, multi-temporal, reliable, quantitative and spatially explicit land cover information on local, regional and global scale (Loveland *et al.*, 1999 and Read and Lam, 2002). Remote sensing and GIS provide tools for capturing the fundamental dataset for land inventorization and monitoring (Skidmore *et al.*, 1997).

This paper presents the results of mapping the spatial patterns of land cover in Kinangop division, central Kenya, by means of geospatial tools. The overall purpose of the study was to bridge the gap in availability of quantitative and spatially-explicit land cover information for effective environmental decision-making, planning, modelling, monitoring and management.

2 METHODS AND MATERIALS

Fig. 1 summarizes the methodological approach used in derivation of the land cover map for Kinangop division, central Kenya.

2.1 Study area

Kinangop division is an administrative unit in Nyandarua district, Central province in Kenya. It is bound by latitudes 0°17′20″ S and 0°55″S and longitudes 36°22″E and 36°41″E and spans over 735km^2 in spatial extent (Fig. 2). The altitude ranges from 2500m above the sea level in the north to 2680m

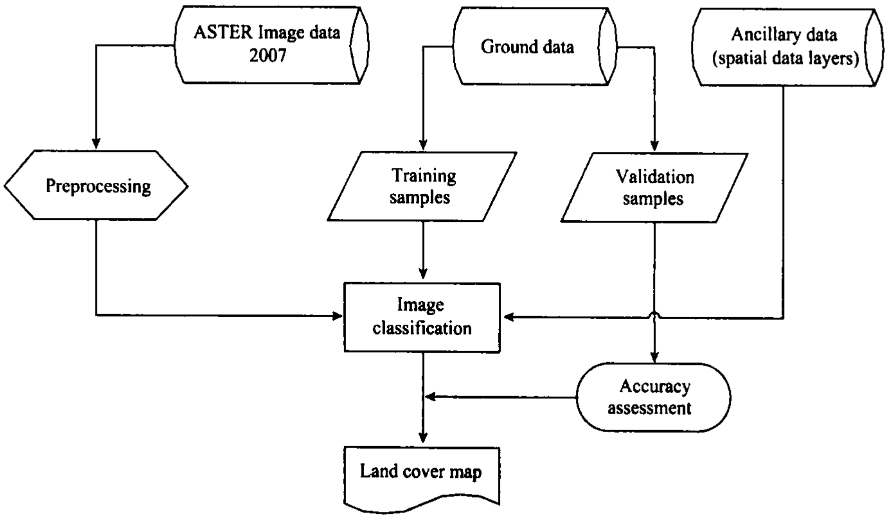

Fig. 1 Schematic illustration of the data and methods used in the study

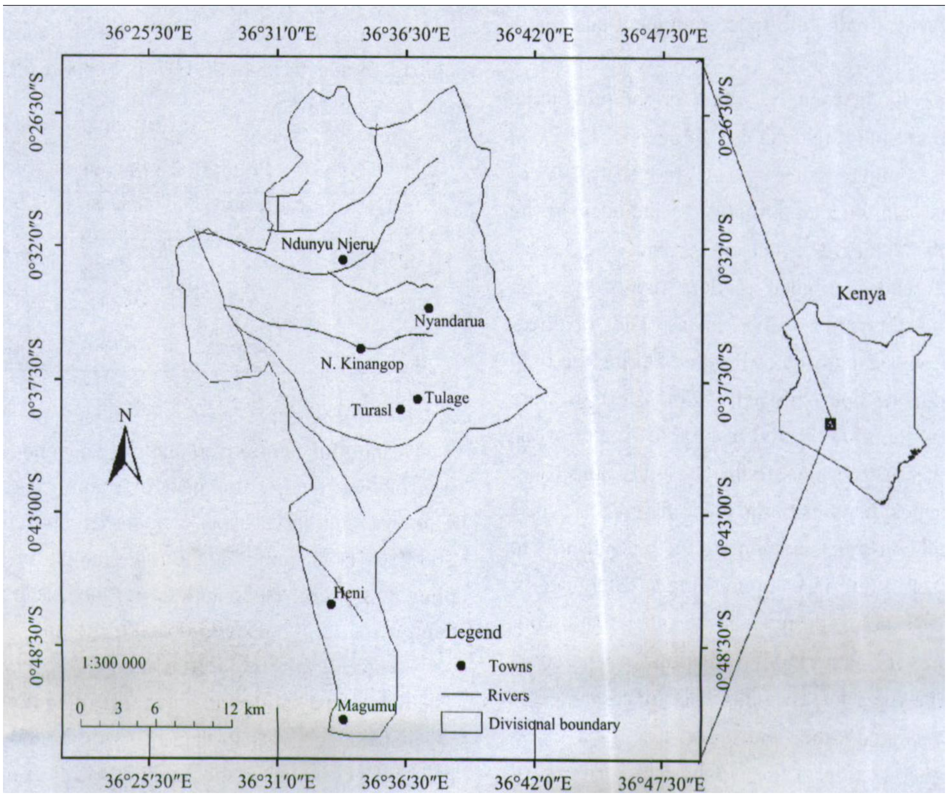

Fig. 2 Location map of Kinangop Division in Kenya

above the sea level in the south. A combination of volcanicity and other tectonic activities and climate led to the formation of vast plateaus, scarps, mountains, hills and huge vents that characterize the area. To the northeast lies Kipipiri hills, which tower above the surrounding plains and are separate from the main Aberdares ranges on the east, which tops at 3906m (Nyandat, 1984; Rachillo, 1978). The surface is, generally, very smooth and deeply dissected in the northwestern part by the tributaries of Malewa River (i.e. Mkungi, Turasha and Kitiri), which eventually drain into Lake Naivasha.

Climate-wise, rainfall in the area diminishes rapidly from 1300—1400mm annually on the eastern side to 700—800mm annually on the western side. From south to north, the rainfall distribution changes from bimodal with a primary peak in March—May and a secondary peak in November to bi-modal with a primary peak in July—August and a secondary peak in April—May from east to west. The mean temperatures, on the other hand, range from 12℃ in the east to 15℃ in the west and north. The predominant vegetation is the *Kikuyu* grass (*Pennisetum clandestinum*) though there have been dramatic changes since independence owing to the rising population. This makes it a suitable study location, as the resultant land cover information is crucial for making decisions on mitigation of the impacts as well as future monitoring and predictions.

2.2 Pre-field work, sampling and response design

In the phase of pre-field work, the sampling strategy, preliminary legend and field data observation data sheets were designed, the supportive spatial data layers and remote sensing data were procured and, finally, the field equipment and logistics were arranged.

Sampling design is the protocol by which the sampling units are selected into the sample (Stehman & Czaplewski, 1998). In this study, random sampling strategy was employed for objective selection of the sampling units that were included in the sample. Hawths tools 3, an ESRI extension for ArcGIS 9.x, was applied to generate well-distributed random points over the entire study area and, thereafter, visited in the field for documentation of the biophysical attributes of land. During the field visits, sampling units of approximately 30m × 30 m were formed taking into account the spatial resolution (scale) of the ASTER imagery that was to be classified. The study objectives, landscape characteristics, features of the mapping process, costs, benefits and practical constraints are among the other factors to be considered in selection of sampling units (Stehman & Czaplewski, 1998). Response design, on the other hand, constitutes the procedures for gathering information for land cover determination and the rules for assigning classifications to the sampling units. In this study, the field observation data sheets formed the basis for collection of the biophysical attributes of land.

2.3 Data sources

Three types of data were collected for the fulfilment of the study objectives. These were: (1) spatial layers, (2) remote sensing, and (3) ground data, details of which are given in the following sub-sections:

2.3.1 Spatial data layers

Topographic map from Survey of Kenya was scanned and geo-referenced. Existing digital vector data from the International Livestock Research Institute's GIS database (http://www.ilri.org/gis/) were reprojected to UTM zone 37 South (projected coordinate system) and WGS 84 (ellipsoid and datum) that had been adopted for the study. These data comprised of agro-ecological zones, roads, towns, markets, administrative boundaries, water bodies, land use, soils, forests and villages. Unsupervised classification of the ASTER imagery was also performed to aid in identification of different land cover types during the field survey. Unsupervised classification implies that neither additional data nor expert knowledge influenced the outcome of the classification (Campbell, 2002). These data were then uploaded onto a mobile GIS (Hp iPAQ) for field use. They, not only, facilitated field navigation but also, image interpretation and classification in the post-fieldwork phase.

2.3.2 Remote sensing data

Geo-coded, radiometrically calibrated and ortho-rectified ASTER imagery, captured on 2007-01-23 was ordered from the United States Geological Survey, Centre for Earth Resources Observation and Science (USGS-EROS). The selection of the imagery was predicated on its cost, date of acquisition, spatial resolution, availability and the percent cloud cover. Scenes of QuickBird and Ikonos satellite imagery (Table 1) that partially covered the study area were also acquired, processed and uploaded onto the mobile GIS in support of field surveys and interpretation process.

Table 1 Properties of the remote sensing data

Satellite sensor	Spatial resolution /m	Spectral resolution	Date of acquisition	Source
ASTER	15	14 bands	2007-01-23	USGS
QuickBird	2.6	4 bands	2003-06-02	Digital Globe
Ikonos	4	4 bands	2002-03-06; 2002-09-10	GeoEye

2.3.3 Ground data

Meaningful land cover mapping depends on careful selection of data for development of training sites and validation. Thus, ground survey was conducted between 2007-09-10 and 2007-10-16 whereby the 150 random and well-distributed sampling units were visited and the pertinent details captured on the hand-held Garmin 12X Global Positioning Systems (GPS) receiver, mobile GIS (Hp iPAQ) and field observation data sheets. The field survey aimed at: (1) determining the land cover types; (2) associating the field data of specific land cover types with their image characteristics and; (3) collecting sufficient field data for validation of the land cover map extracted from the

ASTER imagery. At each sampling unit, visual estimates of the biophysical land attributes (i.e. percent cover of shrubs, grass, herbs, trees, bare soils and water) were made and recorded on the field observation form. Digital photos were also taken at each of the sampling units. At the end of the field campaign, the data collected were input and processed in Microsoft Excel 2003.

2.4 Development of the land cover classification scheme

The processed biophysical data formed the basis for development of a preliminary two-level classification legend for the study. The eight broad classes (Table 2) in level one were then chosen for the classification process taking into account the selected classifier algorithm (i.e. maximum likelihood classifier) and scale of ASTER imagery pixels. However, to overcome the spectral confusion among some land cover classes (which was compounded by the eight-month time lag between image acquisition and field surveys) and enhance classification results, the eight classes were reclassified as follows:

(1) Grasslands& moor lands;
(2) Cultivated croplands;
(3) Forests& woodlands;
(4) Built-up areas, bare& ploughed croplands and;
(5) Marshy lands.

Table 2 Description of the land cover classes

Land cover	Description
Grasslands	Areas dominated by grasses (0—0.2m) and herbs (0.2—2m)
Croplands	Areas covered by growing crops inclusive of ploughed fields
Forests	Areas predominantly covered by trees (> 5m high) with > 40% closed canopy cover
Woodlands	Areas dominated by scattered trees (> 5m high) with < 40% open canopy cover
Built-up	Areas with commercial and residential structures or constructed materials
Bare lands	Areas that are completely non-vegetated or with very low percent vegetation cover
Marshy lands	Wet and muddy areas
Moorlands	Wetter areas, in the Aberdares mountain ranges, with low vegetation on acidic soils

2.5 Pre-processing

These are preliminary operations, particularly, radiometric, geometric and atmospheric corrections, that often precede image analysis (Campbell, 2002) to ensure accurate results. Geometric correction refines the spatial orientation of the satellite imagery whereas radiometric data normalization suppresses the spectral differences emanating from detector disparity, variations in radiation incidence angle and sensor calibration (Lunetta & Elvidge, 1999; Yang & Liu, 2005). The data provider had performed these operations except atmospheric correction. Atmospheric correction, which compensates for electromagnetic signal modifications by scattering and absorption by aerosols and gases, was dispensable in this case since the training data and ASTER image were on the same relative scale. Thus, atmospheric correction would have had minimal effect on the classification accuracy (Song *et al.*, 2001).

2.6 Image classification

Classification of digital images assigns pixels to distinct groups (Campbell, 2002) and is central to land cover mapping. Over time, scientists have developed a myriad algorithm that facilitates distinction of groupings within spectral data and assignment of nominal labels to them. The maximum likelihood classifier (MLC) algorithm in ArcGIS 9.2 software was used to classify the ASTER imagery and design a layout for the resultant land cover map. This algorithm applies the means and variances of brightness values of the different clusters to estimate the probability of correct classification thus making it a robust classification algorithm. The lucid description of MLC is found elsewhere (Campbell, 2002; Kerle *et al.*, 2004). Prior to classification, a false colour composite was created using the green, red and near-infra-red spectral bands to enhance the image for visual interpretation. The quantitative spectral characteristics of the land cover classes were also extracted for scrutiny of between- and within-class variations to determine their separability (Fig. 3).

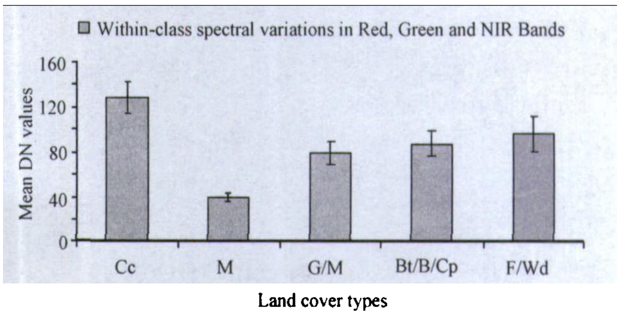

Fig. 3 Within-class spectral variability in the Red, Green and NIR bands

Cc=cultivated croplands; M=marshy lands; G/M= grasslands/moor lands; Bt/B/Cp=built-up/bare lands/ploughed croplands; and F/Wd =forests/woodlands. Spectral variability is greatest within forests& woodlands land cover class and lowest in the marshy land cover type.

Two thirds of the ground data were randomly selected for development of the training sites and the remainder assigned for validation of the resultant land cover map. The scenes of Ikonos and QuickBird satellite images, in addition to, expert knowledge also assisted in discrimination of different land cover types on the ASTER image.

2.7 Accuracy assessment

Statistically rigorous validation of extracted land cover maps prior to their use in policy formulation and planning underpins defensible scientific practice (Stehman & Czaplewski, 1998).

This offers an insight into the thematic uncertainties and guides the end users on map's quality, reliability and suitability for intended applications (Treitz & Rogan, 2004). Uncertainties are inherent in geo-spatial data due to errors in space, value, time, consistency or correctness, variability, instability, conceptual ambiguity or over-abstraction among others (Zhan *et al.*, 2005, Blaschke *et al.*, 2000). In the context of pixel-based land cover classification, the image itself, pre-processing operations or spectral mixtures are some of the potential sources of error. As already intimated in the preceding section, a third of the ground data (reference data) was used for validation of the resultant land cover map. During validation, the pixels on the classified map and reference ground data were compared to determine the number of correctly and incorrectly classified pixels for each land cover type. The measures of map quality and classification performance, i.e. kappa statistic, overall-, producer- and user accuracy, were then computed and presented on the conventional error (confusion) matrix (Table 5). The formulae applied in computation of these measures were after Campbell (2002) and Lund University GIS centre (2004) that is:

(a) Kappa statistic (measure of reproducibility):

$$K = \frac{\text{observed} - \text{expected}}{1 - \text{expected}} \qquad (1)$$

where

observed = accuracy reported in the error matrix; expected = correct classification that can be expected by chance agreement between two images.

(b) Total/ overall accuracy:

$$\text{TA} = \frac{\Sigma A}{N} \times 100\% \qquad (2)$$

where

A = number of correctly mapped points for each class; N = total number of points.

(c) Consumer/ user accuracy (correctness):

$$\text{CA} = \frac{A}{C} \times 100\% \qquad (3)$$

where

A = number of correctly mapped points for each class; C = number of map data points for each class.

(d) Producer accuracy (completeness):

$$\text{PA} = \frac{A}{B} \times 100\% \qquad (4)$$

where

A = number of correctly mapped points for each class; B = number of ground truth points for each class.

Essentially, the producer's accuracy expressed the percentage of reference data that had been explained by the extracted land cover pixels; user's accuracy highlighted the percentage of land cover pixels that had been correctly extracted; and kappa statistic indicated the probability of chance agreement between the reference,data and the classified land cover map.

3 RESULTS AND DISCUSSION

The map showing different land cover types in Kinangop division, central Kenya, in January 2007 coupled with its quality are the primary output of this study.

3.1 Land cover map

The five land cover classes that were mapped are shown in Fig. 4 while the proportions of each of these land cover classes are graphically displayed in Fig. 5. It is evident from the latter that cultivated croplands constitute the largest portion of Kinangop division, while marshy lands occupy the least portion. This implies that agriculture is the predominant human activity or land use in the area.

3.2 Accuracy assessment

The statistical output from the comparison of reference data with the classified ASTER imagery for 2007 is summarized in Table 3. The first column shows the user's classes whereas the other columns show the number of evaluation points (reference data) for each class. The totals of the evaluation points for each class are shown in the last row. Likewise, the last column shows the totals of the classified pixels for each class on the generated land cover map. The matrix reflects the quality of the map in relation to the reference data. For instance, there are forty-seven reference points for the cultivated croplands. Out of these, forty-three have been correctly classified as cultivated croplands but three and one pixels have been misclassified as grasslands/ moorlands and forests/ woodlands respectively. Moreover, out of the twenty-eight pixels that have been classified as forests/ woodlands in the extracted land cover map, a pixel has been confused with the cultivated croplands. Cultivated croplands exhibits the poorest results whereby, lots of confusion occurred with the forests/ woodlands, grasses/ moor lands and built up/ bare lands/ ploughed croplands. Using Eq. (1) and (2), the total accuracy achieved for the classification is 83.5% and the kappa co-efficient is 0.79. The former statistic is an indication of the probability that a randomly selected point either on the map or field is correctly classified whereas the latter implies that 79% of the classification is in consonance with the reference data leaving only 21% to chance. In essence, the kappa statistic is more meaningful in representation of the map quality relative to the traditional overall accuracy (Lunetta *et al.*, 2006). A good accuracy in land cover mapping is paramount since the standard overall accuracy is set at 80%—85% (Treitz & Rogan, 2004). Thus, the performance of this pixel-based ASTER image classification is satisfactory.

Further, from Table 3 above, it is clear that the supplementary measures of map quality are also high. For instance, it shows that the possibility of end-users, to accurately locate cultivated croplands and forests/ woodlands on the ground using this map is 75% and 96% respectively. A finer mapping quality though can be achieved through simultaneous acquisition of ground and satellite data (Wilde, 1996) as well as incorporation of additional ground truths over time. As already mentioned, there was an eight-month time difference between image acquisition and ground surveys in this case and this could have affected the classification results. As such, knowledge on the area's crop calendar was indispensable in compensating for the difficulties encountered during image interpretation and classification.

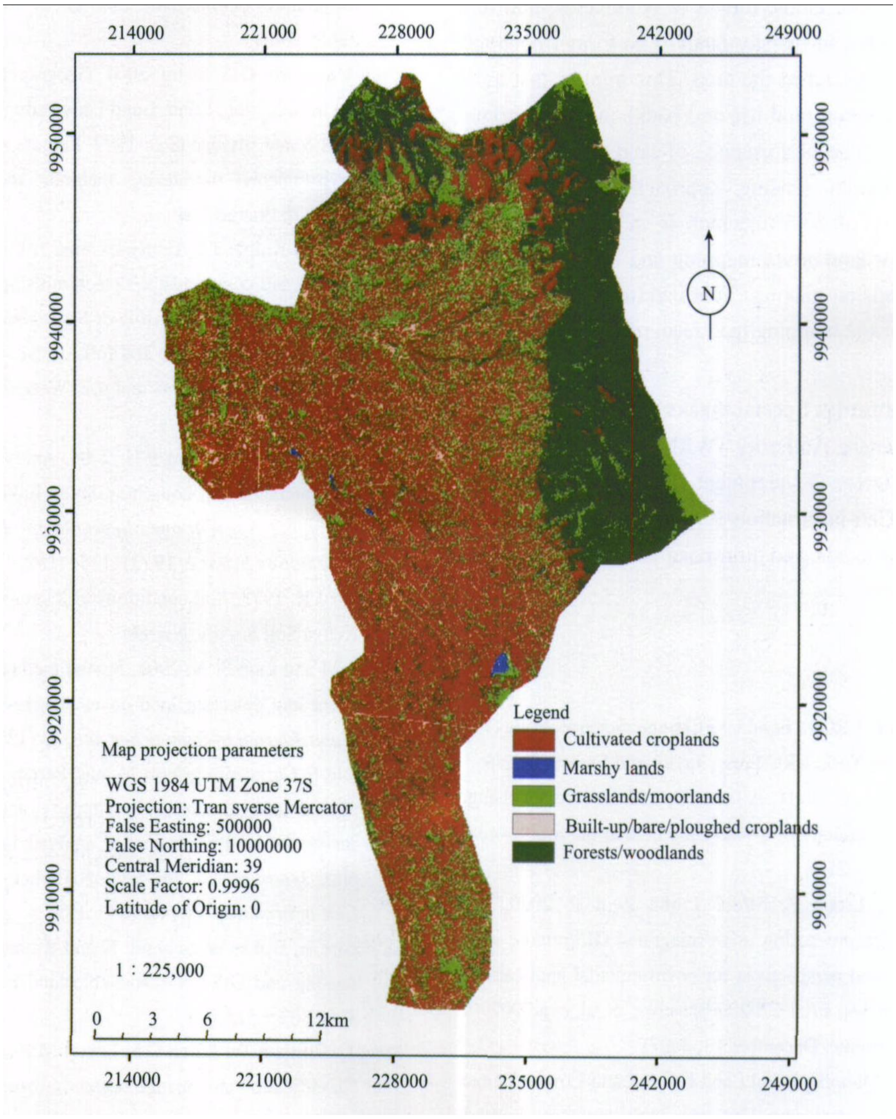

Fig. 4 Land cover classification in Kinangop Division using ASTER image in 2007

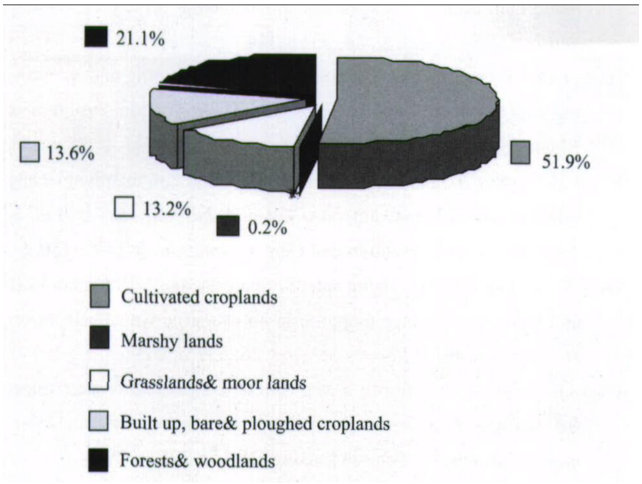

Fig. 5 Proportions of the land cover types in Kinangop Division

Table 3 Error matrix

Classified	Reference						CA /%	EC /%
	Cc	M	G/ M	Bt/B/Cp	F/ Wd	Totals		
Cc	43	0	5	3	6	57	75.4	29.8
M	0	12	0	0	0	12	100.0	0.0
G/ M	3	2	25	1	2	33	77.6	25.8
Bt/B/Cp	0	0	1	15	0	16	93.8	5.3
F/Wd	1	0	0	0	27	28	96.4	2.9
Totals	47	14	31	19	35	146		
PA/%	91.4	85.7	80.6	78.9	77.1			
EO/%	8.5	14.3	19.4	21.1	22.9			

TA=83.5% Kappa=0.79

Cc = cultivated croplands; M = marshy lands; G/ M = grasslands & moor lands; Bt/B/Cp =built-up, bare lands & ploughed croplands; F/Wd = forests & woodlands; PA = Producer's accuracy; EO = Error of omission; TA = Total accuracy; CA = Consumer's accuracy; and EC = Error of commission

4 CONCLUSIONS

In a nutshell, the broad classes of land cover types in Kinangop division, central Kenya, have been mapped using remote sensing and GIS techniques and include: cultivated croplands, grasslands& moor lands, forests & woodlands, built-up, ploughed& bare lands and marshy lands. The former occupies the greatest portion of land in the area. This implies that agriculture is the predominant land use and backbone of economic stability in the area. The performance of land cover mapping using GIS and remote sensing approach has attained a satisfactory accuracy of 83.5%, which is in accord with the quality standards for land cover mapping and hence the output can be used for decision-making. This manifests the utility of geospatial techniques in mapping land resources.

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