DETERMINING THE TYPE AND STARTING TIME OF LAND COVER
AND LAND USE CHANGE IN GHANA BASED ON DISCRETE
ANALYSIS OF DENSE LANDSAT IMAGE TIME SERIES

A Thesis
Presented to the
Faculty of
San Diego State University

In Partial Fulfillment
of the Requirements for the Degree
Master of Science
in
Geography

by
Hsiao-chien Shih
Spring 2015
The Undersigned Faculty Committee Approves the

Thesis of Hsiao-chien Shih:

Determining the Type and Starting Time of Land Cover and Land Use Change in Ghana Based on Discrete Analysis of Dense Landsat Image Time Series

Douglas Stow, Chair
Department of Geography

John Weeks
Department of Geography

Roger Caves
School of Public Affairs

May 5, 2015
Approval Date
ABSTRACT OF THE THESIS

Determining the Type and Starting Time of Land Cover and Land Use Change in Ghana Based on Discrete analyses of Dense Landsat Image Time Series

by
Hsiao-chien Shih
Master of Science in Geography
San Diego State University, 2015

Accra, Ghana and environs have experienced extensive land cover and land use change, which warrants more frequent monitoring. In the study I develop and test approaches for semi-automatically identifying the type and date of land cover and land use change from multi-temporal series of Landsat ETM+ imagery from 2000 to 2014. Clouds, cloud shadows, and scan line corrector-off creates missing or null data in the ETM+ images. Forty-one dates of ETM+ images that partially contain missing data were used in this study. The general approach is to conduct a per-pixel supervised classification on each date of image after masking null data based on stable training sites. Spatial, temporal, and logical filters are applied to correct for misclassification and missing data. Each image is classified into three general classes: Built, Natural Vegetation, and Agricultural, with expansion of Built being our main focus. Reference data for Change-to-Built were independently selected from all available high spatial resolution satellite images, and the beginning time of change was recorded. The change product was used to characterize the urban expansion around Accra.

The result shows that the temporal-filtered product identified both the location and the start of Change-to-Built more precisely and accurately. Based on reference data derived from visual imagery analysis, 40% of the Change-to-Built samples were correctly identified without filtering, whereas 80% were correctly identified when applying temporal filter with low amounts of false positive Change-to-Built pixels. The temporal-filtered products have the highest precision and accuracy in identifying the start of Change-to-Built: the identified Change-to-Built samples are on average 2.1 years difference with the reference data. Under the limitation of frequent cloud effect and limited historical archives of high resolution images, a discrete classification approach to LCLUC mapping is shown to be successful by this study, but continuous index approaches needs to be evaluated in future research.
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This research was funded by National Aeronautic and Space Administration Interdisciplinary Research in Earth Science Program grant G0009708, “The Urban Transition in Ghana and Its Relation to Land Cover and Land Use Change Through Analysis of Multi-Scale and Multi-Temporal Satellite Image Data,” Douglas A. Stow, Principal Investigator.
CHAPTER 1

INTRODUCTION

Land cover and land use change (LCLUC) occurs primarily due to human population growth and economic prosperity, and such changes can lead to environment degradation. Selective logging of pristine forests and planting commercial crops has caused habitat loss of local species (Hill et al., 1995) and increasing impervious surface of urbanization alters the urban hydrology (Shuster et al., 2005). Global LCLUC has led to climate change and increases hazard frequency, so LCLUC warrants more frequent monitoring.

Ghana is a developing country in western Africa that has experienced extensive LCLUC because of population growth and urbanization from rural-to-urban migration (Codjoe, 2007). Agricultural lands have been converted to urban areas, and forest and grassland have been changed to croplands (Braimoh, 2004; Aduah & Aabeyir, 2012). LCLUC has occurred within and around major cities in Ghana, especially around its capital, Accra (Møller-Jensen et al., 2005; Yorke & Margai, 2007; Tsai et al., 2011).

Remote sensing is a cost-effective approach for monitoring LCLUC and the Landsat Thematic Mapper (TM) series of historical satellite imagery and derived products are freely-provided to monitor and investigate LCLUC. The Landsat satellites periodically revisit the same location at least once every 16 days (NASA, 2011), which enables frequent, long-term monitoring of LCLUC. However, previous studies have generally been limited to incorporating just a few Landsat images for monitoring LCLUC within the 30 year archive of (Yang & Lo, 2002; Liu & Zhou, 2004; Zhou et al., 2008) due to the limitation of incomplete imagery caused by cloud cover and cloud shadows. Researchers are able identify the location, the amount, and the type of LCLUC but not the exact time the LCLUC occurred.

The objective of the research is to develop and evaluate a discrete approach for semi-automatically identifying the type and date of LCLUC from multi-temporal series of Landsat Enhanced Thematic Mapper Plus (ETM+) imagery. The specific study area is located in
southeastern Ghana and the study period is 2000 to 2014. Most Landsat images of the study area contain noise (clouds, cloud shadows, SLC-off), which creates gaps of coverage in resultant LCLUC maps. From temporally dense Landsat image time series, continuous data approaches based on spectral vegetation indices have successfully identified LCLUC transitions, but for very general classes and with limited temporal resolution. This study focuses on whether discrete analysis based on classification of each image data enables more precise identification of the data and type of LCLUC than continuous index approaches. This involves exploration of spatial and temporal filtering for accounting for No Data gaps caused by cloud and sensor related effects. Landsat 7 ETM+ imagery is classified into multi-temporal LCLU maps that contain some missing data from clouds and cloud shadows and spatial-temporal filtering is applied compensate for the missing data. Independent reference samples are used for testing the accuracy of the change maps; the maps is used for characterizing the urban expansion around Accra, the capital of Ghana, from 2000 to 2014.

The following questions were addressed in the specific geographic, temporal and satellite imagery contexts of this study:

- How accurate and precise are semi-automatic discrete classification approaches to determining the type and date of LCLUC?
- What types of spatial, temporal and logical filtering approaches are most effective at determining the type and date of LCLUC from a Landsat time series that has “no data” gaps?
- What are the spatial-temporal trends in LCLUC from 2000 to 2014 in terms of types and timing of LCLUC?
CHAPTER 2

BACKGROUND AND LITERATURE REVIEW

2.1 LAND COVER LAND USE CHANGE ANALYSIS IN GHANA

Most analyses of LCLUC in Ghana have been conducted after 1999 because of the availability of Landsat 7 ETM+ satellite imagery. Prior to 1998, a few survey and mapping activities were conducted for limited areas of Ghana for resource development purposes. According to Volta Basin Research Project (1999), the first complete and useful LCLU map for Ghana was completed in 1998. Researchers have observed that LCLUC has occurred throughout Ghana, for example in Tamale in North region (Braimoh, 2004), Wa Municipality in Upper West region (Aduah & Aabeiyir, 2012), and Accra in Great Accra region (Møller-Jensen et al., 2005). The general trend of LCLUC from these studies illustrates that the extent of forest and woodland areas shrunk, and agricultural and built areas expanded, especially in and around Accra. Yankson and Gough (1999) pointed out that the speed of urbanization was too fast in and around Accra to provide enough infrastructure services in terms of water supply and liquid waste disposal. Despite the insufficient services, urbanization has continued to occur, prompting a need for more monitoring of LCLUC, particularly in southern Ghana (Møller-Jensen, 2005; Yorke & Margai, 2008; Tsai et al., 2011).

In Ghana, land is usually communal property, and stools (tribal chief) and clan have to right to distribute and redistribute land to other clan members for farming (Owusu, 2008). Due to the modern development in Accra, more and more migrants have been drawn into the urban areas, and they have competed for land with the local tribes. Here in Accra, stools and clan often sell or lease the tribe’s land to the migrants who offer high prices, and these migrants usually convert farmland into housing construction extensively. The Ministry of Lands and Forestry issued National Land Policy (1999) to control the over-development but failed. Owusu pointed out the main reason of for failure: land transaction between migrants and stools sometimes is often informal, so the District Assembly was not aware of the
transaction. Therefore, the population growth from in-migration and failed regulation of government incite massive illegal, uncontrolled LCLUC.

2.2 Remote Sensing for Land Cover Land Use Change Analysis

Two approaches of identifying LCLUC have primarily been implemented with time-series remotely sensed imagery: continuous and discrete. A continuous approach is to track a spectral index that is sensitive to changes in LCLU. For example, the Normalized Difference Vegetation Index (NDVI) is sensitive to vegetation; healthy and dense vegetation tends to have high NDVI value and non-vegetation land cover has low NDVI value. NDVI and other normalized spectral indices can be generated from different band combinations. Comparing temporal variations of such indices derived from multi-temporal image data sets is an approach for identifying LCLUC types. Van Leeuwen (2010) tracked the Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI to monitor vegetation growth before and after wildfires. Schneider (2012) used Landsat 7 ETM+ NDVI to identify urbanized and urbanizing areas in China and with a relatively coarse estimate of the date of initial LCLUC the changed date. A discrete approach is to classify different dates of images to create a series of LCLU maps and to track the transition among different LCLU classes over time. Past studies using discrete approaches have tended to classify mostly noise-free images (e.g., no clouds, cloud shadows, atmospheric haze, or sensor-related missing data) to identify LCLUC (Liu & Zhou, 2004; Zhou et al., 2008; Yang & Lo, 2002). Thus, the temporal intervals between any two dates of imagery are variable and often longer than when utilizing the continuous approach. Yang and Lo (2002) detected urbanized area in Atlanta, Georgia, with multi-temporal Landsat images. Six dates of images from 1973 to 1998 were used, such that monitoring frequency was too low to determine the start of LCLUC very precisely.

2.3 Filtering

The release of the historical archive of pre-processed Landsat TM/ETM+ imagery and the successful use of stable training sites (Grey & Song, 2013; Stow et al., 2014) enable the opportunity to test whether identifying the starting date and type of LCLUC is reliable using a discrete approach. Also to be evaluated should be whether or not various filters,
including spatial, temporal, and logical, are effective at removing gaps in the LCLU maps produced by noisy images, as well as misclassification errors. Spatial filters have commonly been implemented on individual LCLU maps for removing high spatial frequency noise, often from misclassification and boundary effects on mixed pixels called the “salt and pepper” effect (Yang & Lo, 2002; Im & Jensen, 2005; Liu & Zhou, 2004). For example, a 3 by 3 or 5 by 5 pixel-kernel is applied to force the central pixel to be assigned the majority class of the neighborhood of pixels. Temporal filters are applied to examine the consistency of the LCLU type from a time series of LCLU maps (Liu & Zhou, 2004; Zhou et al., 2008). Similarly, logical filters are used to inspect LCLUC spatially or temporally by removing illogical adjacency relationships or temporal change (e.g., conversion from built to natural vegetation in an urban expansion area would not occur (Liu & Zhou, 2004). Luo and Mountrakis (2011) integrated spectral and spatial information to map impervious surfaces. For unclassified pixels, the spatial distance to a classified pixel was used as a rule to remove possible misclassification. Implementing these filters on a temporally dense Landsat imagery should help refine a series of LCLU maps to identify the type and date of LCLUC.

2.4 Cloud removal

The Landsat-series products, as well as those from other satellite images, can be contaminated by clouds, cloud shadows, and haze, such that the land surface below the atmospheric contamination is not observed, which causes gaps or No Data pixels. This is particularly the case for cloud-prone regions of the world such as Ghana. In addition, the scan-line corrector off malfunction (SLC-off) for the Landsat 7 ETM+ sensor since 2003 has caused more No Data pixels in the images (Markham et al., 2004). In such cloud-prone area, this problem is hard to solve when using a continuous time series analysis approach, even with NDVI product of MODIS 16-day composite, which assumes one of the 16 days is cloud-free. Using a discrete approach, Helmer and Ruefenacht (2005) filled cloud-contaminated areas of a base Landsat image with another temporally-close, cloud-free Landsat image to create a cloud-cleared image for a further classification and detecting LCLUC. However, this method involves radiometric correction between the base and the cloud-free image. Others simply assign No Data pixels the same class as the earlier-date of LCLU map that is cloud-free assuming there is no change (Carreiras et al., 2014). However,
temporal interpolation of No Data should consider not only earlier-date maps but also later-date maps and their surrounding spatial neighborhood of pixels (i.e., spatial-temporal filtering).
CHAPTER 3

METHODS

3.1 STUDY AREA

The study area of this research is located in southeastern Ghana, within the rectangle delineated by geographic coordinates 0°45'55"W to 0°6'57"E, and 6°12'56"N to 5°25'54"N (Figure 1). This area experienced urbanization from 1985 to 2002 (Møller-Jensen et al., 2005) and is within the of Greater Accra, Eastern, and Central regions (equivalent to states in the United States). Agricultural and Built LCLU are often interspersed within natural vegetation. About 10% of the study area is covered by water, which includes the Gulf of Guinea and a few of small inland lakes. This equatorial area has a warm temperature and the rainy season occurs from April to November. During the dry seasons, dry Harmattan winds blow from the northeastern Sahara carrying wind-borne dust, and substantially decreases atmospheric visibility for satellite observations. Ghana Statistical Service (2012) reported an extensive population growth in this area: the population increased 38% from 2000 to 2010 in Greater Accra. Regional and urban populations greatly increased from 2000 to 2010 in the three regions (shown in Table 1). Many small towns along major roads have started to expand, and agricultural plots have been converted to Built LCLU in Great Accra, which warrants LCLUC monitoring.

Table 1. Population and urban proportion in Greater Accra, Eastern, and Central regions

<table>
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<tr>
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<tr>
<td>Greater Accra</td>
<td>2,905,726</td>
<td>87.7</td>
<td>4,010,054</td>
<td>90.0</td>
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<tr>
<td>Eastern</td>
<td>1,635,421</td>
<td>34.6</td>
<td>2,633,154</td>
<td>43.4</td>
</tr>
<tr>
<td>Central</td>
<td>1,593,823</td>
<td>37.5</td>
<td>2,201,863</td>
<td>47.1</td>
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</table>
3.2 Data

Landsat 7 ETM+ imagery was used as the main data source for identifying the type and timing of LCLUC, and most image preprocessing was automatically performed by USGS prior to obtaining the data. The spatial resolution of the ETM+ multi-spectral imagery is 30 m and the satellite sensor revisits the same location every 16 days. The study area is wholly contained within Landsat ETM+ images corresponding to path 193, row 56 of the Worldwide Reference System-2. Only Level 1 terrain-corrected (L1t) image products were used for this study because of their high geometric and geopositional accuracy (Zhu et al., 2012). The products containing less than 33% cloud-cover were downloaded from the USGS website and used to generate the image time series. In total, 68 images meet this cloud-cover criterion from 1999 to 2014. The original seven wavebands of the images were converted into land surface reflectance values by the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) to correct for atmospheric and illumination effects before being downloaded (Masek et al., 2006). The LEDAPS product contains the seven wavebands of reflectance, seven spectral indices (SI; e.g., NDVI), and a Function of Mask (Fmask) routine for screening out noise including water, clouds, clouds shadows, and SLC-off (Zhu & Woodcock, 2012; USGS, 2012; USGS, 2014). The seven bands of surface reflectance, the seven indices, and Fmask were used for further processing.

All available high spatial resolution commercial satellite images (e.g., IKONOS, Quickbird, and WorldView series) covering the study area were used to generate reference data. These high spatial resolution images are listed in Table 2. Google Earth image archives were another source of high spatial resolution images for those areas that were out of the coverage of the commercial satellite images. However, the total coverage of the above high spatial resolution imagery did not cover the entire study area. Also, the date of acquisition of the Landsat and commercial satellite images might not match. In these cases, visual analysis of the original ETM+ images was used to generate reference data. The proportional coverage of the study area by reference imagery and number of ETM+ images per year are illustrated in Figure 2.
Figure 1. Study area in southeastern Ghana. This study area is within the Great Accra, Eastern, and Central regions.

Table 2. Images sources for analysis and validation

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<th>Year</th>
<th>ETM+</th>
<th>Mapping source (scene)</th>
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<th>GeoEyes-1</th>
<th>Quickbird-2</th>
<th>Worldview-1</th>
<th>Worldview-2</th>
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<td>0</td>
</tr>
<tr>
<td>2014</td>
<td>2</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>41</td>
<td></td>
<td>115</td>
<td>24</td>
<td>87</td>
<td>228</td>
<td>12</td>
<td></td>
</tr>
</tbody>
</table>
Figure 2. Spatial coverage of the study area by reference images and the number of Landsat scenes per year.

3.3 IMAGE PROCESSING

The general approach to identifying the type and the starting date of LCLUC was to: (1) conduct per-pixel supervised classification for each date of the downloaded ETM+ images individually based on considerable stable training sites (Gray & Song, 2013) through 2000 to 2014, (2) refine the classified maps with spatial and temporal filtering, and (3) validate the type and time of LCLUC with reference samples that are selected independently. The strategy is to screen out No Data (e.g. water, clouds, cloud shadows, and SLC-off) and then apply a simple classification, refinement routine, and change identification for identifying the type and time of LCLUC as illustrated in Figure 3.

3.4 IMAGE PREPROCESSING

To enhance the separability among various types LCLU, two SIs from the LEDAPS product, Modified Soil adjusted Vegetation Index (MSAVI) and Normalized Difference Moisture Index (NDMI) were used for classification. MSAVI was used for differentiating
vegetation from non-vegetation, while NDMI was used for detecting fire burn area. In addition, two more SIs were derived from ETM+ reflectance based on: SI= (m-n)/(m+n), where (m, n) corresponds to two of different ETM+ wavebands (Stow et al., 2014). These additional SIs were: Normalized Difference Red-Blue (3, 1) and Normalized Difference Green-Red (2, 3), where the numbers in parentheses represent the bands m and n, respectively.

Before LCLU classification, the pixels of clouds, cloud shadows, water, and SLC-off in each image were masked. Six surface spectral reflectance bands and four SIs were composited for each image date meeting the cloud cover criterion. To ensure that a sufficient number of appropriate training sites were selected for various types of LCLU, only images containing less than 70% No Data pixels were used for subsequent LCLU classification. In total, 41 images meet this criterion and are listed in Table 2.

### 3.5 SELECTING STABLE TRAINING SITES

Based on a pilot study, a simple LCLU classification scheme was implemented that emphasizes urbanization and the unique composition and spectral characteristics of the study area (Stow et al., 2014). The ETM+ images were classified into three general classes: Built (Bu), Natural Vegetation (NV), and Agriculture (Ag). Built includes three sub-classes: high-dense built, median-dense built, and low-dense built. Natural vegetation includes five sub-classes: forest, open forest, rangeland, savanna, and wetland plants. Agriculture includes five sub-classes: herbaceous crop, savanna crop, woody crop, slash-and-burn cultivation, and fallow.

Automatic Adaptive Signature Generalization (AASG) was applied to semi-automatically classify each date of images individually (Gray & Song, 2013). The strategy is to: (1) classify a complete, cloud-free image as a base LCLU map, (2) apply per-pixel, bi-temporal image differencing between the cloud-free image and the remainder of images, and (3) select thresholds for the output of image differencing to identify stable training pixels for each date of images. The earliest date ETM+ image containing the least No Data (February 2003) was classified into the base LCLU map with the sub-classes listed above. For the image of February 2003, the training pixels for each sub-class were selected by manually digitizing sample polygons based on high spatial resolution images captured within two years.
of a particular ETM+ image. The training samples of the surface reflectance and spectral indices for each sub-class were extracted from the February 2003 ETM+ image, and the statistics and histograms were found normally distributed. A per-pixel maximum likelihood classifier was used to generate the LCLU map for February 2003 based on the resultant training site statistics.

Figure 3. Image processing flow diagram
Accuracy of the 2003 LCLU map was initially assessed using 50 stratified-randomly selected sample points for each general class. The routine (selecting training pixels, classification, and accuracy assessment) was repeated until the overall accuracy of the LCLU map of February 2003 reaches at least 75%. This relatively high rate of accuracy is desired because the accuracy of other dates of LCLU maps depends on the accuracy of the base map.

Based on the resultant February 2003 LCLU map, temporal image differencing of MSAVI was applied to determine stable pixels for the remainder of the images. The thresholds (t) for the output of MSAVI image difference for the stable pixels were determined by:

\[ t = \mu \pm \sigma \]  

(1.1)

where \( \mu \) is the mean value of output of the image differences, and \( \sigma \) is the standard deviation of the output of image differences. Thus, the stable pixels are located within the range of \( \mu \pm \sigma \).

### 3.6 Image Classification

A per-pixel maximum likelihood classifier was implemented to generate LCLU maps for each image date. The training samples of the surface reflectance and all SI were derived from the stable training samples for each date. Sub-classes of each initial LCLU map were aggregated into the three general classes.

### 3.7 Filtering

Some misclassified and No Data pixels were removed from the temporal sequence of LCLU maps by application of a spatial majority, moving window filter. A 3×3 majority spatial filter was applied to each LCLU product (Figure 4(a)). A pixel and its eight neighboring pixels were taken into account, and the central pixel was assigned the majority class of this 3×3 kernel.

Also, some misclassified and No Data pixels might be removed from the primary LCLU maps by application of a temporal majority filter (Figure 4(b)). A three-date, per-pixel temporal majority filter was applied on each date of the primary LCLU map. For each pixel and for the middle date, the class of the previous date and the class of the following date
were considered. The class of the middle date was the majority class of the three dates. In this manner, temporal-filtered, multi-temporal LCLU maps were generated.

Certain types of LCLUC are illogical or do not tend to occur. For example, a change from Built to another LCLU class will not tend to occur, so a logical filter was applied when such cases arose from the initial image classifications (Figure 4 (c)). Pixels with illogical LCLU sequences were reassigned a class according to the following spatial contexts: (1) if a pixel is adjacent to those that are no-change Built, then that pixel in the later date is recoded as Built; and (2) if an illogical pixel is not adjacent to those that are no-change Built, then the illogical pixels in the early date is recoded according to the class of the latter date.

If individual spatial or temporal filters are ineffective at removing misclassified and No Data pixels may be removed from initial LCLU maps, a combined, spatial-temporal filter may be more effective. Therefore, a combined, three-date-temporal, 3×3-spatial, plus logical filtering was tested for each date of the primary LCLU map (Figure 4 (d)). For the central pixel and the middle date, the classes of surrounding eight pixels per date and the classes of the previous date and the next date were taken into account. That is, the pixel in the middle date was determined by the majority class of the 27 pixels (3×3-spatial×3-temporal). After spatial-temporal-filtering, the logical filter was applied on each two consecutive dates of these maps, using the same re-assignment options described above for logical filtering.

### 3.8 Change Identification

Five different LCLUC products were generated: (1) primary LCLU maps, (2) spatial-filtered LCLU maps, (3) temporal-filtered LCLU maps, (4) logical-filtered LCLU maps, and (5) combined-filtered LCLU maps. After filtering, the number of misclassified and No Data pixels decreased, but not completely removed. During the following change identification, No Data pixels were not considered as potential No Change pixels for all LCLU maps with the caveat that real change might happen but not be identified. Each date (t) of the time series of LCLU maps was compared pixel by pixel for the following five dates (t+1, t+2, t+3, t+4, and t+5) of LCLU maps, respectively. Once the majority class of a pixel and its eight surrounding pixels is identified as Change-to-Built between t and t+1, that pixel is considered to have changed to Built if the majority class of the pixel and its neighborhood pixels is identified Change-to-Built of LCLU at least twice for the dates that follow.
This change identification process was repeated from the beginning of the study period to the end of the period except for the last two dates of LCLU maps. Once a pixel is identified as Change-to-Built in early-date comparisons, subsequent classification maps are ignored. For Built LCLU, all identified Change-to-Built pixels from the identification were labeled the beginning date (t+1) of LCLUC, and all those pixels from the whole time series were aggregated into a LCLUC map. In this manner, a Change-to-Built map was derived from each filtering type to represent the expansion of Built.

3.9 LCLUC ACCURACY ASSESSMENT

To evaluate the five versions of LCLUC maps, both the type and starting date of LCLUC were assessed relative to reference data. Testing samples of reference data were generated independently, primarily from the high spatial resolution images and secondarily from the original ETM+ images. Each sample corresponds to a 3×3 pixel window to minimize effects of misregistration between the Landsat and high spatial resolution imagery. Fifty samples of Change-to-Built and 150 samples of no change (50 for each of the three general classes) were manually digitized based on visual image interpretation. The time of Change-to-Built on the reference samples were determined by flickering through and interpreting all the reference images from the beginning date throughout the end date and visually identifying the date that building starts to appear. Time was recorded as the number of days since the baseline date of December 5, 2000, the date of the first ETM+ image used for the LCLU map time series.

Fifty samples were used for cross-validating the five different Built-LCLUC map products individually. A sample is deemed correctly identified if five out of nine pixels are identified by the Built-LCLUC maps. The timing of the start of LCLUC was evaluated by calculating the time intervals between the Built-LCLUC maps and the recorded dates from the reference data. Because each sample was a 3×3 pixel window, the time interval for each sample was determined by averaging the time interval from the nine pixels. As an example, for a sample to be considered correctly identified, six out of nine pixels must be correctly identified to have changed, and the date for the start of change for this sample is the average of the dates for the six pixels. The time effectiveness of the Built-LCLUC maps was quantified by the ratio of agreement of LCLUC and the mean, the standard deviation, and the
The standard error of the time interval of the identified Change-to-Built samples. The lower the mean, the more accurate is the estimated start date of Change-to-Built, as represented by the LCLUC maps. The lower the standard deviation and standard error, the more precise is the start date of LCLUC is in the Built-LCLUC maps.

The 150 No Change samples were chosen in the similar way (visually identifying and manually digitizing in 3×3 pixel window on reference images), and the samples of no change were used for validating the false positive of Built-LCLUC maps. The lower the number of false positive sample, the higher is the accuracy of identifying no change the Built-LCLUC map.

Figure 4. Illustration of filters. (a) is an example of spatial filter. The class of the middle pixel is the majority class of the nine pixels, which is Built in the example. (b) is an example of temporal filter. The class of the middle date \( t_1 \) is the majority class of the three dates, which is Built in the example. (c) is an example of logical filter. Illogical change indicates that pixels change from Built to others, which will not occur. Pixels with illogical LCLU sequences are reassigned a class according to the following spatial contexts: (1) if a pixel is adjacent to those that are no-change Built, then that pixel in the later date is recoded as Built (i.e. bottom two red pixels); and (2) if an illogical pixel is not adjacent to those that are no-change Built, then the illogical pixels in the early date is recoded according to the class of the latter date (i.e. top two red pixels). (d) is an example of a combined, three-date-temporal, 3×3-spatial, plus logical filtering. For the central pixel and the middle date \( t_1 \) is determined by the majority class of the 27 pixels (3×3-spatial×3-temporal). After spatial-temporal-filtering, the logical filter is applied on each two consecutive dates of these maps, using the same re-assignment options for logical filtering.
CHAPTER 4

RESULTS

4.1 ACCURACY ASSESSMENT FOR THE BASE LCLU MAP

The accuracy of the base (February 2003) LCLU map is critical for accurate batch classification of other image dates, so an error matrix for this map was created and is shown in Table 3. In total, 150 stratified random samples were evaluated at the pixel level for the three general LCLU classes, which means 50 samples for each LCLU. With an overall accuracy of 83.15%, the Built class has the highest class accuracies for both User’s (92.16%) and Producer’s (94.00%) accuracy, relative to Natural Vegetation and Agriculture classes. Confusion exists between Natural Vegetation and Agriculture, especially among the subclasses of Savanna, Savanna Crop, and Fallow, and between the subclasses of Rangeland and Herbaceous Crop. Although effects of between-class confusion exist within the map, it is reliable for identifying Built LCLUC.

Table 3. Error matrix of the base LCLU map derived from Landsat ETM+ (February 2003) of southeastern Ghana.

<table>
<thead>
<tr>
<th>Classified Data</th>
<th>Bu</th>
<th>NV</th>
<th>Ag</th>
<th>Total</th>
<th>User’s accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bu</td>
<td>47</td>
<td>2</td>
<td>2</td>
<td>51</td>
<td>92.16%</td>
</tr>
<tr>
<td>NV</td>
<td>0</td>
<td>37</td>
<td>12</td>
<td>49</td>
<td>75.51%</td>
</tr>
<tr>
<td>Ag</td>
<td>3</td>
<td>11</td>
<td>36</td>
<td>50</td>
<td>72.00%</td>
</tr>
<tr>
<td>Total</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>150</td>
<td>Overall accuracy 83.15%</td>
</tr>
</tbody>
</table>

4.2 ACCURACY ASSESSMENT FOR LCLUC MAPS: TYPES OF TRANSITIONS

LCLUC maps from the different types of filtering are shown in Figure 5 (a, b, c, d, and e). Fifty Change-to-Built samples and 150 No-Change samples selected to evaluate the agreement and disagreement indicated the accuracy of the LCLUC maps based on sampled
reference data derive from visual interpretation of high spatial resolution satellite imagery and when not available, based on the Landsat imagery. These samples were assessed within a 3×3 pixel-window, so the spatial precision is 90 m. Accuracy matrices for the different LCLUC maps are provided in Table 4. The unfiltered LCLUC map is used as a benchmark.

Compared to the unfiltered LCLUC map, the temporal-filtered product and the combined-filtered product yielded higher accuracy according to the Change-to-Built reference data; 80% of the samples for the temporal-filtered and the combined-filtered LCLUC maps were in agreement, while only 40% of the samples of the unfiltered LCLUC map were in agreement. Also, more Change-to-Built samples were correctly identified for the spatial-filtered and the logical-filtered maps than for the unfiltered LCLUC map. Thus, the filtering process was effective at increasing the accuracy of identifying LCLUC.

To understand why some Change-to-Built samples were omitted, the imagery characteristics of these samples were visually inspected on pertinent Landsat and GoogleEarth images and associated LCLU map products. Three reasons were determined for why they were not correctly identified: (1) they were classified as No-change-Built (i.e., incorrectly classified as Built at the start of the study period), (2) they were misclassified as Natural Vegetation or Agriculture in mid/late dates of maps, or (3) a majority of the pixels were masked as No Data because of clouds, cloud shadows, or missing data. As shown in Table 4, 54% of the samples were incorrectly identified as Change-to-Built from the unfiltered LCLUC map because of reasons (2) and (3), while only 6% of the samples were because of reason (1). Note that the disagreement due to reason (2) greatly decreased after logical filtering, but the logical filtering cannot overcome the issue of excessive No Data pixels. Generally, after filtering, the number of unidentified samples due to reasons (2) and (3) dropped in all filtered maps, yet the number of the samples due to reason (1) increased slightly for the temporal-filtered and combined-filtered products.
Figure 5. LCLUC maps derived from five products, including (a) the original, non-filtered product, (b) the spatial-filtered product, (c) temporal-filtered product, (d) logical-filtered product, and (e) combined three-date-temporal, 3x3-spatial-filtered, and plus logical-filtered product.

Table 4. Comparison of Change-to-Built land use products derived with different filters: agreement/disagreement, false positive and time interval displacement relative to reference data.

<table>
<thead>
<tr>
<th></th>
<th>Unfiltered</th>
<th>Spatial</th>
<th>Temporal</th>
<th>Logical</th>
<th>Combined</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agreement of Change-to-Built samples</td>
<td>40%</td>
<td>48%</td>
<td>80%</td>
<td>50%</td>
<td>80%</td>
</tr>
<tr>
<td>(1) Disagreement of Change-to-Built samples due to misclassifying as No- change-Built</td>
<td>6%</td>
<td>6%</td>
<td>10%</td>
<td>6%</td>
<td>10%</td>
</tr>
<tr>
<td>(2) Disagreement of Change-to-Built samples due to misclassifying as Natural Vegetation or Agriculture in mid/late dates</td>
<td>28%</td>
<td>24%</td>
<td>2%</td>
<td>3%</td>
<td>6%</td>
</tr>
<tr>
<td>(3) Disagreement of Change-to-Built samples due to No Data in mid/late dates</td>
<td>26%</td>
<td>22%</td>
<td>8%</td>
<td>38%</td>
<td>4%</td>
</tr>
<tr>
<td>False positive</td>
<td>3.3%</td>
<td>3.3%</td>
<td>8.7%</td>
<td>6.7%</td>
<td>8.7%</td>
</tr>
<tr>
<td>Mean time interval (yr)</td>
<td>2.1</td>
<td>2.5</td>
<td>2.1</td>
<td>2.9</td>
<td>2.2</td>
</tr>
<tr>
<td>Standard Deviation of the time interval (yr)</td>
<td>2.0</td>
<td>2.3</td>
<td>1.8</td>
<td>2.6</td>
<td>1.7</td>
</tr>
<tr>
<td>Standard Error of the time interval</td>
<td>0.5</td>
<td>0.5</td>
<td>0.3</td>
<td>0.5</td>
<td>0.3</td>
</tr>
</tbody>
</table>
The number of pixels that were identified as Change-to-Built within the unidentified samples is graphed in Figure 6. The total amount of the identified Change-to-Built pixels is lower in both the temporal-filtered and the combined-filtered products compared to the unfiltered LCLUC map. This indicates that the filtering processes effectively took advantage of the spatial/temporal context for improving the LCLUC identification, but how to remove the disagreement due to the high presence of No Data pixels remains an issue.

The 150 No-Change samples were used for validating false positives (i.e., errors of commission) of the Built-LCLUC maps. The high percentage of false positives for a LCLUC map indicates that the map over-identifies pixels that are Change-to-Built. The unfiltered LCLUC map has the lowest percent (3.3%) of false positive, whereas the highest percent of false positive (8.7%) occurs in both the temporal-filtered and the combined-filtered products. All of these false positive samples were associated with No-Change Agriculture, which reflects the confusion between Built and Agriculture (e.g., fallow fields) (also shown in Table 3). Yet, the percentage of false positives for the temporal-filtered product and the combined-filtered product is still low.

4.3 ACCURACY ASSESSMENT FOR LCLUC MAPS: TIME OF START OF TRANSITION

The temporal frequency varies because the 41 Landsat images were unevenly distributed (due to cloud cover limitations) between 2000 and 2014; the minimum interval between each two consecutive dates of maps was 16 days and the maximum interval was about 700 days (1.9 years). On average, the temporal frequency is 0.34 images per year.

The time intervals between reference samples and LCLUC maps were used to evaluate whether the starting time of LCLUC was correctly identified. The average time interval from the identified samples for each product represents whether the product can accurately identify the time of LCLUC. A low mean time interval suggests that the LCLUC mapping procedure is able to accurately identify the start of LCLUC transition, with the caveat that there is inaccuracy and uncertainty in estimating time of LCLUC from the reference data, as well. With such a constraint, the mean time interval for the unfiltered product is 2.1 years, but other products have the higher mean time interval except the
temporal-filtered map. Thus, only the temporal-filtered product identified the time of LCLUC accurately.

![Figure 6](image-url)

**Figure 6.** Comparison of unidentified, Change-to-Built samples with the number of identified, Change-to-Built pixels for the five filtered products: including unfiltered product, spatial-filtered product, temporal-filtered product, logical-filtered product, and combined-filtered product. The legend (0, 1, 2, 3, and 4) indicates the number of identified, Change-to-Built pixels for an unidentified, Change-to-Built sample, and the number for vertical axis indicates the number of the unidentified, Change-to-Built samples. Fifty Change-to-Built samples were used to validation. But, samples with over four pixels identified as Change-to-Built were not included because they were deemed as identified Change-to-Built samples.

In terms of the precision of change time, both the standard deviation and the standard error of time intervals represent the precision of the change time. A high standard deviation of the time interval for a product indicates high uncertainty for the time of LCLUC. However, the numbers of identified Change-to-Built samples for different products are different, so the standard errors for the products, which are the normalized standard deviation, were used to compare the different products. The unfiltered, spatial-filtered, and
logical-filtered products have higher standard errors, but the temporal-filtered and combined-filtered products have lower standard errors. This is because more Change-to-Built samples were identified by the temporal-filtered and combined-filtered products, resulting in lower standard errors. The temporal-filtered and combined-filtered products have the lowest standard error, which indicates these products identified the time of start of LCLUC more precisely.

To understand how Change-to-Built samples were correctly identified within certain time lags from the actual start date of LCLU transition, cumulative curves of Change-to-Built samples that were correctly identified from different products (shown in Figure 7) were analyzed. The more samples from a LCLUC map that are identified within short intervals means that both the time and type of LCLUC are identified correctly. About 50% of Change-to-Built samples were correctly identified by both the temporal-filtered and combined-filtered products within a 2-year interval, while only 30% of the samples were identified by the unfiltered, spatial-filtered, and logical-filtered products within the same interval. Within a 3-year interval, over 60% of samples were correctly identified by both the temporal-filtered and the combined-filtered products, yet still about 30% of the samples were identified by the rest of three LCLUC maps. Hence, the temporal-filtered product and the combined-filtered product were more reliable for identifying the type and the time of LCLUC.

Visual analysis of the LCLUC maps reveals that fewer pixels are identified as Change-to-Built in the unfiltered product, and the number of Change-to-Built pixels are greater when filtering processes were applied. Change-to-Built was mapped for 2.7% of the study area in the unfiltered map, increasing to 3.1% after spatial filtering, 6.8% after implementing the logical filter, 10.4% after temporal filtering, and 10.3% when all three filters were combined. However, some of the pixels affected by the SLC-off issue were falsely identified as Change-to-Built in the temporal-filtered and combined-filtered products. Figure 8 shows a LCLUC map for the northwest of the study area, and Change-to-Built pixels many appear to follow the SLC-off pattern. After inspection of the original Landsat images, these pixels were determined to be cloud covered in one date of the image sequence. Weather for the date of image capture was cloudy and very hazy, but the Fmask cloud/shadow detection and masking routine failed to detect all the cloud-affected areas. Thus, these areas were misclassified as Change-to-Built.
Figure 7. Cumulative curves of the identified, Change-to-Built samples derived from five LCLUC products (the unfiltered product, the spatial-filtered product, the temporal-filtered product, the logical-filtered product, and the combined-filtered product) in different time intervals (between reference and the products). The curves exemplify the percentage of the Change to-Built samples were identified by close dates of Landsat images to the reference change time for each product.
Figure 8. The northwestern of the study area. This is the example that one date of the Fmask are fail to identify the cloud-affected areas, so these areas were mis-identified as Change-to-Built in the red strips.
CHAPTER 5

DISCUSSION AND CONCLUSIONS

5.1 LCLUC PRODUCT COMPARISON

This study demonstrates the reliability of identifying the type and start of LCLUC through a discrete classification and filtering approach to analyzing dense time stack of Landsat imagery. Based on reference data derived from visual imagery analysis, 40% of the Change-to-Built samples were correctly identified without filtering, whereas 80% were correctly identified when applying the combined spatial-temporal filter. Yielding a map precision of 90 m x 90 m, spatial filtering was found to only slightly refine the LCLUC maps, as did logical filtering. However, temporal filtering and combined spatial-temporal filtering greatly increased the accuracy of the LCLUC maps to 80%. The temporal- and combined-filtered product exhibit low amounts of false positive Change-to-Built pixels.

From the perspective of identifying the start of LCLUC, the assessment of precision and accuracy is influenced by the time interval between the reference date and the LCLUC-maps-identified date, and the uncertainty resulting from the lack of frequently available reference data. The unfiltered product has a high temporal accuracy (2.1 years in mean time interval), but the precision is relatively low because of the high standard deviation and standard error from the time intervals. The spatial-filtered and logical-filtered products performed relatively poorly in both accuracy and precision of identifying change time, as indicated by their higher mean time intervals, standard deviations, and standard errors. In contrast, the temporal-filtered and combined-filtered products have the highest precision in identifying change time, and the temporal-filtered has the highest accuracy in identifying the start of LCLUC. The temporal-filtered and combined-filtered products performed best overall because they can identify most Change-to-Built cases with the least of time difference.
5.2 LCLUC TREND ANALYSIS

Based on the above assessment, the temporal-filtered product (shown in Figure 9) is deemed the most reliable for analyzing spatial-temporal trends of Built expansion. Built expansion started within the major cities from 2000 to 2002, particularly around the boundary of Accra and Tema District. From 2002 to 2004, most development occurred around Weija Reservoir in Ga and Awutu District. From 2004 to 2010, new Built appeared in the north area of Ga and Tema District, and expanded to the boundary between Ga and Akwapim South District. The general trend of Built expansion began from south to north (mostly because of the southern constraint of the ocean waters of the Gulf of Guinea), converting Agriculture and Natural Vegetation to Built along the major roads and existing Built. The urban boundary of Accra and Koforidua expanded in a sprawling matter, and expansion occurred along the major highways. In general, Built LCLUC expanded extensively from south to north in the southeastern Ghana during 2000 to 2014.

5.3 DISCRETE CLASSIFICATION APPROACH V.S. CONTINUOUS INDEX APPROACH

Whether the type and the starting time of LCLUC can be correctly identified depends on the nature of the data and particularly the image processing approach. For a discrete classification approach, the accuracy of each LCLU map in the time series is critical because the maps are the basis of identifying the type and time of LCLUC. When Gray and Song (2013) tested their AASG approach for automatic classification of same season and different seasons image pairs, they found that the overall accuracy of the AASG-derived LCLU map was higher if the base and other images were acquired in the same season. This is challenging given the cloud cover of the study area, such that the image dates were acquired mostly during the drier season ranging from November to April, with the base image captured in February. Differences in seasonality can influence reflectance signature differences and affect the selection of stable training pixels to generate each date of LCLU map. In addition, Gray and Song (2013) used near infrared and red wavebands (instead of the MSAVI as I have) for image differencing to generate the stable training pixels because they discovered that both bands can differentiate different vegetation land cover types. However, MSAVI was used in this study because the emphasis was on identifying Change-to-Built.
MSAVI values tend to be low in non-vegetated area, which helps to differentiate Built from other LCLU types. Moreover, Gray and Song (2013) examined different thresholds of image differencing to derive the stable training pixels, and they determined that the threshold for one standard deviation \((\sigma)\), such that \(t = \mu \pm \sigma\) is the same as 0.5 standard deviation \((t = \mu \pm 0.5\sigma)\). However, the class separability is greater for the threshold of 0.5\(\sigma\), which all land cover types exceeded 1.8 in Jeffries-Matusita distance. The threshold can be tuned to 0.5\(\sigma\) for this study, but this will result in lower within-class variation, which does not reflect the reality of high within-class variation in the study area.

Incorporating a more continuous data approaches to detecting LCLUC, Schneider (2012) determined the major LCLU types with temporal NDVI curves. For a no-change LCLU, the NDVI curve follows a similar dynamic patterns from year to year, and it is discernible from other no-change LCLU. However, changes in LCLU were observed as dramatic drops in the NDVI curves. NDVI curves of three Change-to-Built samples are shown relative to my discrete classification results for three 3 x 3 pixel sample units in Figures 9, 10, and 11. These sample curves are plotted with the original NDVI values, Quality Assurance (QA) flag NDVI values, and smoothed NDVI values. The cleaned NDVI curves were filtered by removing values having slopes > 0.3/year and < -0.3/year, which are the smoothed NDVI curves depicted in Figures 10-12. Figure 10 illustrates a sample that was correctly identified by the temporal-filtered product in terms of the type and time of LCLUC. LCLUC was correctly identified by the temporal-filtered product for the sample shown in Figure 11, but the time of LCLUC was determined to be delayed by three years relative to date of change from the reference images. Figure 12 shows an example in which the sample block from the temporal filtered product was not identified as Change-to-Built when it should have been. For all three of these examples, the original NDVI curves fluctuate dramatically because of cloud and other “no data” effects, whereas many of these effects are removed when the QA flags are used to eliminate these NDVI data points. Even after removing these likely cloud and cloud shadow pixels, the curves still contain much noise and spurious fluctuations. It is difficult to visually detect major down turns in the NDVI curves for the three samples that would be associated with Change-to-Built LCLUC. In such cloud prone areas, identifying the type and the starting time of LCLUC seems to be challenging.
when using continuous analysis even with the Smoothed NDVI curves, though I plan to conduct a more rigorous comparative analysis in my future studies.

Figure 9. The temporal-filtered product of Built expansion at the southeastern part of the study area.
Figure 10. The NDVI curve of Change-to-Built samples that was identified by temporal-filtered product. The identified change date is the same as the reference data. The noise affected NDVI values are removed in QA flag NDVI, and any slope over 0.3/year or lower -0.3/year are removed in the Smoothed NDVI. The trajectory of LCLU is below the curves: ND is No Data, Bu is Built, NV is Natural Vegetation, and Ag is agriculture.

Figure 11. The NDVI curve of Change-to-Built samples that was identified by temporal-filtered product. The identified change date is later than the reference data for three years. The noise affected NDVI values are removed in QA flag NDVI, and any slope over 0.3/year or lower -0.3/year are removed in the Smoothed NDVI. The trajectory of LCLU is below the curves: ND is No Data, Bu is Built, NV is Natural Vegetation, and Ag is agriculture.
Figure 12. The NDVI curve of Change-to-Built samples that was not identified by temporal-filtered product. The noise affected NDVI values are removed in QA flag NDVI, and any slope over 0.3/year or lower -0.3/year are removed in the Smoothed NDVI. The trajectory of LCLU is below the curves: ND is No Data, Bu is Built, NV is Natural Vegetation, and Ag is agriculture.

5.4 SUGGESTION FOR GENERATING MORE RELIABLE LCLU MAPS

Two improvements to the discrete classification approach to identifying LCLU from noisy Landsat time series are increasing classification accuracy and better interpolating or minimizing the effects of No Data pixels. For the unfiltered product, half of the unidentified Change-to-Built samples resulted from misclassification, and the rest were caused by the lack of observations due to cloud, shadows, haze and the SLC-off effect. After the filtering process, the number of unidentified samples caused by the both misclassification and No Data values decreased substantially, so some fundamental refinements would be useful. One refinement could be to replace the maximum likelihood classifier with a machine learning classifier such as support vector machines and random forests to classify each date of imagery. Machine learning classifiers have been reported to generate more accurate LCLU maps compared to the maximum likelihood Classifier (Schneider, 2012), but normally require a greater number of training samples to be effective. Another potentially useful refinement is to decrease the number of sequential maps/dates used to identify LCLU from
five, where Change-to-Built was identified when Built occurred in at least three out of five dates. More pixel blocks are likely to be identified as Change-to-Built if the threshold is less than three out of five dates. However, the number of false positives will likely increase, resulting in a possible trade-off situation. Although cloud and cloud shadow effects cannot be avoided in Ghana, the discrete classification approach is likely to be even more effective for areas that have a moderate amount of cloud cover.

5.5 LIMITATIONS

One of the limitations of this study is the availability of reference data, which contributes to uncertainty in the ability to determine the accuracy of the derived LCLUC products. Reference samples were evaluated by visual interpretation of all available high spatial resolution images and the original Landsat images. For the high spatial resolution images, small size but low-density Built areas were accurately identified, but only large Built objects could be visually identified from the Landsat images. This discrepancy yielded disagreement in some Change-to-Built samples; the samples were not identified as Change-to-Built in the LCLUC maps, but they were determined to be new occurring, small size, low-dense Built from the reference data. These samples should have been classified as Built at late dates, but they were actually misclassified as Agriculture. Additionally, both the type and starting time of LCLUC were evaluated with the reference data, such that the start of LCLUC is determined as the closest time of LCLUC observed with the available reference data rather than the actual start of LCLUC transition. Alternative sources of information may exist for determining where and when Change-to-Built has occurred, but such sources are especially limited in developing countries like Ghana where official land use records are not archived or difficult to access.

LCLUC monitoring with Landsat image time series is currently much more tractable than in past decades, because image preprocessing is automatically conducted for LEDAPS products. Moreover, the launch of Landsat 8 Operational Land Imager (OLI) and the release of surface reflectance product for Landsat 8 enables remote sensing scientists to continue Earth Observed mission. However, some data quality issues were observed for the Landsat surface reflectance product which undoubtedly reduced the success of the dense temporal image analysis. Some cloud-affected areas in one date of image were not detected by the
LEDAPS routines, so these areas were misclassified as Change-to-Built. Products from these automatic-preprocessing routines should be closely inspected prior to image classification.

5.6 Applications

The products stemming from this thesis research have the potential to be very useful for monitoring LCLUC trajectories, especially for Ghanaian governmental agencies setting policies for legal development. In 1999, the Ghana Ministry of Lands and Forestry issued the National Land Policy to regulate the national land development. However, even under such regulation, illegal development still has occurred extensively around the country, because law enforcement is usually compromised by local tribal chiefs who have strong control over land development. Such LCLUC products can help the Ministry of Lands and Forestry monitor land development status. LCLUC maps may provide insights into locations where development has occurred in light of the disagreements between land policy and tribal chief decisions. By using the date of start of LCLUC information, the District Assembly can regulate illegal development that was built after the passage of the National Land Policy. Also, any local land policy that is passed by District Assembly can use the start if LCLUC information to constrain “unexpected” developments if they were constructed after the release of the local land policy. Thus, illegal development can be regulated and further mitigated, and the National Land Policy can be enforced.

In addition, the products from the research can be used to investigate the relationship between LCLUC and population dynamics. In Ghana, censuses were carried out in 2000 and 2010, and the census data were summed up based on Enumeration Areas (i.e. census tracts). The relationship between Built expansion and population change can be studied by overlapping the LCLUC product with the Enumeration Areas. Researchers can observe whether population growth has a linear/nonlinear relationship with Built expansion. For other countries that have long-terms historical census (e.g. the United States), the LCLUC products that are derived for the country can further be used to understand whether the population growth leads to Built expansion, or the Built expansion causes the population growth.
5.7 FUTURE RESEARCH

A discrete classification approach to LCLUC mapping is shown to be successful by this study. As illustrated in Figures 10, 11, and 12, the type and starting time of LCLUC would seem to be challenging using continuous index approaches in cloud-prone countries such as Ghana, but this needs to be evaluated in future research. Such a comparison should be tested for various geographic locations, for example, under locations having different frequencies of cloud cover and degrees of urbanization.
REFERENCES


