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Spatiotemporal Analysis of Land Cover Changes in the Chemoga Basin, Ethiopia, Using Landsat and Google Earth Images

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Abstract: Land cover change is a major environmental concern in the northwestern highlands of Ethiopia. This study detected land cover transitions over the past 30 years in the Chemoga basin (total area = 118,359 ha). Land cover maps were generated via the supervised classification of Landsat images with the help of the Google Earth (GE) images. A total of 218 unchanged land features sampled from GE images were used as the training datasets. Classification accuracy was evaluated by comparing classified images with 165 field observations during the 2017 field visit. The overall accuracy was 85.4% and the kappa statistic was 0.81, implying that the land classification was satisfactory. Agricultural land is the dominant land cover in the study basin, and increased in extent by 2,337 ha from 1987 to 2017. The second and third most dominant land cover types, grassland and woodland, decreased by 1.9% and 3.6%, respectively, over the past 30 years. The increase in agricultural lands was mostly due to the conversion of grasslands and woodlands, although some agricultural lands changed to Eucalyptus plantations and human settlements. The results revealed that the expansion of built-up space and agricultural lands was the major driver of fragmentation of the landscape, and degradation of natural resources in the Chemoga basin, Ethiopia.

Keywords: land cover change; Google Earth images; supervised classification; transition matrix; dynamic index of land cover

1. Introduction

The biophysical cover on the Earth’s surface is continuously changing at local, national, and global scales, as direct or indirect consequence of human activities. Like many other countries in Africa, Ethiopia has experienced rapid land transitions since the mid-20th century [1,2]. Land cover change is causing significant impacts on people, the economy, and the environment throughout the country. A variety of drivers of land cover change can be found in the literatures, but urban sprawl, rapid population growth, and expansion of arable lands are the main drivers of the recent land conversion in African countries [3–5].

Mapping land cover and its change is now becoming crucial to analyze the magnitude, intensity, and direction of landscape matrix transformation [3,6,7]. Traditionally, land cover mapping has been explicitly performed with the help of field surveys [8]. The site-based observations are costly and time-consuming, as they require massive human efforts [9]. With the recent progress in Earth science, remote sensing has emerged as a promising approach for monitoring the status and dynamic changes of land features on a large spatial scale [6,7,10,11]. Remote sensing simply measures the reflective
response of the surface cover, and so it can be used to directly observe land cover in areas of interest. This photogrammetric approach is superior to conventional field survey when it detects the physical features of a large area [12–14].

Several methods are available for image classification from satellite remotely sensed data. They all fall under two main categories in common: unsupervised and supervised classification [15,16]. In unsupervised classification, the nature of land cover features can be broken down into land classes by their spectral similarity inherent in the images. This method does not require the prior knowledge of ground cover before classification. On the contrary, supervised classification uses the predefined spectral signatures of land surface in order to train a classification algorithm and subsequently classify an entire image [17]. Thus, the availability and quality of training data highly influences the classification accuracy [18]. The training data contains the ‘correct’ label for each land cover type, and is used to establish the respective spectral signature of each land class. This dataset can be obtained in a variety of ways. Ground-based field survey is preferable to remote sensing and image interpretation, yet often impractical or too expensive for large regions, especially in Ethiopia [19]. To overcome this obstacle, an image sampling method was used in recent research to synthesize pseudo training dataset by using Google Earth (GE) images at training locations. GE is available free of charge and offers high spatial resolution images, allowing multitemporal analysis of landscape changes over time [19–21].

In Ethiopia, human and livestock populations are currently concentrated in the northwestern highlands. These highlands have experienced considerable land cover change over the years, due to the excessive pressure on natural resources. Land surface transition in this region has raised a major environmental concern, including biodiversity loss, water pollution, and accelerated soil loss. Thus, a quantitative assessment of land cover, and changes therein, has become a priority of policymakers implementing a national strategy for conserving natural resources. Therefore, this study detected the spatial changes in land cover in the Chemoga basin over time, and quantified the drivers of land cover changes in the study basin.

2. Materials and Methods

2.1. Study Area

This study was conducted in the Chemoga basin located in the northwestern highlands of Ethiopia. The Chemoga basin is situated in latitudes 10°00′15″ N–10°38′42″ N and longitudes 37°16′38″ E–37°53′07″ E (Figure 1). The basin lies 300 km northwest of the capital city, Addis Ababa. The Chemoga basin covers an area of 118,359 hectares, comprising the town Debre Markos and surrounding rural districts, such as Gozamen, Senane, Baso Liben, Debay-Telatgen, Andede, and Awebel. As of 2007, the total population within the basin was estimated to be 212,912 [22].

The Chemoga basin flows into the larger Blue Nile basin. Its land features are heterogeneous, stretching from the 3960 m above sea level (asl) Chokey afro-alpine ecosystem to the 880 m asl Blue Nile Gorge semiarid ecosystem. The basin consists of three agroclimatic zones according to altitude: ‘Dega’ (relatively low temperature), ‘Woyna-Dega’ (medium temperature), and ‘Kola’ (relatively high temperature) [23]. The mean monthly temperature ranges from 14 to 18 °C at Debre Markos, and the mean annual precipitation is estimated to be 1421 mm, based on meteorological data from eight nearby weather stations. The rainy season (‘Meher’) extends from June to mid-September. Readers, refer to the previous study [24] for more detailed information on the Chemoga basin.

The study area is part of the Ethiopia highlands that are known to be most degraded lands in Africa, and presently threatened by land cover shift [25]. The Chemoga basin has heterogeneous land features with a wider range of altitude, and associated diverse meteorological and geographical characteristics. Land cover change has occurred in the basin since the early 1970s to meet increased demand on land resources. The status and dynamics of land cover were reflected with local peoples’ preference and administrative activities. For example, arable land expansion took place near roadsides or residential areas, at the expense of woodlands and grasslands. Fortunately, forest cover has shown
a slight increase with intensive afforestation and reforestation. An accurate understanding on the dynamics of land mosaic is a crucial step for implementing land conservation practices.

![Geographical features of the Chemoga basin.](image)

**Figure 1.** Geographical features of the Chemoga basin.

2.2. **Land Cover Classification**

2.2.1. Data Sources and Preprocessing

Different types of Landsat satellite images were used in this study, because of limited data availability in the study area. These included Landsat Thematic Mapper (TM) 5 for 1987, Landsat 7 Enhanced Thematic Mapper (ETM+) for 2002, and Landsat 8 Operational Land Imager (OLI) for 2017. These virtually cloud-free images were taken in January and February.

ERDAS Imagine 9.2 and QGIS 2.6 software packages were used for land feature analysis. The boundary of the study area was delineated using an ASTER digital elevation model (DEM) of U.S. Geological Survey (USGS) with a spatial resolution of 30 × 30 m.

Preprocessing of satellite images is a very vital procedure for accurate classification. All images were georeferenced with map projection UTM Zone 37N in the WGS 1984 datum. Image-enhancing and noise-reduction techniques were applied for enhancing the visual interpretability. With prior knowledge of the land surface, land cover types were categorized into eight subclasses (Table 1) on the basis of the Global Forest Resources Assessment (FRA) 2015 definitions [26]: natural forest (NF), woodland (WL), afro-alpine forest (AF), planted forest (PF), agricultural land (AL), grassland (GL), built-up area (BA), and inland water (IW). In Table 1, forest lands were further grouped into natural forest, afro-alpine forest, and planation according to their geographical distribution, forest structure, and management objective.
Table 1. Land cover categories for the Chemoga basin (modified from Forest Resources Assessment (FRA) [26]).

| Land Cover               | Description                                                                 |
|--------------------------|-----------------------------------------------------------------------------|
| Natural forest (NF)      | Land spanning more than 0.5 ha with trees higher than 5 m and a canopy cover of more than 10 percent |
| Woodland (WL)            | The canopy cover of trees is less than 5 percent but the combined cover of shrubs, bushes, and trees is more than 10 percent. Includes areas of shrubs and bushes where no trees are present. |
| Afro-alpine forest (AF)  | With tree species that will not reach a height of at least 5 m and with canopy greater than 10 percent or more in the high mountain region |
| Planted forest (PF)      | Plantation with the primary purpose to produce wood or wood-derived products |
| Agricultural land (AL)   | Land predominantly used for cultivation including agroforestry systems when crops are grown under tree cover |
| Grassland (GL)           | Open land area covered with grass and other low plants suitable for grazing, especially cattle. |
| Built-up area (BA)       | Place where landscape has been altered by human activities, including buildings, residential houses, roads, etc., in urban or suburban areas |
| Inland water (IW)        | Inland water generally includes rivers, lakes, canals, and water reservoirs |

2.2.2. Supervised Classification

Figure 2 presents the study workflow for satellite image analysis. Prior to land classification, training datasets were manually extracted from GE images. Next, a supervised classification method was applied to delineate land features in Landsat images using a subset of training images. The GE geo-browser was also used as an auxiliary tool to distinguish land cover that had similar spectral reflectance features after completing the supervised classification. Finally, the reliability of the classification was assessed by comparison with field observations made in 2017.

![Figure 2. Workflow of land cover classification.](image)

The supervised classification was implemented using preexisting information on land features. Maximum likelihood classifier embedded in ERDAS was used to perform supervised classification. It divides the spectral domain into defined regions corresponding to the land cover classes of interest. The principle step in supervised classification is to define the training datasets. With the help of GE, 218
unchanged polygons overlain on each land cover type were extracted. These unchanged datasets have
the same land cover in 2004 and 2017 GE images. The sampled polygons from the 2017 GE images were
used to train 2017 Landsat images. The 2004 GE data were chosen for the 2002 Landsat image, because
the 2002 GE images were too blurred to use. As the GE images were not available at the study area in
1987, the spectral reflectance of 2004 training data was also used to identify land features in 1987 [24].

2.3. Post-Classification

With the similarity of spectral reflectance patterns, it is often difficult to discriminate between
neighboring landscape segments. In this case, post-classification procedure was executed on the
supervised classification results to identify unclear objects based on their geographical and physical
characteristics. Three-dimensional visualization of GE enables us to distinguish relatively diverse
features according to their physical shape, color, and texture of landscape [20,21].

Forest lands or woodlands can be distinguished based on geographical characteristics. Afro-alpine
forests occur at higher altitudes (>3500 m a.s.l.) in the Chemoga basin, while woodlands can be
observed in the lower basin, which is traversed by two rivers. It is not always easy to separate
plantation forests from natural forests by their spectral properties in satellite images, but landform
textures and shapes in GE images enabled them to be distinguished.

The satellite data used in this study are having medium spatial resolution, where each pixel
represents a ground distance of 30 by 30 m. This limitation can often make it difficult to clearly capture
some objects (e.g., building, road, pond) smaller than 30 m when automated classification method
is applied [27]. The reflectance values of built-up areas can be similar to those of agricultural lands,
bare lands, and grasslands [28], where houses and buildings are sparsely scattered over an area. In such
a situation, land cover classification has lower accuracy because some features of built-up areas merged
with neighboring land cover and were thus poorly identified. Thus, built-up areas and small ponds
were manually delineated in this study by comparing their appearance with GE images [27].

2.4. Accuracy Assessment

Accuracy assessment is an essential and crucial step in image classification. It reveals the extent
of correspondence between what are on the ground and the classification results. Land classification
accuracy was assessed by comparing land classes in the classified images with ground truth data.
Field observations and GPS data were used to build ground truth datasets within the study area. In this
study, 165 field data were randomly surveyed through the 2017 ground visits. The ground truth data
differed from those extracted from GE images at training locations. Informal interviews with local
residents and land development agents were done to obtain additional land cover information during
field visits.

A confusion matrix is widely used for accuracy assessment in the remote sensing literature [2,9,29–33].
It provides important information on the correspondence between classification results and reference data
with respect to land class. Many measures of classification accuracy can be derived from a confusion matrix.
Overall classification accuracy is the most prominent measure that counts the proportion of correctly
classified samples of a confusion matrix. It is obtained by dividing the total number of correctly classified
samples by the total number of ground reference samples. This accuracy does not indicate how the
accuracy is distributed across the individual land classes. The land cover classes could exhibit drastically
differing accuracies, and yet combine for equivalent or similar overall accuracies. Therefore, accuracies of
individual classes are needed in order to completely assess the consistency in land cover mapping.

There are two types of errors for land cover classification: omission errors and commission
errors [31,33]. User’s accuracy characterizes the amount of errors of omission (underestimation).
It is calculated by taking the total number of correctly classified samples for each land cover class
and dividing it by the total number of reference samples for the class. The resulting percentage
accuracy indicates the probability that a reference (ground true) sample will be correctly classified.
A misclassification error is not only an omission from the correctly classified class but also a commission

into another class. The amount of errors of commission (overestimation) is described by the producer’s accuracy that is derived by dividing the number of correct samples in one class divided by the total number of samples as derived from reference data. This accuracy measures how well a certain area has been classified.

The kappa statistic has been adopted in many studies as a useful measure of classification accuracy [31–33], where classification results can be compared with randomly assigned values. A value ≥0.8 indicates strong agreement between classification results and field observations [32].

2.5. Land Cover Transition Analysis

Land cover transition refers to changes in biophysical properties of land surface of a particular region over a period of time driven by various factors. The rate of change and the nature of land cover transition can differ in time and space. Thus, transition is represented by changes in area and in speed. Transition matrix is widely used to quantitatively detect the temporal change and spatial distribution of land cover over a long-term perspective [34,35]. Land dynamics among different land cover types can be expressed by a transition matrix, which is derived from the land cover transition occurring for a defined period of time [36]. The land cover transition matrix describes the dynamic process of the mutual transformation between land cover types at the end and beginning of the study period. It also shows the transferred-in and transferred-out information of each land cover category.

The change intensity of land cover can be also quantified by the two indices, such as single and integrated dynamic index of land cover [37,38]. The single dynamic index of land cover describes the change speed of regional land cover. The single dynamic index, $K$, is defined as [37].

$$K(\%) = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100$$  \hspace{1cm} (1)

In the above Equation (1), $U_a$ and $U_b$ are the area of a certain land cover category at the beginning and end moment of the study, respectively, and $T$ is the length of time. When $T$ is the year period, the value of $K$ represents the change rate per year of a certain land cover type [38].

The integrated dynamic index is the transfer rate among land cover categories during the study period, and it can reflect the overall change of all land cover categories in the study area over the study period. The integrated dynamic index is given as [36]:

$$K_t(\%) = \frac{\sum_{i=1}^{n} |U_{bi} - U_{ai}|}{2 \sum_{i=1}^{n} U_{ai}} \times \frac{1}{T} \times 100$$  \hspace{1cm} (2)

In Equation (2), $U_{bi}$ and $U_{ai}$ are the area of a certain land cover category at the end and beginning of the study period, respectively, and $n$ is the quantity of land cover categories. The dynamic index $K_t$ examines the transfer between land cover types with the study time frame, and focuses on the change procedure but not change results.

3. Results

3.1. Land Classification Accuracy

The supervised classification of Landsat images using GE-based training datasets was conducted to classify land cover types in the Chemoga basin. A confusion matrix was made by comparing the labels in the generated map with the 2017 field observations, as shown in Table 2. The matrix comprised observed data (columns) and classified data (rows). The land classification was correct for 141 of 165 reference samples, according to the sum of elements along the main diagonal of the matrix. Thus, the overall classification accuracy was high, at 85.4%, which corresponds to satisfactory land cover classification performance.
Table 2. Confusion matrix for land cover classification.

| Land Cover | Classified Data | Total | PA * (%) |
|------------|-----------------|-------|----------|
|            | AF/NF/PF/WL/AL/GL/IW |       |          |
| Reference Data | AF | NF | PF | WL | AL | GL | IW |       |
| AF          | 8   | 12 | 2  | 3  | 40 | 3  | 165|       |
| NF          | 2   | 12 | 3  | 2  | 19 | 3  | 165|       |
| PF          | 2   | 38 | 40 | 3  | 165| 100.0 |
| WL          | 3   | 17 | 5  | 27 | 63.2 |       |
| AL          | 1   | 17 | 5  | 27 | 63.2 |       |
| GL          | 1   | 17 | 5  | 27 | 63.2 |       |
| IW          | 3   | 17 | 5  | 27 | 63.2 |       |
| Total       | 10  | 16 | 48 | 4  | 17 | 3  | 165|       |

UA * (%) 80.0 75.0 79.2 75.0 100.0 89.6 100.0

Overall accuracy = 85.4 %, Kappa coefficient = 0.81

The producer’s accuracy and user’s accuracy were also computed from the confusion matrix (Table 2). Producer’s accuracy ranged from 63.0% to 100.0%, while user’s accuracy ranged from 75.0% to 100.0%. The two most common misclassifications were agricultural land and natural forest. Of the 27 agriculture samples, 10 were misclassified: 5 as grassland, 4 as plantation, and one as natural forest. Natural forest lands were classified correctly on 12 of 19 occasions. While 67 ground truth points were classified as grasslands, only 60 of them actually were grasslands, where the majority of misclassified locations were agricultural lands (5 samples).

User’s accuracy reflects the actual utility of the classification, while producer’s accuracy is the classification accuracy of a particular land class. Agricultural lands, inland waters, and grasslands have the highest producer’s and user’s accuracy. In this study, the overall kappa statistic for land classification was 0.81, which corresponds to strong agreement between the classification results and ground truth data [29].

3.2. Land Cover Change Estimation

Figure 3 depicts the spatial distribution of land cover types for the years 1987, 2002, and 2017 in the Chemoga basin. The extent of the area associated with each land class for the years 1987, 2002, and 2017 have been summarized in Table 3. The prominent land covers of the basin were agricultural land, woodland, and grassland. These three land covers occupied more than 90% of the basin. The agricultural lands increased in extent from 52,031 ha (44.0%) to 53,208 ha (45.0%) during the first 15 years of the study period, and to 54,368 ha (45.9%) during the second 15 years. This increase was the largest shift among land cover types during the period 1987–2017, and was mostly attributable to conversion from grasslands and woodlands (Table 4), whose areas were located near streams.

Table 3. Changes in land cover across the years 1987, 2002, and 2017.

| Land Cover | 1987 Area-ha | 1987 % Area | 2002 Area-ha | 2002 % Area | 2017 Area-ha | 2017 % Area |
|------------|--------------|-------------|--------------|-------------|--------------|-------------|
| AF         | 104          | 0.1         | 151          | 0.1         | 111          | 0.1         |
| NF         | 3820         | 3.2         | 5679         | 4.8         | 5068         | 4.3         |
| PF         | 1460         | 1.2         | 2996         | 2.5         | 3037         | 2.6         |
| WL         | 29,597       | 25.0        | 25,194       | 21.3        | 25,366       | 21.4        |
| AL         | 52,031       | 44.0        | 53,208       | 45.0        | 54,368       | 45.9        |
| GL         | 30,871       | 26.1        | 30,183       | 25.5        | 28,655       | 24.2        |
| BA         | 475          | 0.4         | 910          | 0.8         | 1711         | 1.5         |
| IW         | 1            | <0.1        | 38           | <0.1        | 43           | <0.1        |
Figure 3. Land cover types in the Chemoga basin in 1987, 2002, and 2017.

Table 4. Land cover transition matrix of the Chemoga basin between 1987 and 2017.

| Land Cover | 1987 Land Cover (ha) | 2017 Land Cover (ha) |
|------------|----------------------|----------------------|
| AF         | 32                   | 12                   |
| NF         | <1 1679              | 287                  |
| PF         | <1 290               | 278                  |
| WL         | <1 186               | 7                    |
| AL         | <1 1842              | 1336                 |
| GL         | 79                   | 1059                 |
| BA         | <1                   | 5                    |
| IW         | <1                   | <1                   |
| Forestlands consist of afro-alpine forest, natural forest, and planted forest of the basin. Forestland area has expanded by 3442 ha in the period of 1987–2002, while the reverse pattern was seen in the next 15 years. Natural forest area was 3820 ha (3.2%), 5679 ha (4.8%), and 5068 ha (4.3%) for 1987, 2002, and 2017, respectively, increased by 1248 ha over 30 years. Afro-alpine forests showed irregular changes, increasing by 47 ha from 1987 to 2002 and declining to 111 ha in 2017 (0.1%). Plantation forests occupied 1460 ha (1.2%) in 1987, 2996 ha (2.5%) in 2002, and 3037 ha (2.6%) in 2017, representing a two-fold increase in area over 30 years. Most of the plantation areas were in the middle and upper parts of the Chemoga and Weterene watersheds, where the dominant tree species is Eucalyptus globulus.

Woodlands decreased by 4403 ha over the first 15 years of the study period, but increased by 172 ha over the second 15 years, giving a cumulative decrease of 4231 ha over the past 30 years. This change in woodlands may be due to the frequent fires that occurred as a result of the dryer climate at low altitudes. Fire damaged areas were clearly seen on GE images.

As Landsat images were acquired during the dry season, grasslands and wetlands had similar reflectance and were thus both categorized as grasslands. Within the first 15 years of the study period, grasslands decreased from 30,871 ha (26.1%) to 30,183 ha (25.5%), and then to 28,655 ha (24.2%) after the second 15 years. Recently, woodlands and grasslands were the most susceptible to change, commonly transitioning to agricultural land (Figure 4).
Table 4 shows the transition matrix that indicates the temporal changes among the different land cover types in two successive periods of time. The diagonal entries in Table 4 represent the portion of each property which remained in the same land cover. Over the 30-year study period, 71.1% of the land cover remained unchanged.

There were clear evidences for land transition in the basin, such as agricultural land expansion, deforestation and afforestation, and urbanization. Agricultural land was the dominant land cover, but 12,327 ha and 9992 ha, respectively, of the land area were converted from, or changed into, other land cover types over 30 years. Deforestation and afforestation have coexisted in the Chemoga basin during the study period. Deforestation of natural forests was accompanied by the conversion of arable land (1081 ha), and a total of 1182 ha of plantation forests was changed into other land cover. Over the same period, 2901 ha of agricultural and woody lands were recovered to natural forests, and 2458 ha of their lands were artificially planted with fast-growing trees. Compared to other forest types, afro-alpine forest remained relatively stable, because of its geographical location (above 3500 m altitude) [24]. The most obvious urbanization occurred in the middle of the basin, surrounding Debre Markos town. During the 30 years, built-up space stretched aggressively into agricultural and grass lands, which accounted for about two times the 1987 build-up area.

Table 4 indicates that the main performances of land transitions were afro-alpine forest transiting to grassland, grassland transiting to agricultural land, and waters transiting to agricultural land. In this context, the transition from grassland to agricultural land was the most obvious, occupying 79.14% of the whole in-transition area in the 2017 agricultural land. Figure 5 depicts the descriptive pathways for land cover transition over 30 years in the basin, indicating the transition probability between land cover types. In Figure 5, only probabilities greater than 0.10 were plotted. A 10% of the transition probability was reasonable to consider a threshold value for land cover change analysis [39]. The behavior of land transition is nearly straightforward, except for shifting between agricultural land and grassland.

Table 5 presents the dynamic index of land cover for each transition period. Even though the single dynamic index of inland water was ultimately high in the period of 1987–2002, it is deceiving because the occupied area was very small in the year 1987 (about 1 ha). Only 37 ha of an increase in waterbodies caused the large number in dynamic index calculation. Except for inland water, the dynamic index of built-up area was the largest out of the seven land cover types and illustrated the rapid expansion of residential and commercial areas in the Chemoga basin. The dynamic index of grassland declined from 1987 to 2017; the value of the index was −0.15% during the period of 1987 to 2002 and decreased to −0.34% during the period of 2002 to 2017. The single land cover dynamic...
index of woodland was −0.99% in the first 15 years, meaning that woodland area declined by nearly 1% annually. The whole area of agricultural land increased steadily with 0.15% over 30 years.

Figure 5. Land cover transition probabilities for the 1987-2017 period. Values in circle indicate unchanged area portion. Probabilities lower than 0.10 were omitted.

Table 5. The dynamic index of land cover in the Chemoga basin between 1987 and 2017.

| Study Period       | Single Dynamic Index (K, %) | Integrated Dynamic Index (Kt, %) |
|--------------------|----------------------------|---------------------------------|
|                    | AF | NF | PF | WL | AL | GL | BA | IW |
| From 1987 to 2002  | 3.05 | 3.24 | 7.02 | −0.99 | 0.15 | −0.15 | 6.11 | 276.22 | 0.29 |
| From 2002 to 2017  | −1.76 | −0.72 | 0.09 | 0.05 | 0.15 | −0.34 | 5.87 | 0.78 | 0.12 |

Tables 4 and 5 indicated that woodland and grassland were much more susceptible to out-transition, and were the largest sources for built-up area, occupying 79.34% of total in-transition area. The integrated dynamic index for the first 15 years was two times higher than the value obtained for the second 15 years, implying that the land cover change was generally faster in the period of 1987–2002.

4. Discussion

Natural forests decreased by only 0.5% over the second 15 years, although previous studies of different regions in Ethiopia have shown relatively greater decrease in natural forests [4,40]. This indicates that the population relocation strategy of the current Ethiopian government, and the efforts of local communities, have been effective for natural forest conservation and protection in the Chemoga basin.

Land conversion in the upper catchment reflects the preference of local communities. Agricultural lands in high and intermediate altitude regions were shifted into Eucalyptus tree plantations. The fast-growing Eucalyptus can directly benefit residents as it is used for food, fuel, and household goods [24,41]. Urbanization and road development are other major drivers for plantation forest expansion. Most Eucalyptus plantations were situated near villages and roadsides. On GE images, plantation sites had distinct geological and textural characteristics that distinguished them from natural forests, woodlands, and afro-alpine forests.

A rapid agricultural expansion was observed in the study area. In the last half-century, many local communities have reclaimed large areas in hilly and mountainous regions for agricultural purposes, which were previously unsuitable for farming [1,3,4,24,42]. In 1997, the Amhara regional government
redistributed grazing lands to local peoples who had no or little cultivable lands. Informal interviews with local residents indicated that most of the new agricultural lands were previously shifted from grasslands; it appears that the land allocation policies of the government of Ethiopia encouraged the illegal conversion of agricultural lands, mainly from grasslands near rivers. Such changes can sometimes be seen in GE images, but are difficult to quantify in Landsat images because they occurred on scales smaller than the 30-m pixel resolution.

In Ethiopia, grasslands and forests are typically considered as communal lands reserved primarily for the use of the adjoining villages. The continued decline in communal lands was mainly due to the increased demand for private lands, especially in grasslands. In the Gedebe watershed, farmers converted grasslands to agricultural lands [40,41]; this also occurred in the Beressa watershed [35]. Grassland shrinkage was also documented in other areas of Ethiopia [4,19,25,39]. On the contrary, grassland enlargement is an emerging issue in the Chemoga basin [24]. Considerable grasslands are now used for livestock grazing. This situation has been exacerbated in recent years, because communities have opted to expand grazing lands in hilly areas (Table 4); this study also revealed that most grazing lands in hilly terrain were originally forests, and not grasslands.

Small size ponds were sparsely seen in the 2002 and 2007 GE images. Some ponds were intentionally constructed for irrigation purposes [24]. In other cases, small gravel pits were dug for supply water to road construction sites. Local communities might use these small ponds for watering their animals after the completion of road works. Landsat images were acquired in dry season, characterized by little rainfall. As evaporated water exceeded rainfall input in this period, the area of inland waters had shrunk and, consequently, some ponds can be misidentified as grasslands according to rainfall–evaporation water balance.

The increase of human population and arable land demand resulted in land conversion in the Chemoga basin. This land cover change posed resource degradation due to the destruction of natural vegetation cover. The Ethiopian government, institutions, and communities had a perception on the present land degradation, and implemented the land conservation programs to rehabilitate degraded environments since the 1970s [25]. The Ethiopian government, with assistance from international aid agencies, also enforced the community reallocation programs throughout the country to control the overexploitation of natural resources and the negative impacts of land cover change. This administrative action has made great progress, showing vegetation coverage improvement in the higher- and mid-altitude regions in the study area. As a local initiative, community afforestation has been successfully established to recover or preserve communal forests at the household level.

Similar studies were conducted to build land cover map on different regions of Ethiopia [2–4]. Bewket [26] used two sets of panchromatic aerial photographs to examine land cover change for the period of 1957–1982. There is no single best method for landscape analysis, but the integration of Landsat and GE enables us to enhance the capability for land feature identification. Land cover mapping is further useful to analyze the level of soil erosion, landslide risk, land use and urban planning, carbon and ecosystem value estimation.

Several studies have been conducted to monitor land cover change over the world by using space-borne imagery [6,9]. Remote sensing techniques have long been recognized as an essential and powerful tool for land cover mapping. Despite the fact that land cover change is occurring rapidly in developing or less-developed countries, remotely sensed observation on land features for a long-term time horizon is still limited in these countries [42], due to lack of accurate reference data for times long past. To overcome this obstacle, GE images were used in this study to extract pseudo-ground truth data. GE allows scientists and researchers to access vast amount of high resolution images free of charge and apply different processing procedures in remote sensing studies.

One powerful approach in this study was the integration of Landsat and GE images for land cover analysis. The scarcity of ground truth for various land features is a major obstacle in employing remote sensing technique for accurate land classification. GE is well implemented to synthesize pseudo-ground
truth data used to represent land features at a suitable scale. The advantages of using GE provides historical imagery, allowing the multi-temporal analysis for landscape change over time [43] when ground truthing is not possible. The further identification of land features is also possible with the help of GE images. Higher spatial resolution of GE images allows for accurate identification of each land cover at different temporal and spatial scales. Generally, GE enabled us to identify relatively diverse features, including shapes, colors, and textures of each land feature. This helped us to build high confidence training datasets for further land classification.

5. Conclusions

Remote sensing is essential for detecting land cover changes. The Chemoga basin in Ethiopia has undergone multiple land cover transitions to meet the demands of local communities. Supervised classification using Landsat images was used to detect spatiotemporal patterns of land cover in the study area. Training datasets were extracted from GE images for each land feature. From 1987 to 2017, agricultural lands increased from 52,031 ha (44.0% of the land) to 54,368 ha (45.9%). Woodlands and grasslands seem to be most susceptible to land changes, frequently transitioning to agricultural land or settlements over the 30-year study period.

Land classification with the medium-resolution (or coarser) images is difficult in areas like the Chemoga basin, which is characterized by highly fragmented and heterogeneous patterns of land cover over small geographic distances. Similarity in spectral reflectance among land features can result in misclassification. To address this issue, emerging technologies such as GE have been exploited to distinguish land cover types according to their geographical and geomorphological characteristics.

GE could be a useful tool to build reference data for fragmented and heterogeneous landscapes, which have difficulty to acquire high-resolution ground truth data. In near recent years, GE serves well-qualified datasets with higher temporal resolution. Therefore, the increasing availability of GE in recent years, as well as in future, enables us to distinguish accurately between similar reflectance objects in land cover change analysis.

This study demonstrated land cover mapping of a large area using freely available data (Landsat and GE images). Spectral information on land features could be extracted from GE images at a much lower cost, and is applicable to an auxiliary training dataset for image classification. With the application of various geospatial techniques, it is now possible to detect land cover changes at a wide range of spatiotemporal scales. Remote sensing could aid in the establishment of reliable conservation measures and land use planning, especially in less-developed countries.

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