THE IMPACT OF LAND USE AND LAND COVER CHANGE ON THE SPATIAL
DISTRIBUTION OF BURULI ULCER IN SOUTHWEST GHANA

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Buruli ulcer (BU) is an environmental bacterium caused by *Mycobacterium ulcerans*. Modes of transmission and hosts of the disease remain unknown. The purposes of this study are to explore the environmental factors that are possibly explain the spatial distribution of BU, to predict BU cases by using the environmental factors, and to investigate the impact of land use and land cover change on the BU distribution. The study area covers the southwest portion of Ghana, 74 districts in 6 regions. The results show that the highest endemic areas occur in the center and expand to the southern portion of the study area. Statistically, the incidence rates of BU are positively correlated to the percentage of forest cover and inversely correlated to the percentages of grassland, soil, and urban areas in the study area. That is, forest is the most important environmental risk factor in this study. Model from zero-inflated Poisson regression is used in this paper to explain the impact of each land use and land cover type on the spatial distribution of BU. The results confirm that the changes of land use and land cover affect the spatial distribution of BU in the study area.

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CHAPTER 1

INTRODUCTION

Buruli ulcer (BU) is a neglected tropical disease, which occurs in hot and humid climates mostly in low standard of living and poor hygiene environments (World Health Organization [WHO], 2010b). It is a skin disease caused by *Mycobacterium ulcerans* (*M. ulcerans*), and the third most common disease of the mycobacterium family after tuberculosis and leprosy (WHO, 2007). However, due to the low awareness of BU, it is difficult to diagnose and treat, and many people fail to recognize the symptoms in the early stage.

At the initial stage, the infected area is well-demarcated with rough edges yet painless or minimally painful. Due to the mild symptoms, patients usually are unaware of the infection or neglect to seek medical treatments. Indeed, the treatment can still be done without hospitalization at this stage (WHO, 2007). Without medical treatment, *M. ulcerans* spreads to other organs through the lymphatic system or bloodstream in approximately three months (Debacker et al., 2004). About 10% of the reported BU cases infect the bones (Portaels, Silva, & Meyers, 2009). Surgery is the only way to treat BU at this stage. Although the infected area is removed, the deformities and scars are permanent. Over 50% of BU patients suffer from functional limitations, social stigmatization, and loss of livelihood after treatment (van der Werf et al., 2005).

Despite considerable research effort, modes of transmission and hosts of the disease still remain unknown; hence, besides surgery (including excision and skin graft), no effective treatment and control have been introduced. Recent research suggests that aquatic plants and aquatic animals, such as fish, insects, and frogs, may

be hosts of the disease (Brou, Broutin, Elguero, Asse, & Guegan, 2008; Eddyani et al., 2008; Drancourt, Jarlier, & Raoult, 2002; Marion et al., 2010; Marsollier et al., 2002; Marsollier et al., 2004; Mosi, Williamson, Wallace, Merritt, & Small, 2008; Portaels, Elsen, Guimaraes-Peres, Fonteyne, & Meyers, 1999; Williamson et al., 2008).

Moreover, *M. ulcerans* can be found in natural environments (WHO, 2008). Since mode(s) of transmission and hosts of the disease are still unknown, investigation of environmental risk factors is essential in order to identify living organisms and possible animals that could be transmitters or hosts. There are possibly six environmental risk factors including water bodies, vegetation types, land elevation, seasonal variation, agriculture, and economic factors (Brou et al., 2008; Duker, Portaels, & Hale, 2006a; Pouillot et al., 2007; Sopoh et al., 2010; Wagner, Benbow, Brenden, Qi, & Johnson, 2008a; Walsh, Portaels, & Myers, 2008).

Ghana is chosen as a study area because it is one of thirteen African countries confirming endemic BU (WHO, 2010) and the rate of new cases is increasing rapidly (van der Werf et al., 2005). According to WHO (2007), Ghana has reported more than 11,000 cases since 1993. In the geographic study, land use and land cover are employed to investigate the relationship between BU and environmental risk factors.

Significance of the Thesis

There is much research identifying risk factors by conducting survey in BU patients. The limitation is that most of BU infections are detected after a long period of time. Thus, many patients could not recall where or when they possibly were exposed to *M. ulcerans*. Moreover, there are also numbers of BU cases that have not been

reported which may contain other risk factors or other association of BU in humans that have not yet been discovered. The study of land use and land cover change can eliminate this limitation by tracking the daily habits of the BU patients in order to investigate where the BU transmission occurred and, hence, to identify the potential risk factors of the disease.

This thesis has two research objectives. First, it is to investigate the effects of environmental factors on the spatial distribution pattern of BU in southwest Ghana. In this study, land use and land cover in the study area represent the environmental factors. The Spearman's rank correlation is employed to determine the relationship between the environmental factors and BU rates. The prediction model is created using Poisson regression. The model not only predicts the prevalence of BU but also explains the impact of each environmental factor on the spread of BU. When the prevalence of BU is predictable, interventional plans and measures will become more effective to prevent BU distribution in highly risk areas in southwest Ghana.

The other objective is to explore the impact of environmental change on the spatial distribution of BU over time in the study area. This objective has not been addressed. Since *M. ulcerans* is an environmental bacterium, the changes of land use and land cover probably affect the spread of BU. According to Yorks and Magai (2007), land use and land cover in Ghana had been changed during 1990 and 2000. Therefore, there is possibility that BU incidence in southwest Ghana in the 1990s and in the 2000s occurred in different areas. The spatial distribution of BU in Ghana is investigated and visualized on maps to compare the changes of land use and land cover between two

time periods. The results would provide better understanding and some clues how the geographic areas affect the spread of BU.

Research Questions

- 1) What is the spatial distribution of BU in southwest Ghana?
- 2) What are the environmental risk factors that explain the spatial distribution of BU in the study area?
- 3) Does land use and land cover change in two periods (in the 1990s and 2000s) impact the spatial distribution of BU?

CHAPTER 2

REVIEW OF LITERATURE

Buruli Ulcer

Buruli ulcer (BU) is first detected in Uganda in 1897 (WHO, 2007). It became a rapid reemergence in the 1980s (Walsh et al., 2008). This led World Health Organization (WHO) to establish the Global Buruli Ulcer Initiative (GBUI) in 1998 to promote research for BU intervention (WHO, 2004b). While most researchers agree that environmental and climate changes were the reasons for the endemic events in the 1980s, the mode of transmission of this disease remains ambiguous. Most BU studies focus on mode of exposure investigations through genetic experiments and surveys of reported BU cases. Researchers point out that *Mycobacterium ulcerans*, which is the cause of BU infection, has been identified in rivers and stagnant water. However, only few researches have applied health geography to study environmental risk factors of BU.

There are three stages of BU infection. At the first stage, BU infection appears in non-ulcerative forms such as nodule, papule, plaque, and edematous (Debacker et al., 2004). According to WHO (2004b), nodule and papule are skin lesions that expand on the epidermis into the subcutaneous tissue, which contains fat and connective tissue, causing itching and discoloration on the surrounding skin area. The difference between nodule and papule are diameter size and geographic location. Nodule is generally found in Africa, and the diameter size is 1 to 2 centimeters (WHO, 2004b). On the other hand, papule is frequently found in Australia and is less than 1 centimeter in diameter (WHO, 2004b). Another non-ulcerative form is plaque. The lesion of plaque from BU is firm

and elevated with the size larger than 2 centimeters. The infected area is well-demarcated with rough edges yet painless or minimally painful (WHO, 2004b). For edematous, the infected skin shows color changes and non-pitting swelling. The edematous causes no pain but may accompany fever in some cases (WHO, 2004b). The period of symptom development varies from several weeks to months before the infection forms ulcerate, which is the second stage of the BU infection (Debacker et al., 2004). During this stage, BU can be treated by injecting Bacille Calmette-Guérin (BCG) vaccine for eight weeks to deactivate *M. ulcerans*. At this stage, the treatment can still be done without hospitalization (WHO, 2007). However, due to the mild symptoms in the early stages, patients usually are unaware of the infection or neglect to seek medical treatments. For example, patients with the first stage of BU in Benin showed a median delay of 1 to 1.5 months and two months in non-ulcerative and ulcerative cases respectively (Debacker et al., 2004).

Without medical treatment, *M. ulcerans* spreads to other organs through the lymphatic system or bloodstream in the third stage. This takes approximately three months (Debacker et al., 2004) and 10% of the found BU cases have infected the bones (Portaels et al., 2009) (Figure 1a and 1b). During this stage, *M. ulcerans* infects the connective tissue and into the bones causing osteomyelitis (bone and bone marrow inflammation). As a result, the patients with BU in this stage face physical deformities and amputation. Up to now, the only way to treat BU in the last stage of infection is surgery. Even if the infected area is removed, the deformities and scars are permanent. Moreover, the scars from BU, particularly ones with lack of pigmentation, can also

develop into Actinic radiation cancer as widely found among patients in the tropical countries (Portaels et al., 2009).

(a)

(b)

Figure 1. Patients with BU disease: (a) disease infects into the leg bone (Malady of the Month, 2002); (b) disease infects into the back bone (Hoover, 2010).

Geographic Distribution

Although BU is not an outbreak or a deadly disease like tuberculosis, it has been discovered in 30 countries around the globe (WHO, 2010a). Most cases occur in the underprivileged environment with low sanitation and high poverty rates. BU patients usually live near rivers or stagnant water in tropical and sub-tropical climates (Williamson et al. 2008). BU occurs mainly in four continents: Australia, Asia, South America, and Africa (Jacobsen & Padgett, 2010; Portaels et al., 2009; van der Werf et al., 2005; Walsh et al., 2008; WHO, 2007).

Australia is one of the only two developed countries that have reported BU cases. The first case was found in 1948 in southeast Australia (Fyfe et al., 2010). The number of BU cases increased from 25 cases in 2004 and 47 cases in 2005 to 72 cases in 2006 (WHO, 2007). Queensland and Victoria comprised most of the BU cases in the country (Fyfe et al., 2010). In Asia, BU has been found in tropical countries (Indonesia, Malaysia, Papua New Guinea, and Sri Lanka) and temperate countries (China and Japan) (van der Werf et al., 2005). Latin American countries that have reported BU cases include Mexico, French Guyana, Peru (van der Werf et al., 2005), and Brazil (McGann et al., 2009). BU has been reported widely in African countries, particularly in West Africa (van der Werf et al., 2005). The collective number of BU cases in Africa alone was estimated at 60,000 cases in 2008, is continuously increasing every year (WHO, 2010), and 20,000 of those cases were located in West Africa (Portaels et al., 2009).

Ghana is one of thirteen African countries confirming endemic BU and the rate of new cases is increasing rapidly (van der Werf et al., 2005). Since 1993, Ghana has reported more than 11,000 cases (WHO, 2007). Ashanti and Central regions had the highest prevalence rates at 20.1 – 60 cases per 100,000 population; Greater Accra, Eastern, and Western Regions had prevalence rates at 15.1 – 20.0 per 100,000; Brong Ahafo and the Upper East Regions had prevalence rates at 10.1 – 15.0 per 100,000; and Northern, Volta, and Upper West had the lowest prevalence rates at 7.0 – 10.0 per 100,000 (WHO, 2004a).

Transmission and Hosts of the Disease

M. ulcerans is believed to be an environmental mycobacterium because it is found in many species of water bugs, aquatic plants, and fishes to small mammals such as koalas, possums, and others in BU endemic areas. Nonetheless, the mode(s) of transmission and reservoir still remain unknown. The hypothesized modes of transmission can be divided into five categories: aquatic plants/aquatic microorganisms, aquatic animals /amphibians, aquatic insects, small mammals, and aerosol.

Freshwater aquatic plants are suspected to be potential intermediate hosts as well as trophic chain in the life cycle of *M. ulcerans* (Marsollier et al., 2004). As the bacterium develops into biofilms on the aquatic plants, it could be transmitted to living organisms and, potentially, cause infection. Marsollier et al. (2004) observed *M. ulcerans* on aquatic plants in Cote d'Ivoire. The study discovered that aquatic plants acted as reservoir and, therefore, could transfer *M. ulcerans* to living organisms including humans. Eddyani et al. (2008) also suggested free-living amoebae (zooplankton) as another reservoir and environmental host for *M. ulcerans*.

M. ulcerans is found in distinct aquatic animals and amphibians such as fishes, snails, and frogs. As some aquatic animals feed on biofilms of aquatic plants, *M. ulcerans* on the biofilms could transmit into the animals (Marsollier et al., 2002). Eddyani et al. (2004) indicated that fishes with positive *M. ulcerans* DNA fed on insects or planktons and could become a source for transmission of BU disease. Drancourt et al. (2002) also found that *M. ulcerans* developed rapidly in XTC-2 cells in amphibians such as frogs.

Much research has sought to identify *M. ulcerans* transmission through aquatic insects. Williamson et al. (2008) reported *M. ulcerans* in specific aquatic insect species i.e. Belostomatidae and Naucoridae. Marion et al. (2010) also detected *M. ulcerans* in saliva of three predacious aquatic insect families including Belostomatidae, Nepidae, and Corixidae. Moreover, Mosi et al. (2008) found that *M. ulcerans* could colonize African belostomatids and be transmitted through trophic transfer in the environment. Marsollier et al. (2002) discovered that these insects sometimes fed on mollusks (i.e. snails). In the case that these mollusks were BU infected, the insects could transfer the bacterium into their bodies. Since *M. ulcerans* is concentrated in the insects' salivary glands (Marsollier et al., 2002), many researchers suspect that *M. ulcerans* is transmitted from insects to mammals through biting (Brou et al, 2008; Marsollier et al., 2002). Mosquitoes with *M. ulcerans* DNA found during the BU outbreak in Australia were another support for this hypothesis (Johnson et al., 2007). Recently, *M. ulcerans* has been successfully isolated from environmental aquatic insects found in a BU endemic area in Benin. This discovery also confirmed that *M. ulcerans* was a human pathogen in an aquatic environment niche (Portaels et al., 2008).

Small mammals, especially koalas and possums, had been reported with *M. ulcerans* infection in Australia (van der Werf et al., 2005). According to Fyfe et al. (2010), feces of infected possums were found to have the highest *M. ulcerans* DNA concentrations. The large number of *M. ulcerans* infected possums reported indicates a possibility that small mammals act as a reservoir for *M. ulcerans* (Fyfe et al., 2010).

Aerosolized *M. ulcerans* could be transmitted into the human body through inhalation and digestion (Duker et al., 2006a) as well as direct skin exposure (Portaels

et al., 2009). Direct contact with aerosols, fomites, or insects from stagnant water, ponds, and swamps contaminated with *M. ulcerans* are suspected to transmit *M. ulcerans* to humans (Walsh et al., 2008). After the exposure, the bacterium would be reactivated in the low temperature area such as arms and legs and causes infection on the body (Duker et al., 2006a).

BU disease in humans is widely believed to be from the introduction of *M. ulcerans* on skin trauma. This introduction could be either through insect bites or contacting contaminated surface directly on the existing skin trauma areas (Portaels et al., 1999).

Environmental Risk Factors

Water bodies that are suspected to be risk factors are reservoirs (dams), ponds, rivers, lakes, swamps, and other stagnant water. Previous research suggests that many areas with high BU prevalence rates in tropical and subtropical countries are close to a river, a swamp, slow-flowing, or stagnant water. In Ghana, BU cases were reported to be located near Densu River, and there was an increasing rate of BU cases in wetlands (Duker, Stein, & Hale, 2006b). In Liberia, BU prevalence rates were higher after a reservoir construction and increased number of swamp rice fields (Duker et al., 2006b). Similarly, the prevalence in Cameroon was also reported to be high among swamp rice farmers and patients living near the Nyong River (Pouillot et al., 2007). Brou et al. (2008) also proposed that aqua alteration might also pose a risk factor for BU. This was supported by the increased BU cases in Nigeria and Australia where flooding and damming in the areas preceded outbreaks (Pouillot et al., 2007). However, Wagner et

al. (2008a) and Brou et al. (2008) pointed out that BU cases in Benin and Cote d'Ivoire were not related to the locations of rivers. Wading in water and contacting contaminated water sources have been confirmed to be risk factors of BU in humans (Pouillot et al., 2007; Sopoh et al., 2010). Therefore, long pants and waterproof outwears have been suggested to reduce the risk of BU.

The first BU outbreak in the early 1980s was believed to be caused from deforestation and climate change (Walsh et al., 2008). This was supported by Pouillot et al. (2007) who observed that humans living close proximity to a forest were at risk of BU. Brou et al. (2008) also pointed that BU prevalence rate in Cote d'Ivoire was higher in evergreen forest areas compared to sub-savanna and savanna areas.

Land elevation is suggested to be a BU risk factor by Wagner et al (2008a). From their study, the remote villages in low elevation located in drainage basin and near forest land cover in Benin showed high rates of BU. The possible explanation was that there was higher prevalence rate in lower elevations because they contained more wet areas, and therefore, presented a higher risk of human contact with *M. ulcerans* in water.

Walsh et al. (2008) proposed seasonal climate change as a risk factor for BU. As supported by Duker et al. (2006b), BU cases showed a temporal relationship with seasonal dimension. BU incidence rates increased during the dry season in Papua New Guinea and Cameroon and, similarly, the rate was lower in Uganda during low rainfall months. However, the number of BU cases in Ghana was higher in September and October, which were raining and flooding seasons (Portaels et al., 2009).

Wagner et al. (2008a) indicated that BU had an association with altered landscape due to the higher rate of BU cases within 20 kilometers radius around agricultural land use. Also, some agriculture required a large quantity of water, and therefore located near rivers, which raised the risk of BU (Duker et al., 2006a). Brou et al. (2008) compared prevalence rates between banana and rice farmers and found that there was higher ratio of rice farmers with BU infection compared to banana farmers. Moreover, Pouillot et al. (2007) noted that Cameroonian villagers living close to cocoa plantations showed high risk of BU.

Poverty and unclean living environment may be factors of BU risk. The related poor housing conditions, malnutrition, lack of clean water supplies, low hygiene, and lack of modern health facilities cause low resistance in humans. Combining with ignorance of medical treatments and poor hygiene of certain cultural practices, these factors raise the risk of exposure to *M. ulcerans* in daily life (Duke et al., 2006a). Populations in remote areas, where poverty is high and education is low, are mostly unable to afford proper healthcare and medical treatments. Consequently, they perceive BU disease as witchcraft and treat the lesion wrongly causing the infection to become more severe (Pouillot et al., 2007). Those who would like to go to the hospital may not be able to afford the medical cost and, therefore, ignore the symptoms until the infection is untreatable.

CHAPTER 3

STUDY AREA, DATA, AND METHODOLOGY

Study Area

Ghana, the focus of this study, is located in West Africa (Figure 2). Ghana is bounded by Togo (to the east), Cote d'Ivoire (to the west), Burkina Faso (to the north), and the Gulf of Guinea (to the south). The area of Ghana is 238,533 square kilometers with a total population of 18,912,079 (Ghana Statistical Service, 2009). Ghana is in a tropical climate zone. The temperature ranges from 21 to 32 degrees Celsius (69.8 to 89.6 degrees Fahrenheit). However, the climate varies throughout the country due to seasonal and elevation differences. Ghana has two seasons – the rainy and dry seasons. The rainy season lasts from late April to October, and the dry season is between November and late March. The elevation also varies from 0 to 885 meters (0 to 2,903.54 feet). Mostly low plains with a flat terrain are in south-central areas. The southeast coast is warm and relatively dry, the southwest region is hot and humid, and the northern part is hot and dry. Ghana is a poor country in West Africa with a per capita GDP estimated at \$1,500 in 2009, 11% (2000 est.) unemployment rate, and 28.5% (2007 est.) of population below poverty line (Central Intelligence Agency [CIA], 2010).

Ghana is divided into ten administrative regions including Ashanti, Brong Ahafo, Central, Eastern, Greater Accra, Northern, Upper East, Upper West, Volta, and Western regions. Originally, Ghana had 110 districts in total. However, Ghana has been announced new districts since 2004 and contains totally 138 districts in the present. In this research, study area covers six regions in southwest Ghana including Ashanti,

Brong Ahafo, Central, Eastern, Greater Accra, and Western regions and 74 administrative districts encompassing 121,324.73 square kilometers (Figure 2).

Figure 2. Map of study area.

Data

Buruli Ulcer

Since this research studies the impact of spatial distribution of BU in two periods, there are two BU datasets. First dataset is derived from the national search for cases of Buruli ulcer in Ghana conducted by the Centers for Disease Control and Prevention (CDC) in 1999 (Amofah et al., 2002). The dataset was collected using an active surveillance technique. For this technique, community health care workers collect data by knock on door method which requires a large amount of time to complete (Woodruff,

Bornemisza, Checchi, & Sondrop, 2009). According to Amofah et al. (2002), 5,619 BU patients with 6,332 clinical lesions were identified. The other dataset is obtained from the Ghana Buruli Ulcer Control Program – Ghana (2008), which is a part of Ghana Health Service. This dataset contains BU cases from 2005 to 2008. This dataset was gathered from the health care centers, a passive surveillance technique (Woodruff et al., 2009). Therefore, only patients who feel sick will go to the health care. Since both datasets have the different collection methods, these data are not compared. Only the spatial distribution pattern can be determined. BU cases in each dataset are grouped at district level and joined to Ghana district shapefiles in ArcMap 9.3.

Geographic Information System

Administrative Ghana district and regional boundary shapefiles are acquired from Map Library (2007). According to Map Library (2007), these shapefiles were updated in January 2007 and the administrative names were verified from reliable sources such as government websites. Since the shapefile contains new districts (138 districts in total), it is adjusted the district boundary to the original districts (110 districts) based on information provided from the government websites. The lake shapefile was obtained from Department of Geography, University of Ghana. Population data were derived from the Ghana census 2000. All geographic files are projected as Universal Transverse Mercator (UTM) Datum, WGS 84, Zone 30N.

Satellite Image Processing

Data Acquisition and Preparation

Landsat 4 and 5 Thematic Mapper (TM) satellite images of the study area are acquired from the United States Geological Survey (USGS)/Earth Resources Observation and Science Center (EROS) in order to classify land use and land cover in the late 1990s. The satellite images are in the late 1980s and the early 1990s image bank and are selected with cloud cover less than 10% condition. Thematic Mapper (TM) has multispectral bands (band 1 to 7), with a resolution of 30 by 30 meters. The study area is covered by nine scenes of Landsat TM including path 193 row 55 to 56, path 194 row 54 to 57, and path 195 row 54 to 56 (Table 1). Due to the limitation of weather, such as the percentage of cloud cover, it is difficult to obtain all scenes in the same month and year. In order to classified land use and land cover consistency, images are selected in dry season during December to February in 1986 to 1991 (Table 1).

Due to the fact that Landsat TM images in the study area in the 2000s are limited, Landsat 7 Enhanced Thematic Mapper (ETM+) images are chosen instead. Landsat 7 ETM+ images are also acquired from USGS/EROS in order to classified land use and cover in the 2000s with cloud cover less than 10% condition. Most satellite images are selected in dry season between January and February from 2000 to 2003 with the same paths and rows as Landsat TM imagery (Table 2).

Since the raw satellite images downloaded from USGS are in tag image file format (TIFF), ERDAS Imagine version 2011 is used to convert TIFF to IMAGINE format. The layers (bands) are stacked excluding band 6 which is a thermal infrared

band. Each Landsat image is georeferenced to Ghana local coordinate system UTM Datum, WGS 84, Zone 30N.

Table 1

Imagery Information of Landsat 4 and 5 TM

Path	Row	ID	Cloud Cover (%)	Date
193	55	LT41930551991010XXX04	10	10-Jan-91
193	56	LT41930561991010XXX03	0	10-Jan-91
194	54	LT41940541988057XXX04	0	26-Feb-88
194	55	LT41940551990350XXX03	0	16-Dec-90
194	56	LT51940561986363XXX09	0	29-Dec-86
194	57	LT51940571986059XXX01	0	28-Feb-86
195	54	LT41950541991008XXX03	0	08-Jan-91
195	55	LT41950551989002XXX02	0	02-Jan-89
195	56	LT41950561989002XXX06	0	02-Jan-89

Table 2

Imagery Information of Landsat 7 ETM+

Path	Row	ID	Cloud Cover (%)	Date
193	55	LE71930552003043EDC00	0	12-Feb-03
193	56	LE71930562003043EDC00	0	12-Feb-03
194	54	LE71940542002047EDC00	0	16-Feb-02
194	55	LE71940552003050EDC00	0	19-Feb-03
194	56	LE71940562001092EDC00	0	02-Apr-02
194	57	LE71940572002015EDC00	0	15-Jan-02
195	54	LE71950542000033EDC00	0	02-Feb-00
195	55	LE71950552000033EDC00	0	02-Feb-00
195	56	LE71950562000033EDC00	0	02-Feb-00

Image Calibration

Though Landsat 4 has been in operation for decades, Landsat TM images are still widely used because it is free and easy to obtain. Due to its age, the image quality

such as accuracy is low. Chander and Markham (2003) provide a calibration method for improving image accuracy. They modified the radiometric calibration method by converting the image digital numbers (DNs) to spectral radiance (L_λ) and top-of-atmosphere (TOA) reflectance (ρ_P). Chander and Markham's method does not only improve image accuracy but also provides a better base for comparing images acquired from different dates or by different sensors. Post calibration of image methods that were developed by Chander and Makham (2003) are:

1) Conversion from image DN to spectral radiance

$$L_\lambda = \left(\frac{LMAX_\lambda - LMIN_\lambda}{Q_{cal\ max}} \right) Q_{cal} + LMIN_\lambda \quad (1)$$

Where, L_λ = spectral radiance at the sensor's aperture in $W/(m^2 \cdot sr \cdot \mu m)$;

Q_{cal} = quantized calibrated pixel value in DN;

Q_{calmin} = minimum quantized calibrated pixel value (DN = 0) corresponding to $LMIN_\lambda$;

Q_{calmax} = maximum quantized calibrated pixel value (DN = 255) corresponding to $LMAX_\lambda$;

$LMIN_\lambda$ = spectral radiance that is scaled to Q_{calmin} in $W/(m^2 \cdot sr \cdot \mu m)$;

$LMAX_\lambda$ = spectral radiance that is scaled to Q_{calmzx} in $W/(m^2 \cdot sr \cdot \mu m)$.

2) Conversion from spectral radiance to TOA reflectance

$$\rho_P = \frac{\pi \cdot L_\lambda \cdot d^2}{ESUN_\lambda \cdot \cos \theta_s} \quad (2)$$

Where, ρ_p = unitless planetary reflectance;
 L_λ = spectral radiance at the sensor's aperture;
 d = earth-sun distance in astronomical units;
 $ESUN_\lambda$ = mean solar exoatmospheric irradiances;
 θ_s = solar zenith angle in degrees.

These calibration methods are provided for Landsat TM imagery only. For Landsat 7 images, although the satellite has been launched since in April 1999, the geometric accuracy still exceeds and meets the requirements (Lee, Storey, Choate, & Hayes, 2004). In this study, ERDAS imagine 2011 is employed to convert digital number to reflectance using Landsat Reflectance, located in Radiometric tool.

Index Calculation

Since each object or target area has different spectral reflectance, many classification indices have been created in order to detect the specific objects/areas. The indices that are employed in this study include normalized difference vegetation index (NDVI), modified normalized difference water index (MNDWI), soil adjusted vegetation index (SAVI), normalized difference built-up index (NDBI), normalized difference blue band built-up index (NDBBI), wetness index (WI), and mineral composition index.

1) Normalized difference vegetation index (NDVI)

NDVI is widely used for detecting the vegetation. It is calculated from red and near infrared (NIR) bands that are reflected by the vegetation (equation (3)). Since green vegetation has the most reflectance on NIR band and has the lowest reflectance

on red band, the brighter areas after calculation are vegetation areas. In this study, NDVI is used to classified closed-forest, woodland (open-forest), and grass land, and these classes are included in vegetation type (Gillespie & McDonald, 2010).

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)} \quad (3)$$

Where, NIR = reflectance value of near-infrared band;

Red = reflectance value of red band.

2) Modified normalized difference water index (MNDWI)

In this study, MNDWI is used as water index. Xu (2006b) modified this index from the normalized difference water index (NDWI) of McFeeters (1996 as cited in Xu, 2006b) by replacing NIR with middle infrared (MIR) (equation (4)). As a result, MNDWI enhances detecting water bodies; especially in urban areas because this index reduces the noise from built-up land areas. In MNDWI scene, brighter areas indicate water bodies.

$$MNDWI = \frac{(Green - MIR)}{(Green + MIR)} \quad (4)$$

Where, MIR = reflectance value of mid-infrared band;

Green = reflectance value of green band.

3) Soil adjusted vegetation index (SAVI)

SAVI is modified from NDVI by introducing a soil-brightness correction factor (equation (5)). The value of correction factor is in range 0 to 1, which indicates high vegetation cover to no vegetation. In this study, a soil-brightness correction factor is defined as 0.5, which is default value and suitable for most locations (Maselli, Gardin, & Bottai, 2008).

$$SAVI = \frac{(NIR - Red)}{(NIR + Red + L)} \times (1 + L) \quad (5)$$

Where, L = soil-brightness correction factor, 0.5.

4) Normalized difference built-up index (NDBI)

NDBI is a new index for mapping built-up areas from the remotely sensed image. It was proposed by Zha, Gao, and Ni (2003). According to their experiment, built-up area and barren land have high reflectance in TM band 5, mid-infrared, and less reflectance in TM band 4, near-infrared. In contrast, woodland and farmland have similar reflectance in both TM band 4 and TM band 5. Therefore, the index for mapping built-up land is calculated from the difference of reflectance in mid-infrared and near-infrared (equation (6)). Though the NDBI might not separate urban areas from dry soil and/or barren land, this index can distinguish built-up land from vegetation.

$$NDBI = \frac{(MIR - NIR)}{(MIR + NIR)} \quad (6)$$

5) Normalized difference blue band built-up index (NDBBI)

Since NDBI cannot illustrate the difference between built-up lands and barren lands, NDBBI is employed to delineate both of them. NDBBI was referred by Baraldi, Puzzolo, Blonda, Bruzzone, and Tarantino (2006). This index is generated by using the relationship of blue band and mid-infrared as shown in equation (7).

$$NDBIB = \frac{(Blue - MIR)}{(Blue + MIR)} \quad (7)$$

6) Wetness index (WI)

Though the indices that are mentioned above are able to delineate soil from other objects, WI is still important to detect soil in order to verify and ensure the

classification since the spectral reflectance of soil depends on many factors such as moisture, texture, soil type, and organic matter content. Moreover, WI can delineate soil background from vegetation. According to Crist (1985), the contrast between shortwave-infrared (SWIR) and visible/ near-infrared (VNIR) reflectance was labeled as wetness, which measures soil moisture content, vegetation density, and other scene class characteristics. Crist (1985) generated the wetness index formula, which obtained from Landsat 4 tasseled cap transformation for reflectance data as shown in equation (8). Since Landsat 4 and 7 have different properties, Huang, Wylie, Yang, Homer, and Zylstra (2002) developed the wetness index formula for Landsat 7 based on tasseled cap transformation for reflectance data as shown in equation (9).

$$WI_{L4} = 0.0315(TM1) + 0.2021(TM2) + 0.3102(TM3) + 0.1594(TM4) - 0.6806(TM5) - 0.6109(TM7) \quad (8)$$

$$WI_{L7} = 0.2626(ETM1) + 0.2141(ETM2) + 0.0926(ETM3) + 0.0656(ETM4) - 0.7629(ETM5) - 0.5388(ETM7) \quad (9)$$

7) Mineral composition index

In this study, mineral composite is employed in order to distinguish soil and built-up land. This index contains three band ratios. Each band ratio has a specific function to classify an object. The equations of each ratio are shown in equation (10) to (12). The results of these equations can detect clays, ferrous oxides, and iron oxide respectively.

$$MC_1 = \frac{(MIR)}{(Band\ 7)} \quad (10)$$

$$MC_2 = \frac{(MIR)}{(NIR)} \quad (11)$$

$$MC_3 = \frac{(Red)}{(Blue)} \quad (12)$$

Image Classification

In this study, the knowledge-based classification method, expert classifier, is processed in ERDAS Imagine 2011 using the “knowledge engineer” tool. In order to perform this method, hypotheses, classification rules, and variables have to be created, designed, and defined based on user’s knowledge. These elements are created as a hierarchical decision tree. When the decision tree is executed, the classified image is illustrated as user’s label. NDVI, MNDWI, SAVI, NDBI, NDBBI, WI, and mineral composite index are included in the decision tree hierarchy to create a classified image. The threshold values of each feature type from its own index are defined in the hierarchical model in order to label class and create rules. The threshold value is derived from random sampling points in each index image. Figure 3 illustrates the example of indices value of various feature types from the Landsat 7 ETM+ path193 row 56 scene. These graphs not only indicate threshold values but also give an idea to discriminate different land cover types. Since the reflectance of images is differed in each scene, each image has its own threshold value and rule (Appendix A).

(a)

(b)

(c)

(d)

(e)

Figure 3. Indices values of various land cover types from Landsat 7 path 193 row 56 scene.

Change Detection

One goal of this research is to determine whether land use and land cover change in two time periods (1990s and 2000s) impacts the spatial distribution of BU. Change detection method is processed to evaluate land use and land cover change. In this study, post-classification comparison change detection technique is processed in ArcMap 9.3. According to Lu, Mausel, Brondizio, and Moran (2003), this technique reduces the atmospheric sensor influence and environmental differences between images that were acquired from different dates (multi-temporal images). This technique is a straight forward subtraction of the 2000s- from the 1990s- classified image.

Spatial Analysis

Spatial Distribution of Buruli Ulcer

According to Beyer and Rushton (2008), creating the disease map based on administrative units (choropleth map) does not contain sufficient information on the local distribution. Since it does not provide the spatial unit, the fundamental limitation of this method is small number of cases, which mostly occur in epidemiology study (Waller & Carlin, 2010). Therefore, the Web-based Disease Mapping and Analysis Program (WebDMAP) software by Tiwari (2008) is used to create the smoothen disease map. Grid point is generated based on geographic units and control population (Yiannakoulis, Karosas, Schopflocher, Svenson, & Hodgson, 2007). Then the disease rate is generated and computed using spatial filtering and kernel density estimate (Tiwari & Rushton, 2005; Rushton & Tiwari, 2009).

In order to create the disease mapping of the BU prevalence, two BU datasets, which are the cases in 1999 and in the 2000s, are aggregated to the district level. After that, these data are geocoded using district centroids with latitude and longitude in decimal degree coordinate system. The spatial distribution of BU at the district level is analyzed by WebDMAP. As a result, a point shapefile is created. It contains the disease rate with geographic coordinate system as GCS, WGS 84 datum, which is in decimal degree unit. The shapefile is reprojected as UTM Datum, WGS 84, Zone 30N in ArcMap 9.3. In order to visualize the smoothen map, inversed distance weighted (IDW) interpolation in ArcMap 9.3 is employed and defined power as 2, nearest neighborhood point as 8, and cell size as 30 meters.

Influence of Environmental Factors and Buruli Ulcer Distribution

To identify the impact of environmental factors on the spread of BU in spatial analysis, it requires two major steps. Firstly, each land use and land cover type from the classified images, which are derived from Image Classification section, is calculated in each district as a percentage. Secondly, the data are joined to BU rate shapefile using district column as an index. Subsequently, the results will be analyzed using statistical methods, which will be discussed in detail in the next section.

Initially, two classified images, which are raster datasets, are imported to ArcMap 9.3. All shapefiles are projected as UTM Datum, WGS 84, Zone 30N. Fundamentally, the percentage of each land use and land cover type could be calculated following equation (13). In this study, land use and land cover calculation is processed in ArcMap 9.3 using zonal statistics “Tabulate Area” from Spatial Analyst Tool. Ghana district shapefile and classified images are defined as “Zone Data” and “Input Raster Data” respectively. Each land use and land cover type is calculated an area in each district. The results are displayed as a distributed table in ArcMap 9.3. Since the table contains only the percentages of land use and land cover types and is not a geographic file, it is joined to the BU rate shapefile using district column as an index. As a result, the shapefile contains both BU rates and the percentages of land use and land cover types.

$$\%LULC_{ij} = \frac{\# \text{ Pixels}_{ij}}{\text{Total pixels}_j} \times 100 \quad (13)$$

Where, $\%LULC_{ij}$ = the percentage of land use and land cover type i in district j

$\# \text{ Pixel}_{ij}$ = number of pixels of land use and land cover type i in district j

Total pixel_{*j*} = total pixels in district *j*

When, *i* = closed-forest, open-forest, agriculture/grass land, water,
soil, or built-up land

j = administrative district in Ghana

Evaluating the Spatial Distribution of Buruli Ulcer Over Time

Two steps are required in order to illustrate the geographic areas of the impact of land use and land cover change on the spread of BU. These steps are processed in ArcMap 9.3. At the beginning, the changes of land use and land cover are determined using two classified images. Raster calculator is employed to calculate the changed areas. Then zonal statistics is used to determine the changed areas at district level by defining Ghana district shapefile as “Zone Data” and the changed area raster dataset as “Input Value Raster”. The districts with the majority of changed area are selected and exported as a shapefile in order to acquire the BU rates in those areas. Last but not least, the distribution of BU in each time period is overlaid to visualize the spread of BU in the changed area.

Statistical Models

In order to investigate the relationship between the incidence of BU and environmental risk factors, which are the percentage of land use and land cover in this study, Spearman’s rank correlation, a non-parametric test, is performed because BU rate is not normally distributed. Since this study contains two BU datasets, two sets of correlations are analyzed. Those are between the incidence of BU in 1999 and the

percentages of land use and land cover in the 1990s and between BU incidence in the 2000s and the percentages of land use and land cover in the 2000s. These data are obtained from Spatial Analysis section as previously mentions. Several hypotheses are determined in this test.

Hypothesis 1: The percentages of water and both forest types (closed- and open-forests) have a positive correlation with BU rates.

Hypothesis 2: The percentage of built-up land has inversely correlation with BU rates.

The model of each dataset is generated in order to identify how the environmental risk factors affect the spread of BU. Poisson and zero-inflated Poisson regressions are performed and compared. The best model of each dataset is selected based on the Akaike's information criterion (AIC) values (Akaike, 1973 as cited in Wagner et al., 2008b). These regressions are used in this study because this method is deemed appropriate for analyzing rare events occurring over a period of time ("Poisson Regression Analysis," 2011). The general form of these regressions is illustrated in equation (14). Since these regressions are used to model count data (dependent variable), the number of BU cases and the percentages of land use and land cover types are defined as a dependent/response and predictor variables respectively. Before performing the models, multicollinearity between independent variables are determined in order to avoid the overestimation.

$$\log_e (Y_j) = \beta_0 + \beta_{ij}X_{ij} + \beta_{i+1, j}X_{i+1, j} + \dots + \beta_{nj}X_{nj} \quad (14)$$

Where, Y_j = the number of BU cases in district j

β_0 = the intercept

β_i = the coefficient of covariate X_{ij}

X_{ij} = the percentage of land use and land cover i in district j

n = the total number of predictors

When, i = land use and land cover type (closed-forest, open-forest, agriculture/grass land, water, soil and built-up land)

j = administrative district in Ghana

In order to investigate whether land use and land cover change impacts on the spread of BU, the BU rates in the districts with the majority of changed areas over two time periods are tested using Kolmogorov-Smirnov test (KS test), a nonparametric method. The BU rates in the changed districts are obtained from Evaluating the Spatial Distribution of BU Over Time section as previously mentioned. Before analyzing, districts that have the majority of changed areas and contain no reported cases are excluded in order to avoid misinterpreting. The hypothesis of this statistic test is as follow:

Hypothesis 3: The changes of land use and land cover affect the distribution of BU.

CHAPTER 4

RESULTS AND DISCUSSION

Spatial Distribution of Buruli Ulcer

The first nationwide Buruli ulcer (BU) survey in Ghana was collected in 1999 (WHO, 2004b). Nonetheless, up until today geographic studies about this disease are still very limited. Understanding the pattern of BU spatial distribution would help the health agencies to control and reduce the BU cases. This study attempts to investigate the effects of geographic factors on the spatial distribution of BU in the study area using two datasets which are in 1999 and between 2005 and 2008. Moreover, this research studies the BU spatial distribution pattern at district level. Therefore, this study provides more accurate results and illustrates more specific areas than studying at regional level.

In 1999, 11 of 74 districts in the study area reported no cases of BU. The incidence of BU in the study area, in 1999, ranges from 0 to 433.98 per 100,000 population. According to Amofah et al. (2002), the national rate of BU in Ghana was 20.7 per 100,000 population compared to the average rate in the study area in 1999 is 42.83 per 100,000 population. The incidence rate from the study area is considered relatively high. Five districts have extremely high rates, exceeding 165 per 100,000 population, including Amansie West (434.11, the darkest color south of Kumasi), Upper Denkyira (350.41, around the darkest color south of Kumasi), Asutifi (209.50, the darkest color south of Sunyani), Ga (201.65, the small darkest color north of Accra), and Afigya-Sekyer (165.62, the darkest color in north of Kumasi). The geographic distribution of BU in the study area in 1999 is shown in Figure 4a. It clearly illustrates that the higher rates occur in the southwest Kumasi area, whereas the northeast portion

of the study area have much lower rates. Notably, the high incidence rates of BU in 1999 occur away from the urban areas.

Figure 4. The BU incidence rates and distributions (a) in 1999 and (b) between 2005 and 2008.

The incidence rate of BU from 2005 to 2008 ranges from 0 to 134.63 per 100,000 population, and the average incidence rate is 20.08 per 100,000 population. However, this figure may be an underestimate because the dataset from 2005 to 2008 was collected using a passive surveillance method, while the dataset in 1999 was collected using an active surveillance method. 37 districts reported no cases. As shown in Figure 4b, the spatial distribution of BU in this period has a similar pattern compared to the

incidence rate in 1999. That is, the higher rates occur in the central part of the study area and the lower rates are in the eastern study area. Even though this map (Figure 4b) illustrates the overall distribution of BU from 2005 to 2008, it cannot show the trend of spatial distribution of BU. Therefore, the annual maps of BU incidence rates are created in order to compare the spatial distribution of BU over this period.

During 2005 to 2008, the incidence rates of BU in the study area range from 0 to 245.01, 0 to 152.15, 0 to 130.02, and 0 to 195.49 per 100,000 population respectively. The averages of incidence rates in the study area from 2005 to 2008 are 31.97, 31.59, 20.59, and 30.45 per 100,000 population correspondingly. The BU rates do not differ much between these years except in 2007, where the rate dropped by 35% to 20.6 per 100,000 population and then boosted up by 48% to 30.5 per 100,000 population in the year after (Figure 5). However, Kruskal-Wallis test indicates that the BU incidence rates between 2005 and 2008 are not statistically different ($p = 0.436$). As can be seen in Figure 5, the BU incidence rate in 2005 is 34% lower than 1999. Unfortunately, the BU rates from 2005 to 2008 cannot be compared to the BU rate in 1999 since these two datasets employed different data collection methods as mentioned in the previous section. Therefore, this research does not attempt to identify and compare the different incidence rates between two datasets; instead it illustrates the geographic trend of BU rates between these two periods (in 1999 and during 2005 to 2008).

The BU incidence rates in the study area from 2005 to 2008 are shown in Figure 6. In order to illustrate the spatial distribution of BU trend from 1999 to 2008, the scale classification of each annual map is assigned with the same scale as the BU incidence rate in 1999. In 2005, the higher rates are in the west to the middle portions of the study

area. Interestingly, even though the two datasets have different collection methods, the highest endemic area in 2005 is similar to that of 1999. That is, the high BU rates occur from the center of the study area to the border of Ghana and Cote d'Ivoire. Likewise, the highest rates of BU occur around the south area of Kumasi and Sunyani. Nonetheless, the spatial distribution of BU in each year (2005 to 2008) is slightly different. In comparing between distribution in 2005 and 2006, the spread of high BU rates in 2006 around the south portions of Sunyani and Kumasi are wider than in 2005 but the rates in 2006 are still lower than in 2005. The interesting point is the BU distribution in 2006 increasingly spread to the east of the study area. In 2007, the BU rates obviously drop off from the early years (Figure 5). The BU rates (Figure 6) around Sunyani are lower and appear to have a smaller cluster compared to the BU rates in 2006. Meanwhile, the areas in the eastern portion of Kumasi have the higher rate. When considering the BU distribution in 2008, the BU rates increase again around the west of study area, while the BU rates in the east portions of Kumasi still continue to be high.

Figure 5. The annual average of BU incidence rate in 1999 and 2005 to 2008.

Due to inadequate and insufficient data, this research cannot provide the explanation of the incidence of BU changes between years. However, it appears that the highest concentration shifts from Central region to the west of the study area. Several reasons can explain this phenomenon. First, since *Mycobacterium ulcerans* can be found in natural environments (WHO, 2008), it is possible that west Ghana has more optimal environment conditions for bacterial population growth than the eastern portion of the study area. The relationship between BU rates and environmental conditions, which are land covers in this research, will be explained in much detail later. Another reason for the higher BU rates in the west of the study area may be due to proximity to Cote d'Ivoire because it is the African country with the worst BU prevalence (Zamble, 2006). As a result, the higher BU rates probably occur along the border of Ghana and Cote d'Ivoire. Last but not least, since the higher BU rate areas are away from urban towns and cities, the inadequate infrastructure is another factor that probably facilitates the spread of BU (WHO, 2010b).

Influence of Environmental Risk Factors

According to the incidence of BU over certain time periods, though the spatial distribution of BU has relatively similar patterns, the high endemic areas are different. In order to address the second question which is the environmental factors facilitating the spread of BU in the study area, the classified images were created. Both images have the same classification including closed-forest, open-forest, agriculture/sparse land, water bodies, soil, built-up land, and cloud cover. The average percentages of land use and land cover types of both images are shown in Table 3.

Figure 6. The incidence rate of BU from 2005 to 2008.

Table 3

The Averages and Standard Deviation of Land Use and Land Cover Types in the Study Area

LULC types	Early 1990s		Early 2000s	
	Average (%)	S.D.	Average (%)	S.D.
Closed-forest	37.09	27.39	32.92	27.51
Open-forest	30.80	16.19	29.49	18.18
Agriculture/sparse land	17.73	14.51	11.15	12.99
Water bodies	2.19	6.24	2.04	5.74
Soil	9.95	17.32	19.12	26.64
Built-up land	1.12	3.75	2.80	6.93
Cloud cover	1.05	3.03	1.63	5.41
Unclassified	0.07	0.20	0.87	1.61

The results show that the land use and land cover types of two time periods in the study area are slightly different. In the early 2000s, the average percentages of closed-forest, open-forest and agriculture/sparse land decreased from the early 1990s, whereas soil land cover and built-up land increased. These results suggest that the expansion of urban areas and/or built-up land probably led to deforestation and decreased agriculture/sparse land in the study area. Statistically, the mean of land use and land cover types are not different between the two datasets. However, geographically, the locations of each land use and land cover types differed (Figure 7).

Relationship between Buruli Ulcer and Environmental Factors

According to Figure 7a, closed-forest mostly covers the western study area along the border of Ghana and Cote d'Ivoire toward the south of Kumasi. Soil mainly covers the northern study area and around the water bodies. Built-up land only occurs in regional capital cities. Notably, overlaying the incidence of BU in 1999 map (Figure 4a) on Figure 7a, the higher endemic areas that the BU rates are greater than 43 per

(a)

(b)

Figure 7. Land use and land cover classification (a) in the early 1990s and (b) in the early 2000s.

100,000 population have the same spatial distribution pattern as closed-forest. Moreover, the lower endemic areas that mostly appears in northern and eastern portions of the study area have soil and agriculture/sparse land as the majority of land covers. Likewise, the results from Spearman's rank correlation confirm that the incidence of BU in 1999 has a significantly positive correlation with closed-forest areas ($r = 0.382$, $p < 0.001$) but inversely correlates to agriculture/sparse land and soil areas ($r = -0.319$, $p < 0.006$ and $r = -0.384$, $p < 0.001$ respectively) (Table 4). These results also confirm the previous studies of Pouillot et al. (2007) and Brou et al. (2008). When considering the correlation between water bodies and BU rates, even though previous studies stated that water bodies are suspected to be a risk factor (Duker et al, 2006b; Pouillot et al., 2007), due to the remotely sensed data limitations, the results cannot confirm the relationship between these two variables (Table 4), which correspond to Wagner et al. (2008a) and Brou et al. (2008) studies.

Table 4

Spearman's Rank Correlation among BU Rates and the Percentage of Land Use and Land Cover Types

LULC types	Incidence of BU in 1999 with 1990s classified image		Incidence of BU from 2005 to 2008 with 2000s classified image	
	<i>r</i>	<i>P</i> -value	<i>r</i>	<i>P</i> -value
Closed-forest	0.382**	0.001	0.351**	0.002
Open-forest	0.090	0.447	0.351**	0.002
Agriculture/sparse land	-0.319**	0.006	-0.372**	0.001
Water bodies	0.018	0.878	-0.155	0.187
Soil	-0.384**	0.001	-0.218	0.062
Built-up land	-0.152	0.195	-0.391**	0.001
** Correlation is significant at the 0.01 level (2-tailed).				

Considering the land use and land cover in the early 2000s (Figure 7b), the areas that used to be closed-forest along the border of Ghana and Cote d'Ivoire in the early 1990s are changed to be open-forest. Closed-forest in this period mostly occurs around Koforidua. Agriculture/sparse land at the northern part of the study area and the north of Accra are changed to soil. Also, built-up land is expanded around the regional capital cities. Using geographic visualization on Figure 4b and Figure 7b, the spatial distribution of higher endemic areas (greater than 43 per population) do not correspond to the distribution pattern of closed-forest, unlike the distribution of BU in 1999. However, the high endemic areas at the south of Sunyani and Kumasi are still in closed-forest and open-forest land covers. The distribution of low endemic areas, less than 20 per population, in the northern portion of the study area have the similar pattern as soil, whereas the low endemic areas in the southern portion of the study area show expansive built-up land impact. Correspondingly, Spearman's rank correlation confirms that closed-forest and open-forest land covers significantly have positive relationships to the incidence of BU between 2005 and 2008 ($r = 0.351$, $p < 0.002$ for both land covers) (Table 4). Agriculture/sparse and built-up land covers inversely correlate to the BU rates ($r = -0.372$, $p < 0.001$ and $r = -0.391$, $p < 0.001$ respectively) (Table 4). These results also confirm the previous studies from Duke et al. (2006a), Pouillot et al. (2007), and Brou et al. (2008). However, the relationship between water bodies and the geographic distribution of BU in the study area cannot be determined due to the limitations of data/satellite imagery, which will be discussed in much detail in Limitations section.

Buruli Ulcer Prediction

Poisson regression and zero-inflated Poisson regression (ZIP) were used to create the BU models for predicting the cases at district level using the percentages of land use and land cover types as predictors. Since two BU datasets have different data collecting methods, two models were created: one for predicting BU cases in 1999 (active data collection method) and another model for predicting BU cases after 2005 (passive data collection method). The multicollinearity between predictor variables was calculated before testing the regression. It was determined using correlation coefficient from Spearman's rank correlation. The objective of creating a model is not only to predict the BU cases but also to better understand the impact of land use and land cover (predictors) on the spatial distribution pattern of BU.

The results from Table 5 show that agriculture/sparse land and closed-forest, soil and closed-forest, and agriculture/sparse land and soil variables are highly correlated. That is, correlation coefficients are greater than 0.700 and/or less than -0.700. The meaning of multicollinearity is the two variables that are highly correlated provide the same information (Motulsky, 2002), which can cause misinterpretation. Therefore, one of these variables can be removed in order to obtain the reasonable model. Since it could not be confirmed which particular one of the three variables can explain the other two variables, the best possible way to identify the variable to be excluded is to run all possible combinations of the variables. In this case, there are three variables that cause multicollinearity namely closed-forest, agriculture/sparse land, and soil; therefore, eight different models were run (Appendix B). The best five possible models are illustrated in Table 6. The candidate models are selected based on the Akaike information criterion

(AIC) (Akaike, 1973 as cited in Wagner et al., 2008) and p -values of parameter estimates. The model that has the least AIC is considered as the primary priority. Considering the model from Poisson regression in Table 6, model P45 is the first model that can be omitted since it has the greatest AIC. That is, removing all three variables (P45) causes more information loss. Meanwhile, model P42 has the smallest AIC, but one of the variables is not significant. Model P42 can be removed. Likewise, model P41 and P44 have closed AICs, but they still have insignificant variables. Therefore, the best possible model for Poisson regression is model P43.

Table 5

Correlation Coefficient among Predictor Variables in the 1990s

LULC 1990s	Closed-forest	Open-forest	Agriculture	Water	Soil	Built-up
Open-forest	-0.024	1				
Agriculture	-0.896	0.033	1			
Water	-0.450	-0.244	-0.457	1		
Soil	-0.773	-0.355	-0.791	0.542	1	
Built-up	-0.364	-0.224	-0.282	0.236	0.453	1

However, since the BU dataset in 1999 consists of 11 districts that have no case, the results of zero-inflated Poisson regression (ZIP) compared with the results from previous Poisson regression in order to acquire the best suitable model. Similar to Poisson regression, eight models in total were run (Appendix B) and the best five possible models from ZIP are shown in Table 6. The results from ZIP show that the excess zeroes problem of all models are corrected (inflation probability < 0.05) and AICs of all models from ZIP are lower than AICs from Poisson regression. Model ZIP45 contains all significant variables. However, it is not selected as the best possible model

Table 6

BU₁₉₉₉ Prediction Models from Poisson Regression and Zero-inflated Poisson Regression (ZIP)

Parameters		Poisson regression					ZIP				
		P41	P42	P43	P44	P45	ZIP41	ZIP42	ZIP43	ZIP44	ZIP45
Goodness of fit	AIC	9089.38	9088.27	9105.23	9155.67	10388.88	7773.3	7771.9	7775.9	7847.6	8876.9
Inflation probability	Estimate	-	-	-	-	-	0.1390	0.1395	0.1381	0.1473	0.1487
	P-value	-	-	-	-	-	0.001	0.001	0.001	< 0.001	< 0.001
Intercept (b_0)	Estimate	4.4760	5.0846	7.0940	-0.9587	4.5800	5.7925	5.2871	7.1706	-0.1292	4.8465
	P-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	0.4501	< 0.001	< 0.001	0.5771	< 0.001
Closed-forest percentage (b_1)	Estimate	0.0061	-	-0.0200	0.0600	-	-0.00503	-	-0.01873	0.05377	-
	P-value	0.3496	-	< 0.001	< 0.001	-	< 0.001	-	< 0.001	< 0.001	-
Open-forest percentage (b_2)	Estimate	-0.0181	-0.0243	-0.0447	0.0379	-0.0074	-0.03121	-0.02602	-0.04528	0.02983	-0.01145
	P-value	0.0074	< 0.001	< 0.001	< 0.001	< 0.001	0.0394	< 0.001	< 0.001	< 0.001	< 0.001
Agriculture/sparse land percentage (b_3)	Estimate	0.0264	0.0205	-	0.0782	-	0.01393	0.01890	-	0.07074	-
	P-value	< 0.001	< 0.001	-	< 0.001	-	0.0747	< 0.001	-	< 0.001	-
Water bodies percentage (b_4)	Estimate	0.0033	-0.0023	-0.0206	0.0511	-0.0309	-0.01289	-0.00810	-0.02582	0.04146	-0.02685
	P-value	0.6314	0.5019	< 0.001	< 0.001	< 0.001	< 0.001	0.018	< 0.001	< 0.001	< 0.001
Soil percentage (b_5)	Estimate	-0.0696	-0.0768	-0.0995	-	-	-0.07372	-0.06791	-0.08910	-	-
	P-value	< 0.001	< 0.001	< 0.001	-	-	< 0.001	< 0.001	< 0.001	-	-
Built-up land percentage (b_6)	Estimate	-0.0521	-0.0579	-0.0765	-0.0073	-0.1488	-0.07864	-0.07436	-0.08980	-0.0334	-0.1254
	P-value	< 0.001	< 0.001	< 0.001	0.521	< 0.001	< 0.001	< 0.001	< 0.001	0.008	< 0.001

AIC: Akaike's information criterion

Set 1: All predictor variables

Set 2: Exclude closed-forest variable

Set 3: Exclude agriculture/sparse land variable

Set 4: Exclude soil variable

Set 5: Exclude closed-forest, agriculture/sparse land, and soil variables

because AIC of ZIP45 is much greater comparing to other models from ZIP. Also, model ZIP41 and ZIP44 are removed because they contain insignificant variables. Both model ZIP42 and ZIP43 comprise all significant variables, but model ZIP42 is chosen from ZIP because it has the lowest AIC.

Model ZIP42 is selected as the most suitable model for prediction BU cases in 1999 (equation (15)). It predicts that 13.95% of all districts have no case, which is closer to the BU dataset in 1999, 11 districts of 74 districts (14.85%). According to equation 15, the intercept coefficient as 5.2871 can be interpreted that since all predictors in the model is evaluated as zero, the log of BU_{1999} is 5.2871. The open-forest coefficient at -0.02602 means that if the percentage of open-forest increases 1%, the difference in the log of BU_{1999} is expected to decrease by -0.02602 units. Notably, for agriculture/sparse land coefficient, the expectation of log of BU_{1999} will increase by 0.01890 units, whereas the results from Spearman's rank correlation show that incidence of BU in 1999 is significantly positively correlated to agriculture/sparse land. Since agriculture/sparse land inversely correlates to closed-forest, while closed-forest highly correlates to BU incidence, it implies that it also expresses closed-forest. This indicates the importance of multicollinearity investigation before testing the regression. For water body coefficient, when the percentage of water bodies increases 1%, the expectation of log of BU_{1999} will decrease by 0.00810 units. Likewise, the increase in 1% of soil and built-up land will decrease the difference in the log of BU_{1999} by 0.06791 and 0.07436 respectively.

$$BU_{1999} = \exp (5.2871 - 0.02602 (\% \text{ Open-forest}) + 0.01890 (\% \text{ Agriculture/sparse land}) - 0.00810 (\% \text{ Water body}) - 0.06791 (\% \text{ Soil}) - 0.07436 (\% \text{ Built-up land})) \quad (15)$$

The results from Table 7 clearly illustrate that there is no multicollinearity among variables from the early 2000s. Therefore, all variables are included in the model.

Similarly, Poisson regression and ZIP are run and the most suitable model was selected. In order to predict the BU cases between 2005 and 2008, the average cases from this time period are used as the response variable and the percentages of land use and land cover from Landsat 7 are predictor variables. The BU case data that contains decimal unit is rounded by increasing one increment.

Table 7

Correlation Coefficient among Predictor Variables in the Early 2000s

LULC 2000s	Closed-forest	Open-forest	Agriculture	Water	Soil	Built-up
Open-forest	0.244	1				
Agriculture	-0.504	0.108	1			
Water	-0.434	-0.252	0.216	1		
Soil	-0.609	-0.522	-0.062	0.290	1	
Built-up	-0.494	-0.175	0.343	0.485	0.209	1

There are only two candidate models for predicting BU cases between 2005 and 2008, called BU_{2000s} (Table 8). Obviously, the model from ZIP is the best fit model for BU_{2000s} . Due to the fact that 37 of 74 districts (50%) during 2005 to 2008 have no reported cases, AIC from ZIP model is lower than AIC from Poisson regression model. ZIP model also predicts that 50% of all districts have zero case, which is the same as

BU dataset between 2005 and 2008. The model is illustrated in equation 16. When all variables in the model are evaluated as zero, the difference in the log of BU_{2000s} is expected to be 38.1316. In this model, when closed-forest, open-forest, agriculture/sparse land, water bodies, soil, and built-up land increase by 1%, the difference in log of BU_{2000s} will be decreased by -0.3538, -0.3437, -0.3572, -0.4397, -0.3577, and -0.3510 units respectively.

$$\begin{aligned}
 BU_{2000s} = & \exp (38.1316 - 0.3538 (\% \text{ Closed-forest}) - 0.3437 (\% \text{ Open-forest}) - \\
 & 0.3572 (\% \text{ Agriculture/sparse land}) - 0.4397 (\% \text{ Water body}) - \\
 & 0.3577 (\% \text{ Soil}) - 0.3510 (\% \text{ Built-up land}))
 \end{aligned} \tag{16}$$

Table 8

BU_{2000s} Prediction Models from Poisson Regression and Zero-inflated Poisson Regression (ZIP)

Parameters		Poisson regression	ZIP
Goodness of fit	AIC	2566.93	1626.8
Inflation probability	Estimate	-	0.500
	P-value	-	< 0.001
Intercept (b_0)	Estimate	-1.0861	38.1316
	P-value	0.580	< 0.001
Closed-forest percentage (b_1)	Estimate	0.0343	-0.3538
	P-value	0.082	< 0.001
Open-forest percentage (b_2)	Estimate	0.0565	-0.3437
	P-value	0.004	< 0.001
Agriculture/sparse land percentage (b_3)	Estimate	-0.0152	-0.3572
	P-value	0.489	< 0.001
Water bodies percentage (b_4)	Estimate	-0.0214	-0.4397
	P-value	0.402	< 0.001
Soil percentage (b_5)	Estimate	0.0332	-0.3577
	P-value	0.098	< 0.001
Built-up land percentage (b_6)	Estimate	0.0357	-0.3510
	P-value	0.111	< 0.001

Influence of Land use and Land Cover Change on the Spatial Distribution of Buruli Ulcer

Previous results illustrate the spatial distribution of BU in each period of time. The results also explain how environmental factors impact the BU distribution. In this section, the effect of environmental changes on the spatial distribution of BU will be determined. The changed areas in Figure 8a were computed using post-classification comparison changed technique based on the classified images shown in Figure 7. Changed land use and land covers mostly occur along the coast of the study area and around the regional capital cities. These can imply that the economic growth and infrastructure developments are mainly in urban areas.

Figure 8. Land use and land cover change between 1990s and 2000s: (a) Changed area from the classified images; (b) Majority of changed area at district level.

However, Figure 8a cannot be used to determine the BU rate in each changed area because there are many small groups of changed area (isolated pixel) throughout the image and some districts only have few changed areas. Also, both BU datasets, 1999 and between 2005 and 2008, provide the number of cases at district level so that it would not be reasonable to assign the BU rate of the small changed area to the whole district. The best possible technique to solve the problem shown in Figure 8a was to use zonal statistics in order to investigate the majority area (change or no change) in each district. The result, Figure 8b, shows that 57 of 74 districts have land use and land cover change in this new map. The changed land use and land cover represented in Figure 8b does not mean that there is no change in land use and land cover in the district. It rather means that the areas with no change are smaller than the areas with land use and land cover change.

Overlaying each BU incidence dataset on the majority of changing area clearly shows that the high endemic areas of both datasets occur in the changed areas (Figure 9a and 9b). Nevertheless, the rates between the two datasets in the high endemic areas are visually different. The rate in 1999 is higher than the rate in 2005 to 2008. Considering the southeast Kumasi, BU rates in the early 2000s noticeably drop from 1999. In order to determine the impact of land use and land cover change on the spread of BU, the BU rates between these two datasets are tested using Kolmogorov- Smirnov test (KS test). Since BU dataset between 2005 and 2008 have many no reported cases, the districts that have no reported cases are not included in the KS test. Only 27 of 57 districts are included in the KS test. Figure 9c and 9d illustrate the districts that are concerned. They also show the changed areas that are excluded (cyan color). The

result from the KS test confirms that there is a significant difference between the incidence of BU in 1999 and the incidence of BU between 2005 and 2008 ($p = 0.023$). Thus changes of land use and land cover probably influence the spatial pattern of BU.

Figure 9. Overlaying the incidence of BU on the land use and land cover change: (a) BU incidence rate in 1999 on changed area; (b) BU incidence rate between 2005 and 2008 on changed area; (c) BU incidence rate in 1999 on changed area that excludes no reported case; (d) BU incidence rate in between 2005 and 2008 on changed area that excludes no reported case.

Limitations

There are several limitations with medical data that are worth to be mentioned. First, there is no periodic BU dataset from the same source; therefore, it is difficult to investigate the trend of BU distribution and minimize the ability of health care intervention. Also, BU datasets in this research are acquired from the different sources which have the different data collection techniques. Therefore, analyzing data between these two datasets are limited.

Another limitation is geographic files. Originally, Ghana considered 110 districts, but new districts have been announced since 2004. Nowadays, there are 138 districts in total. One problem is the geographic shapefile at district level. There are 138 districts generated based on administrative districts in 2007, whereas BU data collected in 1999 contains 110 districts. The district shapefile of year 2007 is adjusted to the originated districts (110 districts). Moreover, BU dataset from 2005 to 2008 is rearranged based on the originated districts since this dataset contains new districts.

The satellite imagery in the study area also faces some limitations. It is not possible to obtain the remotely sensed images in the same month and year. Moreover, the percentage of cloud cover is a major factor that is unavoidable. The best possible action is to collect images of the same month in order to avoid the condition of seasonal change. In addition, Landsat imagery has coarse resolution (30 m by 30 m); therefore, it cannot detect water bodies that have surface area less than 900 square meters, which is roughly equal to a football field. Therefore, small water and/or stagnant water that would be a major risk environmental factor to facilitate BU cannot be classified. Since the high resolution of remotely sensed images are very limited accessibility, only six

types of land use and land cover can be classified from Landsat. Due to lacks of high resolution images, ground truth data, and aerial photograph, the study cannot measure the accuracy assessment of the classified images, which is an important process of classifying remotely sensed image. Last but not least, in order to distinguish between soil and built-up land, many indices are applied together because of the similarity background reflectance of soil and built-up land.

CHAPTER 5

CONCLUSIONS

The BU incidence rate in 1999 (42.83 per 100,000 population) in the study area is considered relatively high compared to the average prevalence rate from Amofah et al. (2002) and WHO (2004a). It is also higher than that of between 2005 and 2008. However, the incidence of BU in these two time periods could not be compared due to the different data collection methods. Nonetheless, it is interesting that the distribution of BU in these two time periods have similar patterns. Thus, the highest endemic areas of both periods occur in the southern portion of Sunyani and Kumasi and seem to expand to the western portion of the study area along the border of Ghana and Cote d'Ivoire. In contrast, the northeast portion of the study area appears to be low endemic areas during both periods. That is less than 27 and 20 per 100,000 population in 1999 and 2005 to 2008 respectively. Another similarity of BU distribution in these two periods is that there are lower BU rates around the regional capital cities.

Overlaying the incidence of BU in 1999 map on the early 1990s classified image, the spatial distribution of high BU endemic areas have the same pattern as the closed-forest. The results from Spearman's rank correlation confirm that closed-forest areas have a significantly positive correlation to the BU incidence in 1999. Meanwhile, the incidence of BU in 1999 inversely correlates to agriculture/sparse land and soil areas. Considering BU incidence between 2005 and 2008 and land use and land cover in the early 2000s, the highest endemic areas still occur in the closed-forest similar to the incidence of BU in 1999. The Spearman's rank correlation results certify that closed-forest and open-forest areas significantly have positive relationship to BU incidence

between 2005 and 2008, whereas agriculture/sparse land and built-up land inversely correlate to the incidence of BU between 2005 and 2008. These results indicate that closed-forest and open-forest are the most important environmental factors that explain the spatial distribution of BU. The results also suggest that BU mostly occurs in rural areas, which comprise the large forest, rather than in urban areas, which have better infrastructure.

Although ZIP does not provide the coefficient of determination (R^2) like other linear regressions, the ZIP model is selected for this study because of the statistical technique and the significance of parameters. The model can predict the occurrence of BU in each district in the present and in the future using the percentages of land use and land cover as predictors. It would be helpful for public health agencies to develop intervention and control strategies in order to reduce the incidence of BU. Moreover, the ZIP model can explain the impact of each land use and land cover type on the BU distribution.

The study found that land use and land cover change statistically affects the spatial distribution of BU; however, further research is needed in order to investigate the changes of land use and land cover in each type. The results would show how those changes affect the BU rates. Unlike previous studies, the results could not determine the relationship between water bodies and the spatial distribution pattern of BU due to imagery limitations. In future research, higher resolution satellite images should be used to classify land use and land cover in order to detect more small water bodies to confirm this finding. Due to the fact that forest areas appear to be the highest risk factor in this study, the target areas of high resolution images in future research should center on

forest areas. One reason is that the forests, especially closed-forest, probably have more small water bodies, which include stagnant water, the major risk environmental factors that impact the spatial distribution of BU.

APPENDIX A

KNOWLEDGE-BASED CLASSIFICATION MODELS

Figure A.1. Classification rules and condition for Landsat 4 path 193 row 055.

Figure A.2. Classification rules and condition for Landsat 4 path 193 row 056.

Figure A.3. Classification rules and condition for Landsat 4 path 194 row 054.

Figure A.4. Classification rules and condition for Landsat 4 path 194 row 055.

Figure A.5. Classification rules and condition for Landsat 5 path 194 row 056.

Figure A.6. Classification rules and condition for Landsat 5 path 194 row 057.

Figure A.7. Classification rules and condition for Landsat 4 path 195 row 054.

Figure A.8. Classification rules and condition for Landsat 4 path 195 row 055.

Figure A.9. Classification rules and condition for Landsat 4 path 195 row 056.

Figure A.10. Classification rules and condition for Landsat 7 ETM+ path 193 row 055.

Figure A.11. Classification rules and condition for Landsat 7 ETM+ path 193 row 056.

Figure A.12. Classification rules and condition for Landsat 7 ETM+ path 194 row 054.

Figure A.13. Classification rules and condition for Landsat 7 ETM+ path 194 row 055.

Figure A.14. Classification rules and condition for Landsat 7 ETM+ path 194 row 056.

Figure A.15. Classification rules and condition for Landsat 7 ETM+ path 194 row 057.

Figure A.16. Classification rules and condition for Landsat 7 ETM+ path 195 row 054.

Figure A.17. Classification rules and condition for Landsat 7 ETM+ path 195 row 055.

Figure A.18. Classification rules and condition for Landsat 7 ETM+ path 195 row 056.

APPENDIX B
POISSON REGRESSION MODELS

Table B.1

The Results of Poisson Regression Model for BU₁₉₉₉ for All Predictor Variables

The SAS System The GENMOD Procedure							
	Model Information						
	Data Set		WORK.BINK				
	Distribution		Poisson				
	Link Function		Log				
	Dependent Variable		bu_1999				
Number of Observations Read				74			
Number of Observations Used				74			
Criteria For Assessing Goodness Of Fit							
Criterion		DF	Value		Value/DF		
Deviance		67	8744.6051		130.5165		
Scaled Deviance		67	8744.6051		130.5165		
Pearson Chi-Square		67	16791.7191		250.6227		
Scaled Pearson X2		67	16791.7171		250.6227		
Log Likelihood			16440.4388				
Full Log Likelihood			-4537.6910				
AIC (smaller is better)			9089.3819				
AICC (smaller is better)			9091.0789				
BIC (smaller is better)			9105.5104				
Algorithm converged.							
Analysis of Maximum Likelihood Parameter Estimates							
Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	Pr > ChiSq
Intercept	1	4.4760	0.6517	3.1988	5.7533	47.18	<.0001
L4_PerCFor	1	0.0061	0.0065	-0.0066	0.0188	0.87	0.3496
L4_PerOFor	1	-0.0181	0.0068	-0.0314	-0.0049	7.19	0.0074
L4_PerGrs	1	0.0264	0.0065	0.0137	0.0391	16.67	<.0001
L4_PerH2O	1	0.0033	0.0069	-0.0102	0.0168	0.23	0.6314
L4_PerSoil	1	-0.0696	0.0084	-0.0861	-0.0532	69.07	<.0001
L4_PerBuil	1	-0.0521	0.0124	-0.0764	-0.0278	17.70	<.0001
Scale	0	1.0000	0.0000	1.0000	1.0000		
NOTE: The scale parameter was held fixed.							
LR Statistics For Type 3 Analysis							
Source	DF	Chi-Square	Pr > ChiSq				
L4_PerCFor	1	0.89	0.3460				
L4_PerOFor	1	6.91	0.0086				
L4_PerGrs	1	17.88	<.0001				
L4_PerH2O	1	0.23	0.6305				
L4_PerSoil	1	68.29	<.0001				
L4_PerBuil	1	21.35	<.0001				

Table B.2

The Results of Poisson Regression Model for BU₁₉₉₉ for Open-forest, Agriculture/sparse Land, Water, Soil, and Built-up Land

The SAS System The GENMOD Procedure								
	Model Information							
	Data Set		WORK.BINK					
	Distribution		Poisson					
	Link Function		Log					
	Dependent Variable		bu_1999					
Number of Observations Read				74				
Number of Observations Used				74				
Criteria For Assessing Goodness Of Fit								
Criterion		DF	Value		Value/DF			
Deviance		68	8745.4933		128.6102			
Scaled Deviance		68	8745.4933		128.6102			
Pearson Chi-Square		68	16850.3139		247.7987			
Scaled Pearson X2		68	16850.3139		247.7987			
Log Likelihood			16439.9946					
Full Log Likelihood			-4538.1351					
AIC (smaller is better)			9088.2702					
AICC (smaller is better)			9089.5239					
BIC (smaller is better)			9102.0946					
Algorithm converged.								
Analysis of Maximum Likelihood Parameter Estimates								
Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	Pr > ChiSq	
Intercept	1	5.0846	0.0387	5.0088	5.1604	17284.5	<.0001	
L4_PerOFor	1	-0.0243	0.0011	-0.0265	-0.0222	478.79	<.0001	
L4_PerGrs	1	0.0205	0.0011	0.0183	0.0226	335.48	<.0001	
L4_PerH2O	1	-0.0023	0.0034	-0.0090	0.0044	0.45	0.5019	
L4_PerSoil	1	-0.0768	0.0035	-0.0837	-0.0700	486.77	<.0001	
L4_PerBuil	1	-0.0579	0.0108	-0.0790	-0.0367	28.73	<.0001	
Scale	0	1.0000	0.0000	1.0000	1.0000			
NOTE: The scale parameter was held fixed.								
LR Statistics For Type 3 Analysis								
Source	DF	Chi-Square	Pr > ChiSq					
L4_PerOFor	1	492.26	<.0001					
L4_PerGrs	1	317.17	<.0001					
L4_PerH2O	1	0.46	0.4995					
L4_PerSoil	1	1302.49	<.0001					
L4_PerBuil	1	44.24	<.0001					

Table B.3

The Results of Poisson Regression Model for BU₁₉₉₉ for Closed-forest, Open-forest, Water, Soil, and Built-up Land

The SAS System The GENMOD Procedure							
	Model Information						
	Data Set		WORK.BINK				
	Distribution		Poisson				
	Link Function		Log				
	Dependent Variable		bu_1999				
Number of Observations Read				74			
Number of Observations Used				74			
Criteria For Assessing Goodness Of Fit							
Criterion		DF	Value	Value/DF			
Deviance		68	8762.4824	128.8600			
Scaled Deviance		68	8762.4824	128.8600			
Pearson Chi-Square		68	17264.3209	253.8871			
Scaled Pearson X2		68	17264.3209	253.8871			
Log Likelihood			16431.5001				
Full Log Likelihood			-4546.6296				
AIC (smaller is better)			9105.2592				
AICC (smaller is better)			9106.5129				
BIC (smaller is better)			9119.0836				
Algorithm converged.							
Analysis of Maximum Likelihood Parameter Estimates							
Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	Pr > ChiSq
Intercept	1	7.0940	0.1201	6.8586	7.3295	3487.39	<.0001
L4_PerCFor	1	-0.0200	0.0011	-0.0222	-0.0177	306.30	<.0001
L4_PerOFor	1	-0.0447	0.0018	-0.0483	-0.0411	587.74	<.0001
L4_PerH2O	1	-0.0206	0.0036	-0.0276	-0.0136	33.39	<.0001
L4_PerSoil	1	-0.0995	0.0045	-0.1083	-0.0907	429.09	<.0001
L4_PerBuil	1	-0.0765	0.0110	-0.0981	-0.0549	48.01	<.0001
Scale	0	1.0000	0.0000	1.0000	1.0000		
NOTE: The scale parameter was held fixed.							
LR Statistics For Type 3 Analysis							
Source	DF	Chi-Square	Pr > ChiSq				
L4_PerCFor	1	300.18	<.0001				
L4_PerOFor	1	584.79	<.0001				
L4_PerH2O	1	36.45	<.0001				
L4_PerSoil	1	1015.00	<.0001				
L4_PerBuil	1	86.24	<.0001				

Table B.4

The Results of Poisson Regression Model for BU₁₉₉₉ for Closed-forest, Open-forest, Agriculture/sparse Land, Water, and Built-up Land

The SAS System The GENMOD Procedure							
	Model Information						
	Data Set		WORK.BINK				
	Distribution		Poisson				
	Link Function		Log				
	Dependent Variable		bu_1999				
Number of Observations Read				74			
Number of Observations Used				74			
Criteria For Assessing Goodness Of Fit							
Criterion		DF	Value		Value/DF		
Deviance		68	8812.8960		129.6014		
Scaled Deviance		68	8812.8960		129.6014		
Pearson Chi-Square		68	16803.5168		247.1105		
Scaled Pearson X2		68	16803.5168		247.1105		
Log Likelihood			16406.2933				
Full Log Likelihood			-4571.8364				
AIC (smaller is better)			9155.6729				
AICC (smaller is better)			9156.9266				
BIC (smaller is better)			9169.4972				
Algorithm converged.							
Analysis of Maximum Likelihood Parameter Estimates							
Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	Pr > ChiSq
Intercept	1	-0.9587	0.2416	-1.4323	-0.4852	15.75	<.0001
L4_PerCFor	1	0.0600	0.0025	0.0552	0.0648	598.38	<.0001
L4_PerOFor	1	0.0379	0.0025	0.0330	0.0427	234.50	<.0001
L4_PerGrs	1	0.0782	0.0031	0.0721	0.0842	639.12	<.0001
L4_PerH2O	1	0.0511	0.0046	0.0421	0.0601	124.35	<.0001
L4_PerBuil	1	-0.0073	0.0113	-0.0295	0.0149	0.41	0.5205
Scale	0	1.0000	0.0000	1.0000	1.0000		
NOTE: The scale parameter was held fixed.							
LR Statistics For Type 3 Analysis							
Source	DF	Chi-Square	Pr > ChiSq				
L4_PerCFor	1	1235.09	<.0001				
L4_PerOFor	1	338.95	<.0001				
L4_PerGrs	1	964.59	<.0001				
L4_PerH2O	1	120.70	<.0001				
L4_PerBuil	1	0.43	0.5122				

Table B.5

The Results of Poisson Regression Model for BU₁₉₉₉ for Open-forest, Water, Soil, and Built-up Land

The SAS System The GENMOD Procedure							
	Model Information						
	Data Set	WORK.BINK					
	Distribution	Poisson					
	Link Function	Log					
	Dependent Variable	bu_1999					
Number of Observations Read			74				
Number of Observations Used			74				
Criteria For Assessing Goodness Of Fit							
Criterion		DF	Value		Value/DF		
Deviance		69	9062.6644		131.3430		
Scaled Deviance		69	9062.6644		131.3430		
Pearson Chi-Square		69	22928.6863		332.2998		
Scaled Pearson X2		69	22928.6863		332.2998		
Log Likelihood			16281.4091				
Full Log Likelihood			-4696.7206				
AIC (smaller is better)			9403.4412				
AICC (smaller is better)			9404.3236				
BIC (smaller is better)			9414.9615				
Algorithm converged.							
Analysis of Maximum Likelihood Parameter Estimates							
Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	Pr > ChiSq
Intercept	1	5.0973	0.0376	5.0236	5.1710	18373.4	<.0001
L4_PerOFor	1	-0.0182	0.0010	-0.0203	-0.0162	305.39	<.0001
L4_PerH2O	1	0.0005	0.0033	-0.0059	0.0069	0.03	0.8705
L4_PerSoil	1	-0.0506	0.0022	-0.0549	-0.0462	512.02	<.0001
L4_PerBuil	1	-0.0440	0.0092	-0.0620	-0.0259	22.69	<.0001
Scale	0	1.0000	0.0000	1.0000	1.0000		
NOTE: The scale parameter was held fixed.							
LR Statistics For Type 3 Analysis							
Source	DF	Chi-Square	Pr > ChiSq				
L4_PerOFor	1	312.04	<.0001				
L4_PerH2O	1	0.03	0.8706				
L4_PerSoil	1	987.44	<.0001				
L4_PerBuil	1	32.72	<.0001				

Table B.6

The Results of Poisson Regression Model for BU₁₉₉₉ for Open-forest, Agriculture/sparse Land, Water, and Built-up Land

The SAS System The GENMOD Procedure							
	Model Information						
	Data Set		WORK.BINK				
	Distribution		Poisson				
	Link Function		Log				
	Dependent Variable		bu_1999				
Number of Observations Read				74			
Number of Observations Used				74			
Criteria For Assessing Goodness Of Fit							
Criterion		DF	Value		Value/DF		
Deviance		69	10047.9857		145.6230		
Scaled Deviance		69	10047.9857		145.6230		
Pearson Chi-Square		69	24346.8531		352.8529		
Scaled Pearson X2		69	24346.8531		352.8529		
Log Likelihood			15788.7485				
Full Log Likelihood			-5189.3812				
AIC (smaller is better)			10388.7625				
AICC (smaller is better)			10389.6448				
BIC (smaller is better)			10400.2828				
Algorithm converged.							
Analysis of Maximum Likelihood Parameter Estimates							
Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	Pr > ChiSq
Intercept	1	4.5653	0.0386	4.4895	4.6410	13965.7	<.0001
L4_PerOFor	1	-0.0076	0.0010	-0.0096	-0.0057	58.69	<.0001
L4_PerGrs	1	0.0015	0.0011	-0.0005	0.0036	2.14	0.1436
L4_PerH2O	1	-0.0318	0.0034	-0.0383	-0.0252	89.90	<.0001
L4_PerBuil	1	-0.1556	0.0162	-0.1874	-0.1238	92.06	<.0001
Scale	0	1.0000	0.0000	1.0000	1.0000		
NOTE: The scale parameter was held fixed.							
LR Statistics For Type 3 Analysis							
Source	DF	Chi-Square	Pr > ChiSq				
L4_PerOFor	1	59.34	<.0001				
L4_PerGrs	1	2.12	0.1452				
L4_PerH2O	1	111.28	<.0001				
L4_PerBuil	1	215.81	<.0001				

Table B.7

The Results of Poisson Regression Model for BU₁₉₉₉ for Closed-forest, Open-forest, Water, and Built-up Land

The SAS System The GENMOD Procedure							
	Model Information						
	Data Set		WORK.BINK				
	Distribution		Poisson				
	Link Function		Log				
	Dependent Variable		bu_1999				
Number of Observations Read				74			
Number of Observations Used				74			
Criteria For Assessing Goodness Of Fit							
Criterion		DF	Value		Value/DF		
Deviance		69	9777.4871		141.7027		
Scaled Deviance		69	9777.4871		141.7027		
Pearson Chi-Square		69	28418.5261		411.8627		
Scaled Pearson X2		69	28418.5261		411.8627		
Log Likelihood			15923.9977				
Full Log Likelihood			-5054.1320				
AIC (smaller is better)			10118.2640				
AICC (smaller is better)			10119.1463				
BIC (smaller is better)			10129.7843				
Algorithm converged.							
Analysis of Maximum Likelihood Parameter Estimates							
Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	Pr > ChiSq
Intercept	1	3.7791	0.0648	3.6521	3.9060	3403.99	<.0001
L4_PerCFor	1	0.0107	0.0007	0.0094	0.0120	251.56	<.0001
L4_PerOFor	1	0.0009	0.0012	-0.0014	0.0031	0.57	0.4520
L4_PerH2O	1	-0.0060	0.0035	-0.0129	0.0008	2.97	0.0851
L4_PerBuil	1	-0.0672	0.0117	-0.0901	-0.0443	32.97	<.0001
Scale	0	1.0000	0.0000	1.0000	1.0000		
NOTE: The scale parameter was held fixed.							
LR Statistics For Type 3 Analysis							
Source	DF	Chi-Square	Pr > ChiSq				
L4_PerCFor	1	272.62	<.0001				
L4_PerOFor	1	0.57	0.4516				
L4_PerH2O	1	3.05	0.0806				
L4_PerBuil	1	55.46	<.0001				

Table B.8

The Results of Poisson Regression Model for BU₁₉₉₉ for Open-forest, Water, and Built-up Land

The SAS System The GENMOD Procedure							
	Model Information						
	Data Set		WORK.BINK				
	Distribution		Poisson				
	Link Function		Log				
	Dependent Variable		bu_1999				
Number of Observations Read				74			
Number of Observations Used				74			
Criteria For Assessing Goodness Of Fit							
Criterion		DF	Value	Value/DF			
Deviance		70	10050.1074	143.5730			
Scaled Deviance		70	10050.1074	143.5730			
Pearson Chi-Square		70	24864.5178	355.2074			
Scaled Pearson X2		70	24864.5178	355.2074			
Log Likelihood			15787.6876				
Full Log Likelihood			-5190.4421				
AIC (smaller is better)			10388.8842				
AICC (smaller is better)			10389.4639				
BIC (smaller is better)			10398.1004				
Algorithm converged.							
Analysis of Maximum Likelihood Parameter Estimates							
Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	Pr > ChiSq
Intercept	1	4.5800	0.0371	4.5072	4.6527	15231.3	<.0001
L4_PerOFor	1	-0.0074	0.0010	-0.0094	-0.0055	57.05	<.0001
L4_PerH2O	1	-0.0309	0.0033	-0.0373	-0.0244	88.30	<.0001
L4_PerBuil	1	-0.1488	0.0153	-0.1787	-0.1188	94.74	<.0001
Scale	0	1.0000	0.0000	1.0000	1.0000		
NOTE: The scale parameter was held fixed.							
LR Statistics For Type 3 Analysis							
Source	DF	Chi-Square	Pr > ChiSq				
L4_PerOFor	1	57.53	<.0001				
L4_PerH2O	1	109.88	<.0001				
L4_PerBuil	1	223.19	<.0001				

Table B.9

The Results of ZIP Model for BU₁₉₉₉ for All Predictor Variables

The SAS System The NLMIXED Procedure								
	Specification							
	Data Set				WORK.BINK			
	Dependent Variable				bu_1999			
	Distribution for Dependent Variable				General			
	Optimization Technique				Dual Quasi-Newton			
	Integration Method				None			
	Dimension							
	Observations Used				74			
	Observations Not Used				0			
	Total Observations				74			
	Parameters				8			
Parameters								
b0	b1	b2	b3	b4	b5	b6	a0	NegLogLike
0	0	0	0	0	0	0	0	21088.9767
Iteration History								
Iter	Calls	NegLogLike		Diff	MaxGrad	Slope		
1	7	6380.54455		14708.43	252631.5	-7.914E8		
2	13	5705.30997		675.2346	215508	-4.703E7		
3	17	5549.40342		155.9066	224597.6	-1.293E7		
4	21	5518.34917		31.05424	225670.7	-1600032		
5	25	5496.23082		22.11835	224456.7	-73311.2		
6	26	4656.77885		839.452	98863.47	-15705.3		
7	30	4141.78465		514.9942	42561.42	-50697.6		
8	32	3940.66705		201.1176	7219.278	-347.752		
9	34	3918.70213		21.96492	1785.321	-31.0332		
10	36	3912.08		6.622129	2084.321	-10.1882		
11	37	3903.33358		8.746424	3223.023	-4.92678		
12	39	3898.93924		4.39434	1558.443	-5.84963		
13	40	3893.28754		5.651702	1951.323	-2.56024		
14	41	3889.36542		3.922122	1283.952	-3.60698		
15	43	3886.94326		2.422153	483.8855	-3.27069		
16	45	3881.30631		5.636953	1178.743	-1.43585		
17	47	3879.28268		2.023627	399.1041	-3.23178		
18	49	3878.70481		0.577868	419.825	-0.94079		
19	51	3878.67206		0.032753	87.59112	-0.06286		
20	53	3878.67139		0.000672	7.692786	-0.0012		
21	55	3878.67135		0.000038	2.34818	-0.00007		
22	57	3878.67135		1.088E-6	0.256283	-1.85E-6		
NOTE: GCONV convergence criterion satisfied.								
	Fit Statistics							
	-2 Log Likelihood				7757.3			
	AIC (smaller is better)				7773.3			
	AICC (smaller is better)				7775.6			
	BIC (smaller is better)				7791.8			

Table B.9

The Results of ZIP Model for BU₁₉₉₉ for All Predictor Variables (Continued)

Analysis of Maximum Likelihood Parameter Estimates									
Para- meter	Estimate	Standard Error	DF	t Value	Pr > t	Al- pha	Lower	Upper	Gradient
b0	5.7925	0.6668	74	8.69	<.0001	0.05	4.4639	7.1211	-0.00573
b1	-0.00503	0.006623	74	-0.76	0.4501	0.05	-0.01823	0.008168	-0.25628
b2	-0.03121	0.006920	74	-4.51	<.0001	0.05	-0.04500	-0.01742	-0.23178
b3	0.01393	0.006639	74	2.10	0.0394	0.05	0.000696	0.02715	-0.03392
b4	-0.01289	0.007130	74	-1.81	0.0747	0.05	-0.02709	0.001319	-0.02103
b5	-0.07372	0.008312	74	-8.87	<.0001	0.05	-0.09028	-0.05716	-0.01476
b6	-0.07864	0.01260	74	-6.24	<.0001	0.05	-0.1037	-0.05355	-0.00246
a0	-1.8234	0.3432	74	-5.31	<.0001	0.05	-2.5073	-1.1395	0.000066
Additional Estimates									
Label		Estimate	Standard Error	DF	t Value	Pr > t	Al- pha	Lower	Upper
Inflation probability		0.1390	0.04108	74	3.38	0.0011	0.05	0.05717	0.2209

Table B.10

The Results of ZIP Model for BU₁₉₉₉ for Open-forest, Agriculture/sparse Land, Water, Soil, and Built-up Land

The SAS System The NLMIXED Procedure							
	Specification						
	Data Set				WORK.BINK		
	Dependent Variable				bu_1999		
	Distribution for Dependent Variable				General		
	Optimization Technique				Dual Quasi-Newton		
	Integration Method				None		
	Dimension						
	Observations Used				74		
	Observations Not Used				0		
	Total Observations				74		
Parameters				7			
Parameters							
b0	b1	b2	b3	b4	b5	a0	NegLogLike
0	0	0	0	0	0	0	21088.9767
Iteration History							
Iter	Calls	NegLogLike		Diff	MaxGrad	Slope	
1	9	9630.02491		11458.95	64972.75	-2.884E8	
2	13	9573.20566		56.81926	57338.54	-2186422	
3	16	9508.80734		64.39832	56092.79	-94899.3	

Table B.10

The Results of ZIP Model for BU₁₉₉₉ for Open-forest, Agriculture/sparse Land, Water, Soil, and Built-up Land (Continued)

Iter	Calls	NegLogLike	Diff	MaxGrad	Slope				
4	19	9480.47846	28.32889	59146.66	-108009				
5	21	9381.39687	99.08158	56791.56	-73277.3				
6	24	5308.91314	4072.484	97070.11	-350339				
7	26	4316.41127	992.5019	47097.07	-8826.43				
8	29	4012.33334	304.0779	14797.86	-661.511				
9	31	3918.30813	94.02521	2833.169	-183.921				
10	33	3898.01578	20.29235	5208.529	-17.956				
11	34	3889.24829	8.767484	4472.812	-13.9504				
12	35	3881.10878	8.139516	723.3594	-14.4163				
13	37	3879.61834	1.490435	772.821	-2.25131				
14	39	3879.06388	0.554465	182.3394	-0.51455				
15	41	3879.02013	0.043744	38.74505	-0.06199				
16	42	3878.97483	0.045301	190.7012	-0.01162				
17	44	3878.95743	0.017404	19.38043	-0.02325				
18	46	3878.95627	0.001162	2.03298	-0.00181				
19	48	3878.95626	0.000013	0.368405	-0.00002				
NOTE: GCONV convergence criterion satisfied.									
	Fit Statistics								
	-2 Log Likelihood				7757.9				
	AIC (smaller is better)				7771.9				
	AICC (smaller is better)				7773.6				
	BIC (smaller is better)				7788.0				
Analysis of Maximum Likelihood Parameter Estimates									
Para- meter	Estimate	Standard Error	DF	t Value	Pr > t	Al- pha	Lower	Upper	Gradient
b0	5.2871	0.03790	74	139.49	<.0001	0.05	5.2116	5.3627	-0.00415
b1	-0.02602	0.001068	74	-24.36	<.0001	0.05	-0.02815	-0.02390	-0.36841
b2	0.01890	0.001088	74	17.38	<.0001	0.05	0.01673	0.02107	0.21911
b3	-0.00810	0.003337	74	-2.43	0.0176	0.05	-0.01475	-0.00145	0.044763
b4	-0.06791	0.003162	74	-21.48	<.0001	0.05	-0.07421	-0.06161	0.045623
b5	-0.07436	0.01129	74	-6.59	<.0001	0.05	-0.09685	-0.05187	-0.0009
a0	-1.8198	0.3426	74	-5.31	<.0001	0.05	-2.5024	-1.1371	-0.00006
Additional Estimates									
Label		Estimate	Standard Error	DF	t Value	Pr > t	Al- pha	Lower	Upper
Inflation probability		0.1395	0.04112	74	3.39	0.0011	0.05	0.05754	0.2214

Table B.11

The Results of ZIP Model for BU₁₉₉₉ for Closed-forest, Open-forest, Water, Soil, and Built-up Land

The SAS System The NLMIXED Procedure							
	Specification						
	Data Set				WORK.BINK		
	Dependent Variable				bu_1999		
	Distribution for Dependent Variable				General		
	Optimization Technique				Dual Quasi-Newton		
	Integration Method				None		
	Dimension						
	Observations Used				74		
	Observations Not Used				0		
	Total Observations				74		
	Parameters				7		
Parameters							
b0	b1	b2	b3	b4	b5	a0	NegLogLike
0	0	0	0	0	0	0	21088.9767
Iteration History							
Iter	Calls	NegLogLike		Diff	MaxGrad	Slope	
1	7	7138.49991		13950.48	206027.7	-7.271E8	
2	12	6751.97625		386.5237	185454.8	-2.633E7	
3	18	6348.3346		403.6417	183741.1	-1798006	
4	21	6243.93554		104.3991	182912.3	-159854	
5	25	6157.01699		86.91854	172012.1	-10509.9	
6	26	5164.16564		992.8514	59520.01	-30223.9	
7	27	4246.67696		917.4887	52050.45	-1662.4	
8	29	3976.41669		270.2603	8343.236	-1079.32	
9	32	3900.73237		75.68431	5282.178	-102.829	
10	34	3886.84943		13.88295	144.7719	-33.4997	
11	36	3883.66336		3.186071	1373.201	-3.71395	
12	38	3881.66168		2.001673	863.8748	-1.31807	
13	40	3881.2718		0.389881	257.0517	-0.43324	
14	42	3881.00471		0.267096	311.5981	-0.24813	
15	44	3880.95524		0.049464	61.5802	-0.05291	
16	46	3880.94568		0.009559	30.74498	-0.01006	
17	48	3880.94491		0.000773	5.392872	-0.0012	
18	50	3880.94491		4.651E-6	0.090996	-8.19E-6	
NOTE: GCONV convergence criterion satisfied.							
	Fit Statistics						
	-2 Log Likelihood				7761.9		
	AIC (smaller is better)				7775.9		
	AICC (smaller is better)				7777.6		
	BIC (smaller is better)				7792.0		

Table B.11

The Results of ZIP Model for BU₁₉₉₉ for Closed-forest, Open-forest, Water, Soil, and Built-up Land (Continued)

Analysis of Maximum Likelihood Parameter Estimates									
Parameter	Estimate	Standard Error	DF	t Value	Pr > t	Al-pha	Lower	Upper	Gradient
b0	7.1706	0.1145	74	62.62	<.0001	0.05	6.9424	7.3988	0.0019
b1	-0.01873	0.001098	74	-17.05	<.0001	0.05	-0.02091	-0.01654	0.039942
b2	-0.04528	0.001748	74	-25.90	<.0001	0.05	-0.04876	-0.04179	0.090996
b3	-0.02582	0.003558	74	-7.26	<.0001	0.05	-0.03290	-0.01873	0.014404
b4	-0.08910	0.004074	74	-21.87	<.0001	0.05	-0.09722	-0.08098	0.024715
b5	-0.08980	0.01128	74	-7.96	<.0001	0.05	-0.1123	-0.06732	-0.00718
a0	-1.8309	0.3443	74	-5.32	<.0001	0.05	-2.5170	-1.1447	0.000291
Additional Estimates									
Label	Estimate	Standard Error	DF	t Value	Pr > t	Al-pha	Lower	Upper	
Inflation probability	0.1381	0.04100	74	3.37	0.0012	0.05	0.05645	0.2198	

Table B.12

The Results of ZIP Model for BU₁₉₉₉ for Closed-forest, Open-forest, Agriculture/sparse Land, Water, and Built-up Land

The SAS System The NLMIXED Procedure							
	Specification						
	Data Set				WORK.BINK		
	Dependent Variable				bu_1999		
	Distribution for Dependent Variable				General		
	Optimization Technique				Dual Quasi-Newton		
	Integration Method				None		
	Dimension						
	Observations Used				74		
	Observations Not Used				0		
	Total Observations				74		
	Parameters				7		
Parameters							
b0	b1	b2	b3	b4	b5	a0	NegLogLike
0	0	0	0	0	0	0	21088.9767
Iteration History							
Iter	Calls	NegLogLike	Diff	MaxGrad	Slope		
1	7	6418.22625	14670.75	250940.1	-7.885E8		
2	13	5747.89675	670.3295	214971.5	-4.605E7		

Table B.12

The Results of ZIP Model for BU₁₉₉₉ for Closed-forest, Open-forest, Agriculture/sparse Land, Water, and Built-up Land (Continued)

Iter	Calls	NegLogLike	Diff	MaxGrad	Slope				
3	17	5446.0847	301.812	223547.9	-1.333E7				
4	20	5402.2292	43.8555	222337.2	-78548.7				
5	21	4631.89914	770.3301	109846.6	-13637				
6	24	42943.50496	337.3942	33969.64	-41591.5				
7	25	3965.92062	328.5843	14426.74	-3239.25				
8	27	3938.72461	27.19601	7612.552	-51.4853				
9	29	3926.61697	12.10764	1529.278	-14.3518				
10	30	3919.89661	6.720361	3111.049	-5.07816				
11	32	3916.91479	2.981823	457.111	-4.4643				
12	34	3916.85718	0.057606	47.54121	-0.08928				
13	36	3916.83339	0.02379	85.23923	-0.01797				
14	38	3916.82396	0.009429	74.70327	-0.00772				
15	40	3916.82313	0.000836	14.05868	-0.00122				
16	41	3916.82221	0.000914	13.50862	-0.00021				
17	43	3916.82218	0.000036	2.433143	-0.00007				
18	45	3916.82217	4.993E-7	0.004301	-8.68E-7				
NOTE: GCONV convergence criterion satisfied.									
	Fit Statistics								
	-2 Log Likelihood			7833.6					
	AIC (smaller is better)			7847.6					
	AICC (smaller is better)			7849.3					
	BIC (smaller is better)			7863.8					
Analysis of Maximum Likelihood Parameter Estimates									
Para-meter	Estimate	Standard Error	DF	t Value	Pr > t	Al-pha	Lower	Upper	Gradient
b0	-0.1292	0.2306	74	-0.56	0.5771	0.05	-0.5886	0.3303	-0.00013
b1	0.05377	0.002340	74	22.97	<.0001	0.05	0.04910	0.05843	-0.00347
b2	0.02983	0.002361	74	12.63	<.0001	0.05	0.02512	0.03453	-0.0043
b3	0.07074	0.002986	74	23.69	<.0001	0.05	0.06479	0.07669	-0.00359
b4	0.04146	0.004344	74	9.55	<.0001	0.05	0.03281	0.05012	-0.00069
b5	-0.03334	0.01223	74	-2.73	0.0080	0.05	-0.05771	-0.00898	0.000105
a0	-1.7561	0.3297	74	-5.33	<.0001	0.05	-2.4131	-1.0991	2.204E-6
Additional Estimates									
Label		Estimate	Standard Error	DF	t Value	Pr > t	Al-pha	Lower	Upper
Inflation probability		0.1473	0.04141	74	3.56	0.0007	0.05	0.06477	0.2298

Table B.13

The Results of ZIP Model for BU₁₉₉₉ for Open-forest, Water, Soil, and Built-up Land

The SAS System The NLMIXED Procedure									
	Specification								
	Data Set				WORK.BINK				
	Dependent Variable				bu_1999				
	Distribution for Dependent Variable				General				
	Optimization Technique				Dual Quasi-Newton				
	Integration Method				None				
	Dimension								
	Observations Used				74				
	Observations Not Used				0				
	Total Observations				74				
	Parameters				6				
Parameters									
b0	b1	b2	b3	b4	a0	NegLogLike			
0	0	0	0	0	0	21088.9767			
Iteration History									
Iter	Calls	NegLogLike		Diff	MaxGrad	Slope			
1	9	10773.0537		10315.92	45215.24	-2.241E8			
2	15	10399.7067		373.347	46053.7	-1483582			
3	20	10248.5864		151.1203	45206.31	-185139			
4	24	9994.70445		253.8819	44165.02	-56142.3			
5	28	4541.61417		5453.09	63698.22	-149583			
6	30	4131.14598		410.4682	115.506	-4197.23			
7	32	4073.70313		57.44285	18672.45	-304.53			
8	34	4033.07291		40.63021	596.479	-78.4815			
9	36	4028.27139		4.801524	2642.485	-8.49658			
10	37	4022.7628		5.508594	921.1426	-5.30462			
11	39	4021.30011		1.462682	418.8757	-1.71399			
12	41	4020.90261		0.397503	279.9235	-0.3878			
13	43	4020.67933		0.223285	61.90414	-0.18887			
14	45	4020.67765		0.001677	8.360876	-0.00295			
15	47	4020.67763		0.000018	0.193449	-0.0004			
NOTE: GCONV convergence criterion satisfied.									
	Fit Statistics								
	-2 Log Likelihood				8041.4				
	AIC (smaller is better)				8053.4				
	AICC (smaller is better)				8054.6				
	BIC (smaller is better)				8067.2				
Analysis of Maximum Likelihood Parameter Estimates									
Para- meter	Estimate	Standard Error	DF	t Value	Pr > t	Al- pha	Lower	Upper	Gradient
b0	5.3190	0.03683	74	144.43	<.0001	0.05	5.2456	5.3924	-0.00251
b1	-0.02111	0.001017	74	-20.77	<.0001	0.05	-0.02314	-0.01909	-0.19345
b2	-0.00251	0.003174	74	-0.79	0.4308	0.05	-0.00884	0.003810	-0.06676

Table B.13

The Results of ZIP Model for BU₁₉₉₉ for Open-forest, Water, Soil, and Built-up Land

(Continued)

Parameter	Estimate	Standard Error	DF	t Value	Pr > t	Alpha	Lower	Upper	Gradient
b3	-0.04464	0.002071	74	-21.56	<.0001	0.05	-0.04877	-0.04051	-0.00717
b4	-0.05504	0.009164	74	-6.01	<.0001	0.05	-0.07330	-0.03678	-0.00406
a0	-1.7462	0.3270	74	-5.34	<.0001	0.05	-2.3979	-1.0946	-0.0002
Additional Estimates									
Label	Estimate	Standard Error	DF	t Value	Pr > t	Alpha	Lower	Upper	
Inflation probability	0.1485	0.04136	74	3.59	0.0006	0.05	0.06611	0.2309	

Table B.14

The Results of ZIP Model for BU₁₉₉₉ for Open-forest, Agriculture/sparse Land, Water, and Built-up Land

The SAS System The NLMIXED Procedure						
	Specification					
	Data Set			WORK.BINK		
	Dependent Variable			bu_1999		
	Distribution for Dependent Variable			General		
	Optimization Technique			Dual Quasi-Newton		
	Integration Method			None		
	Dimension					
	Observations Used			74		
	Observations Not Used			0		
	Total Observations			74		
	Parameters			6		
Parameters						
b0	b1	b2	b3	b4	a0	NegLogLike
0	0	0	0	0	0	21088.9767
Iteration History						
Iter	Calls	NegLogLike		Diff	MaxGrad	Slope
1	9	9643.49728		11445.48	60169.76	-2.854E8
2	13	9554.26913		98.22815	54211.62	-2525431
3	18	9459.23088		95.03825	53529.26	-102128
4	20	9185.61791		273.613	47325.69	-45283
5	23	4747.21836		4438.4	35545.13	-235731
6	26	4537.15473		210.0636	15470.07	-914.031
7	28	4483.95323		53.2015	6579.765	-328.838
8	30	4454.20661		29.74662	5552.331	-32.2745

Table B.14

The Results of ZIP Model for BU₁₉₉₉ for Open-forest, Agriculture/sparse Land, Water, and Built-up Land (Continued)

Iter	Calls	NegLogLike	Diff		MaxGrad	Slope			
9	32	4437.34972	16.8569		636.2084	-15.7386			
10	34	4433.1824	4.16732		70.25724	-4.7622			
11	36	4432.88729	0.295107		32.97562	-0.4313			
12	38	4432.87939	0.007897		5.443563	-0.0137			
13	40	4432.87818	0.001211		11.63889	-0.00045			
14	41	4432.87698	0.001199		3.490932	-0.00105			
15	43	4432.87692	0.000062		0.315623	-0.00012			
16	45	4432.87692	8.787E-8		0.041411	-1.5E-7			
NOTE: GCONV convergence criterion satisfied.									
	Fit Statistics								
	-2 Log Likelihood				8865.8				
	AIC (smaller is better)				8877.8				
	AICC (smaller is better)				8879.0				
	BIC (smaller is better)				8891.6				
Analysis of Maximum Likelihood Parameter Estimates									
Para- meter	Estimate	Standard Error	DF	t Value	Pr > t	Al- pha	Lower	Upper	Gradient
b0	4.8343	0.03787	74	127.64	<.0001	0.05	4.7588	4.9098	0.000462
b1	-.001153	0.000965	74	-11.94	<.0001	0.05	-0.01345	-0.00960	0.041411
b2	0.001121	0.001027	74	1.09	0.2785	0.05	-0.00093	0.003168	0.000248
b3	-0.02760	0.003417	74	-8.08	<.0001	0.05	-0.03441	-0.02079	-0.00897
b4	-0.1306	0.01528	74	-8.55	<.0001	0.05	-0.1611	-0.1002	-0.0003
a0	-1.7452	0.3268	74	-5.34	<.0001	0.05	-2.3964	-1.0941	-0.00003
Additional Estimates									
Label		Estimate	Standard Error	DF	t Value	Pr > t	Al- pha	Lower	Upper
Inflation probability		0.1486	0.04135	74	3.59	0.0006	0.05	0.06625	0.2310

Table B.15

The Results of ZIP Model for BU₁₉₉₉ for Closed-forest, Open-forest, Water, and Built-up Land

The SAS System The NLMIXED Procedure		
	Specification	
	Data Set	WORK.BINK
	Dependent Variable	bu_1999
	Distribution for Dependent Variable	General
	Optimization Technique	Dual Quasi-Newton
	Integration Method	None

Table B.15

The Results of ZIP Model for BU₁₉₉₉ for Closed-forest, Open-forest, Water, and Built-up Land (Continued)

	Dimension								
Observations Used					74				
Observations Not Used					0				
Total Observations					74				
Parameters					6				
Parameters									
b0	b1	b2	b3	b4	a0	NegLogLike			
0	0	0	0	0	0	21088.9767			
Iteration History									
Iter	Calls	NegLogLike		Diff	MaxGrad	Slope			
1	7	7191.64447		13897.33	204700.9	-7.241E8			
2	12	6849.08426		342.5602	185184	-2.456E7			
3	17	6452.57405		396.5102	183192.8	-306434			
4	22	6318.52745		134.0466	169591.5	-12494.4			
5	23	5051.21488		1267.313	27785.55	-24356.9			
6	26	4401.23797		649.9769	11783.35	-2620.13			
7	28	4356.40642		44.83155	6284.883	-299.836			
8	30	4336.25511		20.1513	2552.452	-40.3038			
9	32	4332.12112		4.133991	865.783	-6.3554			
10	33	4329.28004		2.841078	3932.461	-4.53807			
11	34	4326.19802		3.082023	1000.964	-5.32887			
12	36	4325.75573		0.442288	267.3661	-0.5406			
13	38	4325.72622		0.029516	16.87096	-0.04911			
14	40	4325.72571		0.000508	6.062958	-0.00091			
15	42	4325.72569		0.000017	1.890612	-0.00002			
NOTE: GCONV convergence criterion satisfied.									
	Fit Statistics								
	-2 Log Likelihood				8651.5				
	AIC (smaller is better)				8663.5				
	AICC (smaller is better)				8664.7				
	BIC (smaller is better)				8677.3				
Analysis of Maximum Likelihood Parameter Estimates									
Para- meter	Estimate	Standard Error	DF	t Value	Pr > t	Al- pha	Lower	Upper	Gradient
b0	4.1634	0.06217	74	66.96	<.0001	0.05	4.0395	4.2873	0.04218
b1	0.009272	0.000655	74	14.16	<.0001	0.05	0.007967	0.01058	0.789507
b2	-0.00450	0.001118	74	-4.03	0.0001	0.05	-0.00673	-0.00228	1.890612
b3	-0.00479	0.003506	74	-1.37	0.1761	0.05	-0.01178	0.002197	0.189904
b4	-0.06761	0.01064	74	-6.36	<.0001	0.05	-0.08881	-0.04642	-0.07517
a0	-1.7453	0.3268	74	-5.34	<.0001	0.05	-2.3964	-1.0942	-0.00044
Additional Estimates									
Label		Estimate	Standard Error	DF	t Value	Pr > t	Al- pha	Lower	Upper
Inflation probability		0.1486	0.04135	74	3.59	0.0006	0.05	0.06624	0.2310

Table B.16

The Results of ZIP Model for BU₁₉₉₉ for Open-forest, Water, and Built-up Land

The SAS System The NLMIXED Procedure									
	Specification								
	Data Set				WORK.BINK				
	Dependent Variable				bu_1999				
	Distribution for Dependent Variable				General				
	Optimization Technique				Dual Quasi-Newton				
	Integration Method				None				
	Dimension								
	Observations Used				74				
	Observations Not Used				0				
	Total Observations				74				
	Parameters				5				
	Parameters								
b0	b1	b2	b3	a0	NegLogLike				
0	0	0	0	0	21088.9767				
Iteration History									
Iter	Calls	NegLogLike		Diff	MaxGrad	Slope			
1	9	10895.1997		10193.78	46624.91	-2.211E8			
2	13	10678.3739		216.8257	38955.07	-317916			
3	17	10407.103		271.271	38742.63	-65777.2			
4	20	4935.14303		5471.96	44340.44	-133761			
5	22	4521.89671		413.2463	6081.685	-3271.61			
6	24	4492.33225		29.56447	4120.629	-140.241			
7	25	4460.42202		31.91023	8562.901	-102.22			
8	27	4441.49601		18.926	928.5269	-40.9672			
9	29	4436.54596		4.950057	459.658	-3.78065			
10	31	4433.94512		2.600834	1402.148	-2.48205			
11	33	4433.60001		0.345115	273.402	-0.47044			
12	35	4433.51476		0.085253	347.9632	-0.0434			
13	37	4433.47005		0.044708	12.15068	-0.05032			
14	39	4433.46985		0.000193	0.524034	-0.00037			
15	41	4433.46985		3.822E-6	0.054421	-8.46E-6			
NOTE: GCONV convergence criterion satisfied.									
	Fit Statistics								
	-2 Log Likelihood				8866.9				
	AIC (smaller is better)				8876.9				
	AICC (smaller is better)				8877.8				
	BIC (smaller is better)				8888.5				
Analysis of Maximum Likelihood Parameter Estimates									
Para- meter	Estimate	Standard Error	DF	t Value	Pr > t	Al- pha	Lower	Upper	Gradient
b0	4.8465	0.03600	74	134.62	<.0001	0.05	4.7748	4.9183	0.005823
b1	-0.01145	0.000961	74	-11.91	<.0001	0.05	-0.01337	-0.00954	-0.03388
b2	-0.02685	0.003337	74	-8.05	<.0001	0.05	-0.03350	-0.02020	0.054421

Table B.16

The Results of ZIP Model for BU₁₉₉₉ for Open-forest, Water, and Built-up Land

(Continued)

Parameter	Estimate	Standard Error	DF	t Value	Pr > t	Alpha	Lower	Upper	Gradient
b3	-0.1254	0.01413	74	-8.87	<.0001	0.05	-0.1536	-0.09726	0.014197
a0	-1.7452	0.3268	74	-5.34	<.0001	0.05	-2.3963	-1.0941	0.000273
Additional Estimates									
Label	Estimate	Standard Error	DF	t Value	Pr > t	Alpha	Lower	Upper	
Inflation probability	0.1487	0.04135	74	3.59	0.0006	0.05	0.06625	0.2311	

Table B.17

The Results of Poisson Regression Model for BU_{2000s} for All Predictor Variables

The SAS System The GENMOD Procedure							
	Model Information						
	Data Set		WORK.BINK				
	Distribution		Poisson				
	Link Function		Log				
	Dependent Variable		bu_05to08				
Number of Observations Read					74		
Number of Observations Used					74		
Criteria For Assessing Goodness Of Fit							
Criterion		DF	Value		Value/DF		
Deviance		67	2403.0915		35.8670		
Scaled Deviance		67	2403.0915		35.8670		
Pearson Chi-Square		67	4025.8710		60.0876		
Scaled Pearson X2		67	4025.8710		60.0876		
Log Likelihood			1704.4200				
Full Log Likelihood			-1276.4633				
AIC (smaller is better)			2566.9267				
AICC (smaller is better)			2568.6236				
BIC (smaller is better)			2583.0551				
Algorithm converged.							
Analysis of Maximum Likelihood Parameter Estimates							
Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	Pr > ChiSq
Intercept	1	-1.0861	1.9641	-4.9357	2.7635	0.31	0.5803
L7_PerCFor	1	0.0343	0.0197	-0.0044	0.0729	3.02	0.0821
L7_PerOFor	1	0.0565	0.0196	0.0181	0.0949	8.31	0.0039
L7_PerGrs	1	-0.0152	0.0218	-0.0580	0.0275	0.49	0.4855
L7_PerH2O	1	-0.0214	0.0255	-0.0714	0.0287	0.70	0.4024
L7_PerSoil	1	0.0332	0.0200	-0.0061	0.0724	2.74	0.0981

Table B.17

The Results of Poisson Regression Model for BU_{2000s} for All Predictor Variables

(Continued)

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	Pr > ChiSq
L7_PerBuil	1	0.0357	0.0224	-0.0082	0.0795	2.54	0.1112
Scale	0	1.0000	0.0000	1.0000	1.0000		
NOTE: The scale parameter was held fixed.							
LR Statistics For Type 3 Analysis							
Source	DF	Chi-Square	Pr > ChiSq				
L7_PerCFor	1	3.34	0.0677				
L7_PerOFor	1	9.95	0.0016				
L7_PerGrs	1	0.47	0.4909				
L7_PerH2O	1	0.69	0.4066				
L7_PerSoil	1	3.02	0.0822				
L7_PerBuil	1	2.63	0.1046				

Table B.18

The Results of ZIP Model for BU_{2000s} for All Predictor Variables

The SAS System The NLMIXED Procedure								
	Specification							
	Data Set					WORK.BINK		
	Dependent Variable					bu_05to08		
	Distribution for Dependent Variable					General		
	Optimization Technique					Dual Quasi-Newton		
	Integration Method					None		
	Dimension							
	Observations Used					74		
	Observations Not Used					0		
	Total Observations					74		
	Parameters					8		
Parameters								
b0	b1	b2	b3	b4	b5	b6	a0	NegLogLike
0	0	0	0	0	0	0	0	3057.58552
Iteration History								
Iter	Calls	NegLogLike		Diff		MaxGrad	Slope	
1	5	1042.55191		2015.034		7095.835	-2.708E7	
2	10	897.820121		144.7318		6948.815	-1140195	
3	14	888.685937		9.134183		5848.122	-101373	

Table B.18

The Results of ZIP Model for BU_{2000s} for All Predictor Variables (Continued)

Iter	Calls	NegLogLike	Diff		MaxGrad	Slope				
4	18	878.474813	10.21112		5860.281	-4839.1				
5	21	877.60804	0.866773		5852.422	-369.859				
6	23	877.374403	0.233637		5835.658	-191.517				
7	25	866.844715	10.52969		2206.473	-70.0917				
8	27	863.860003	2.984712		237.2805	-10.2122				
9	29	863.632278	0.227725		57.89012	-0.35498				
10	31	862.950497	0.68178		657.9407	-0.12346				
11	34	837.471553	25.47894		3853.024	-1.21893				
12	35	809.462743	28.00881		752.8998	-34.4857				
13	37	806.131791	3.330952		235.9439	-6.32603				
14	39	805.560272	0.571518		151.9353	-0.75238				
15	41	805.450006	0.110266		95.28833	-0.15247				
16	43	805.399447	0.050559		53.21843	-0.04553				
17	45	805.384179	0.014269		22.98354	-0.01511				
18	47	805.384135	0.001044		1.849932	-0.00167				
19	49	805.384116	0.000019		0.766595	-0.00003				
20	51	805.384116	3.888E-7		0.110842	-7.17E-7				
NOTE: GCONV convergence criterion satisfied.										
	Fit Statistics									
	-2 Log Likelihood					1610.8				
	AIC (smaller is better)					1626.8				
	AICC (smaller is better)					1629.0				
	BIC (smaller is better)					1645.2				
Analysis of Maximum Likelihood Parameter Estimates										
Para- meter	Estimate	Standard Error	DF	t Value	Pr > t	Al- pha	Lower	Upper	Gradient	
b0	38.1316	3.4282	74	11.12	<.0001	0.05	31.3007	44.9624	0.003132	
b1	-0.3538	0.03426	74	-10.33	<.0001	0.05	-0.4221	-0.2856	0.102895	
b2	-0.3437	0.03491	74	-9.85	<.0001	0.05	-0.4133	-0.2742	0.110842	
b3	-0.3572	0.03394	74	-10.53	<.0001	0.05	-0.4248	-0.2896	0.023555	
b4	-0.4397	0.03987	74	-11.03	<.0001	0.05	-0.5191	-0.3603	0.001848	
b5	-0.3577	0.03550	74	-10.08	<.0001	0.05	-0.4284	-0.2870	0.070172	
b6	-0.3510	0.03481	74	-10.08	<.0001	0.05	-0.4203	-0.2816	0.001391	
a0	-1.63E-7	0.2325	74	-0.00	1.0000	0.05	-0.4633	0.4633	0.000016	
Additional Estimates										
Label		Estimate	Standard Error	DF	t Value	Pr > t	Al- pha	Lower	Upper	
Inflation probability		0.50000	0.05812	74	8.60	<.0001	0.05	0.3842	0.6158	

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