

Examination of Urban Expansion and
its Environmental Impacts using
Remotely Sensed Time-Series
Imagery in Ulaanbaatar, Mongolia

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Examination of Urban Expansion and its Environmental Impacts using Remotely Sensed Time-Series Imagery in Ulaanbaatar, Mongolia

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Abstract

Urban areas are expanding rapidly because of the inability of existing urban infrastructure to sustain the population and its activities. Ulaanbaatar is one of cities in developing countries in terms of its swift development, and this has occurred particularly since its transition from a planned economy to a free-market economy in 1992. However, the insufficient authority of the current master plan and the lack of implementation of the land privatization policy since 2003 have resulted in a failure to effectively manage land use. Consequently, large numbers of residential plots have been developed in peripheral regions of the city. This research aims to clarify the urban expansion processes and understand their environmental impacts in Ulaanbaatar. Remotely sensed imagery has recently become a standard tool for the analysis of urban expansion processes, but analysis conducted using only a specific type of remotely sensed imagery can lead to a misunderstanding of such processes. Therefore, the use of multi-scale analyses using remotely sensed imagery with different spatial and temporal resolutions should be explored. In this research, very high spatial resolution satellite imagery from IKONOS and Quickbird, and medium-resolution satellite imagery from the MODerate resolution Imaging Spectroradiometer (MODIS) were mainly used. Analysis using object-based spatial data of urban components extracted from very high spatial resolution satellite imagery in a time series was used to delineate the residential-scale process of urban expansion in a fringe area. This, in combination with a spatial modeling approach, indicates

that urban infrastructure significantly contributed to the urban expansion. To understand the urban expansion processes in a wider range of the city, the pixel-based analysis was applied using MODIS time series with a more spatially rough, but high frequency resolution. The breaks for additive seasonal and trend (BFAST) method, which is able to robustly and automatically derive the timing and locations of land cover changes from spatio-temporal data, was applied for the first time in urban expansion analysis. This analysis showed that land cover changes occurred at the edge of the city center region in Ulaanbaatar in earlier time, and that the changes tended to occur at a later time with increasing distance from the city center during the period 2000–2010. Owing to the population concentration, which is the primary cause of urban expansion in Ulaanbaatar, vegetation biomass and vegetation land cover around the city have been highly affected by anthropogenic pressures. Thus, environmental changes to vegetated surfaces were estimated as a proxy of the environmental impacts of urban expansion. This analysis found that vegetation biomass decreased around the urban area in grassland and forests where anthropogenic activities such as overgrazing and illegal logging were reported. This research highlights the effects of the clash between two different land management legislation frameworks, the master plan and the land privatization policy. This research not only reinforces the need for an effective urban plan for Ulaanbaatar, but also provides operational information such as maps and GIS layers for planning purposes, which document the actual extent of the urban surfaces, the patterns of development, and the location of expanded and degraded areas of urban expansion using remote sensing technologies.

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CHAPTER 1 INTRODUCTION

1-1 BACKGROUND

Rapid urbanization is an urgent issue that needs to be addressed, monitored, and controlled. The global population is forecasted to rise from 7 billion in 2011 to more than 8 billion by 2030, with 60% of this population concentrated in urban areas (United Nations, 2012). On average, urban areas in developing countries are expanding at a rate that is twice as fast as the rate of population growth (Angel, Parent, & Civco, 2012). These areas are economic, social, cultural, and political centers that serve as the hub of regional development (Seto, Roberto, & Fragkias, 2010). However, substantial urban development comes at a price, with haphazard expansion affecting environmental sustainability in and around urban areas. Such a phenomenon drives land cover changes, which potentially result in environmental degradation such as the loss of farmland (Döös, 2002; Habibi & Asadi, 2011), natural resources (DeFries, Rudel, Uriarte, & Hansen, 2010; Hasse & Lathrop, 2003), and biodiversity (McDonald, Kareiva, & Forman, 2008; Rojas, Pino, Basnou, & Vivanco, 2013). From the perspective of human habitation, one of the most crucial problems faced by developing countries is the rapid growth of informal settlements in peripheral regions (Augustijn-Beckers, Flacke, & Retsios, 2011; Dubovyk, Sliuzas, & Flacke, 2011). Such informal settlements develop without planning controls, and the basic infrastructure required for living is significantly

lacking (Augustijn-Beckers et al., 2011). Accordingly, an understanding of urban expansion processes and their environmental impacts is essential to enable urban planners and policy makers to realize well-balanced urban growth for citizens and environments.

As with other capital cities in developing countries, Ulaanbaatar, the capital of Mongolia, has rapidly expanded in parallel with an increase in its population, causing critical developmental issues (Kamata, Reichert, Tsevegmid, Kim, & Sedgewick, 2010). Mongolia experienced a drastic transition from a central planning system to a market-based economy in the 1990s. Following a change in policy that previously restricted internal migration, many Mongolians moved from rural areas to Ulaanbaatar seeking education, employment, an income, and an improved standard of living (Byambadorj, Amati, & Ruming, 2011; Solongo, 2007). In accordance with this population concentration, many residential plots have developed rapidly in the peripheral regions, where 60% of the population of Ulaanbaatar now lives (Kamata et al., 2010).

The unprecedented development of residential plots in the fringe areas of Ulaanbaatar has a negative impact on the natural environment and on living conditions (UN-Habitat, 2010). The main problem in peripheral areas is the deficit of basic infrastructure, such as the lack of a piped water system, sanitation facilities, paved roads, public transportation, and heating systems (Kamata et al., 2010). It is therefore considered important to

address topics of social and spatial inequality, water supply and sanitation, waste management, flood risk reduction, and air pollution within these areas.

Remotely sensed imagery from space-borne sensors has become a standard tool in the implementation of analysis of urban expansion processes. When using such imagery, it is important to consider spatial resolution (the size of the area on the ground that comprises the image derived from satellite sensors) (Myint, Gober, Brazel, Grossman-Clarke, & Weng, 2011), which is a fundamental characteristic of remotely sensed imagery (Woodcock & Strahler, 1987). However, investigators are limited to specific scales of observation (Woodcock & Strahler, 1987). For example, medium-resolution satellite imagery from the MODerate resolution Imaging Spectroradiometer (MODIS) satellite, monitors a wide range of surfaces that include urban areas, but such imagery cannot fully capture individual urban objects due to insufficient spatial resolution. On the contrary, Very High spatial Resolution (VHR) satellite imagery taken by such as IKONOS and Quickbird satellites, visually capture urban land cover in detail, but such imagery is subject to a limited spatial extent of observation. It is also necessary to consider the frequency of observation; while medium-resolution satellites can observe at a certain time interval, regular monitoring using VHR imagery is always limited. Thus, analysis using only one specific type of remotely sensed imagery can deliver a misleading interpretation of the process of urban expansion. It is considered necessary to explore the use of

undertaking multi-scale analysis using remotely sensed imagery at different spatial and temporal scales.

1-2 RESEARCH OBJECTIVES

The main objective of this research is to clarify the process of urban expansion and its environmental impacts in Ulaanbaatar. In handling urban expansion, the government should consider when and where urban expansion occurs, obtain knowledge of the factors causing such expansion, and understand the extent of the associated environmental impacts. Such knowledge would be useful for urban planners and policy makers in their management of urban expansion and related environmental issues. In order to gain an understanding of this on different scales, urban expansion processes are analyzed on a residential-scale level and a city-scale level. These are implemented using VHR and medium spatial resolution satellite imagery, respectively. The analysis of environmental impacts is examined on a municipality-scale level, and also uses medium spatial resolution satellite imagery. In particular, the aims of this study are to:

1. Delineate time-series changes on urban surfaces on a residential-scale level, and to determine their driving forces;
2. Explore the spatio-temporal changes in land cover on a city-scale level;

3. Estimate environmental changes on vegetated surfaces as a proxy of environmental impacts caused by population concentration and urban expansion in the municipality of Ulaanbaatar.

1-3 RESEARCH OUTLINE

Chapter 2 presents the conceptual background related to urban expansion and the use of satellite sensors for monitoring of it. Chapter 3 gives an overview of the study area within the Municipality of Ulaanbaatar. It also explains the data acquisition used in the analysis of urban expansion and its environmental impacts. Chapter 4 depicts the urban expansion from time-series object-based GIS data, and detects the driving factors using a spatial model. Chapter 5 estimates the land cover changes from MODIS time-series in order to monitor the urban expansion processes. Chapter 6 presents an estimation of the environmental changes on vegetated surfaces as a proxy of the environmental impacts, with focus on the change in vegetation biomass and vegetation cover in Ulaanbaatar. Chapter 7 concludes these findings and offers recommendations for a future urban plan.

CHAPTER 2 MONITORING URBAN EXPANSION PROCESSES

2-1 URBAN EXPANSION

Urban expansion is defined as the increase in developed and residential areas within urban and suburban areas (Zhan, Jiang, & Townshend, 2000), and often occurs on urban fringes around developed city centers (Frenkel & Ashkenazi, 2008; Sudhira, Ramachandra, & Jagadish, 2004). Although the land cover of urban areas in the form of built-up or paved-over areas occupies less than 2% of the earth's land surface (Lambin et al., 2001), urban areas are expanding due to the inability of existing urban infrastructure to sustain the population and its activities. (Seto, Fragkias, & Gu, 2011). When urban areas expand, natural land cover such as grasslands, forests, and agricultural land cover are transformed into residential, industrial, and commercial land (Ji, Ma, Twibell, & Underhill, 2006). Such anthropogenic changes affect not only hydrological systems, the biogeochemistry, local climate, and biodiversity, but also human living environments (Seto et al., 2011). Because of rapid emergence of unplanned and uncontrolled development at urban fringes, there is often a lack of basic infrastructure such as sewerage, electricity, garbage disposal, roads, and shops; this lack of infrastructure can inflate the cost of urban management (Frenkel & Ashkenazi, 2008; Hasse & Lathrop, 2003).

In managing the rapid urban expansion of cities in developing countries, future development needs to be planned and properly monitored in order to maintain internal equilibrium through the sustainable management of natural resources (Tv, Aithal, & Sanna, 2012). Appropriate strategies for managing urban expansion must be identified and effectively employed (Angel, Parent, Civco, Blei, & Potere, 2011). It is therefore clear that an analysis of urban expansion would assist regional planners and decision-makers in understanding growth patterns, thereby allowing plans to be made include the provision of essential infrastructure (Verbesselt, Hyndman, Newnham, & Culvenor, 2010).

2-2 CURRENT ISSUES IN RESEARCH IN RELATION TO URBAN EXPANSION

Past studies of urban expansion have often been implemented at a city or metropolitan scale level (J. Cheng & Masser, 2003; Fang, Gertner, Sun, & Anderson, 2005; Gimblett, Daniel, Cherry, & Meitner, 2001; Irwin & Bockstael, 2004; Ji et al., 2006; Martinuzzi, Gould, & Gonzalez, 2007; Sudhira et al., 2004; Weber & Puissant, 2003). Through these studies, many techniques using spatial grids have been developed to detect and analyze land cover change by urban expansion and to then apply these techniques to different regions. The most popular techniques are: post-classification comparison, principal component analysis (PCA), and wavelet decomposition (Alphan, 2003; Deng, Wang, Deng, & Qi, 2008; Galford et al.,

2008; Jat, Garg, Khare, & Jat, 2008; Kleynhans et al., 2011; Lasaponara, 2006; Lu, Mausel, Brondízio, & Moran, 2003; Lunetta, Knight, Ediriwickrema, Lyon, & Worthy, 2006; Millward, Piwowar, & Howarth, 2006; Running et al., 1995; Verbesselt, Hyndman, Newnham, et al., 2010; Weber & Puissant, 2003; X. J. Yu & Ng, 2007). The post-classification comparison technique is used to compare images in which the land use/cover has been classified over different time periods using high spatial resolution satellite imagery such as that of Landsat and SPOT. This method has been widely used (Alphan, 2003; Jat et al., 2008; Weber & Puissant, 2003; X. J. Yu & Ng, 2007); however, a certain amount of pre-processing of these images is necessary due to differences between observing sensors, serious effects of atmospheric disturbances, missing data due to clouds and shadows, and correction of inaccurately observed time spans (Patino & Duque, 2013). PCA is a simple and effective technique for enhancing information in relation to land cover change, but it usually neglects seasonal variation by intentionally summarizing time series data (e.g. yearly composite imagery), resulting in the loss of temporal change information (Deng et al., 2008; Lasaponara, 2006; Lu et al., 2003; Millward et al., 2006). In comparison, wavelet decomposition, normally using vegetation indices like the normalized difference vegetation index (NDVI), which is the most commonly used measure of vegetation, is a useful basis for the development of a land cover change analysis (Galford et al., 2008; Kleynhans et al., 2011; Lunetta et al., 2006). NDVI reflects changes in chlorophyll content and vegetation biomass, and has proved to be a useful tool in the monitoring of vegetation resources

(Bajgiran, Shimizu, Hosoi, & Omasa, 2009; Hirano, Komiyama, & Toriyama, 2006), using the calculation:

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}} \quad (2-1)$$

where ρ_{RED} and ρ_{NIR} are the reflectance for the red band (620–670 nm) and the near-infrared band (841–876 nm), respectively. However, until recently, one of the main problems associated with the application of wavelet decomposition was that it required the determination of several thresholds (Galford et al., 2008; Kleynhans et al., 2011; Lunetta et al., 2006), and it often led to misleading outputs, caused by the different spectral and phenological characteristics of differing land cover types (Verbesselt, Hyndman, Newnham, et al., 2010).

Although these above approaches explore pixel-based land cover changes on urban surfaces, urban expansion is ultimately a spatial phenomenon driven by accumulated human activities influenced by complex forces (e.g. social, economic, political, and physical ones), their interactions, and associated processes (Hu & Lo, 2007; Irwin, Bell, & Geoghegan, 2003; Irwin & Bockstael, 2004). Due to the inability to integrate information related to these things, it is usually difficult to utilize object-based GIS data which represent human activities on urban surface in the analysis. Although national and local governments may possess optimal databases for official

land management systems, which contain detailed land information (such as land boundaries and ownership), administrative offices in developing countries are often not allowed to share such data with the public because of a lack of law allowing the publication of official data. In most cases, government-owned data such as cadastral maps are considered to be secret sources because of the associated security and privacy. In addition, some governments may not be able to afford an up-to-date database for land management information, and such limited governmental funds are also an obstacle to allowing government-owned data to be made public. Consequently, owing to a lack of spatial data available for urban objects, this contributes to the difficulty in understanding urban expansion directly and precisely.

2-3 THE USE OF SATELLITE SENSORS FOR MONITORING URBAN EXPANSION PROCESSES

Since the advent of the Landsat Multispectral Scanner System (MSS) in 1972, remotely sensed imagery has become an effective tool for characterizing urban landscapes (Novak & Wang, 2004). However, it remained difficult to monitor and comprehend individual urban components on a residential scale for many years because of the low resolution of remote sensing sensors (e.g., 80 m and 30 m for the Landsat MSS and Landsat-7 Enhanced Thematic Mapper Plus (ETM+), respectively). Today, owing to the

development of VHR satellite sensors, these sensors enable determination of urban components individually (Taubenbock, Esch, Wurm, Roth, & Dech, 2010). For example, IKONOS (launched in 1999) and Quickbird (launched in 2011) have spatial resolutions of 3.3 m and 2.4 m, respectively, and thus both of these satellites can observe buildings, houses, and roads in detail (J. Cheng & Masser, 2003; Digital Globe, 2007; Tatem & Hay, 2004; Volpe & Rossi, 2003). The development of fine-scale digital elevation model (DEM) data has also been a relatively recent occurrence. The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global DEM (GDEM), released to the public in 2009, is a DEM dataset with a resolution of approximately 26 m, in which cloudy pixels have been removed and residual anomalies corrected (ASTER GDEM Validation Team, 2009).

Despite the lack of fine spatial resolution, the MODIS time series is an alternative tool for monitoring urban expansion because it has the advantage of being able to make frequent observations at regular intervals at no cost. The MODIS applications are of interest not only to researchers in the land, ocean, and atmosphere disciplines but also for application by interdisciplinary, and environmental scientists, because MODIS senses the Earth's entire surface in 36 spectral bands spanning the visible (0.415 μm) to infrared (14.235 μm) spectrum at nadir spatial resolutions of 1 km, 500 m, and 250 m (Qu & Kafatos, 2006). This is one of five instruments carried on board the Terra and Aqua satellites launched in December 1999 and May 2002, respectively (Justice et al., 2002; Qu & Kafatos, 2006). The MODIS

science team has made significant progress in characterizing the performance of the MODIS instrument, and have developed MODIS instrument data (Level 1B) and high-order geophysical products (Levels 2, 3 and 4) (Justice et al., 2002). For example, MODIS data product MOD09A1 is constructed by calibrating reflectance for seven spectral bands within the 400 nm to 2500 nm spectral region, and surface reflectance quality control flags at a resolution of 500 m pixels. Each MOD09A1 pixel contains the best possible observation during an 8-day period, selected on the basis of high observation coverage, low viewing angle, the absence of clouds or cloud shadow, and low aerosol loading (Vermote, Kotchenova, & Ray, 2011). Recently, MODIS time series have been applied to several pieces of urban expansion research in the analysis and implementation of land cover detection (Buyantuyev & Wu, 2009; Buyantuyev & Wu, 2012; Lunetta et al., 2006).

CHAPTER 3 STUDY AREA AND DATA ACQUISITION

3-1 STUDY AREA

The study area comprises the main part of the Municipality of Ulaanbaatar; approximately 4000 km² in which the urbanized area is located in the central region between mountains (Figure 1). The Municipality of Ulaanbaatar consists of nine administrative districts, which are sub-divided into 124 sub-districts, called “*khoroos*”. Two districts, Baganuur and Bagakhangai are excluded from the study area because of their remote and disparate locations. There are two national parks in the study area. One is the Gorkhi-terelj national park, located in the eastern part of the study area, which is a famous natural sightseeing spot with a beautiful landscape in close proximity to Ulaanbaatar. Although in principle a variety of environmental regulations and land use restrictions apply to this region, in reality humans heavily utilize large parts of the area, and increasingly it is put under the pressure of heavy grazing by livestock and tourist developments (The World Bank, 2009a). Another is the Bogd-khan national park, located to the south of the urban area, which is a protected holy foothill that was declared a nature reserve in 1778.

In Ulaanbaatar, the average elevation, temperature, and annual precipitation are 1,573 m, -0.83 °C and 238.53 mm, respectively (Figure 2). The study area contains ten different types of land cover (Figure 3, Table 1) (Saandar & Sugita, 2004). The principal land covers are *mountain meadow*

steppe, *mountain forest*, and *urban*, which together make up 71% of the study area. Forested areas, mainly composed of larches, birches, and shrubs, are found in *mountain taiga*, *mountain forest*, and *mountain meadow steppe*. Grasslands are distributed across the entire study area except *cropland*, *mountain taiga*, and a part of *urban*, which are all affected by livestock grazing.

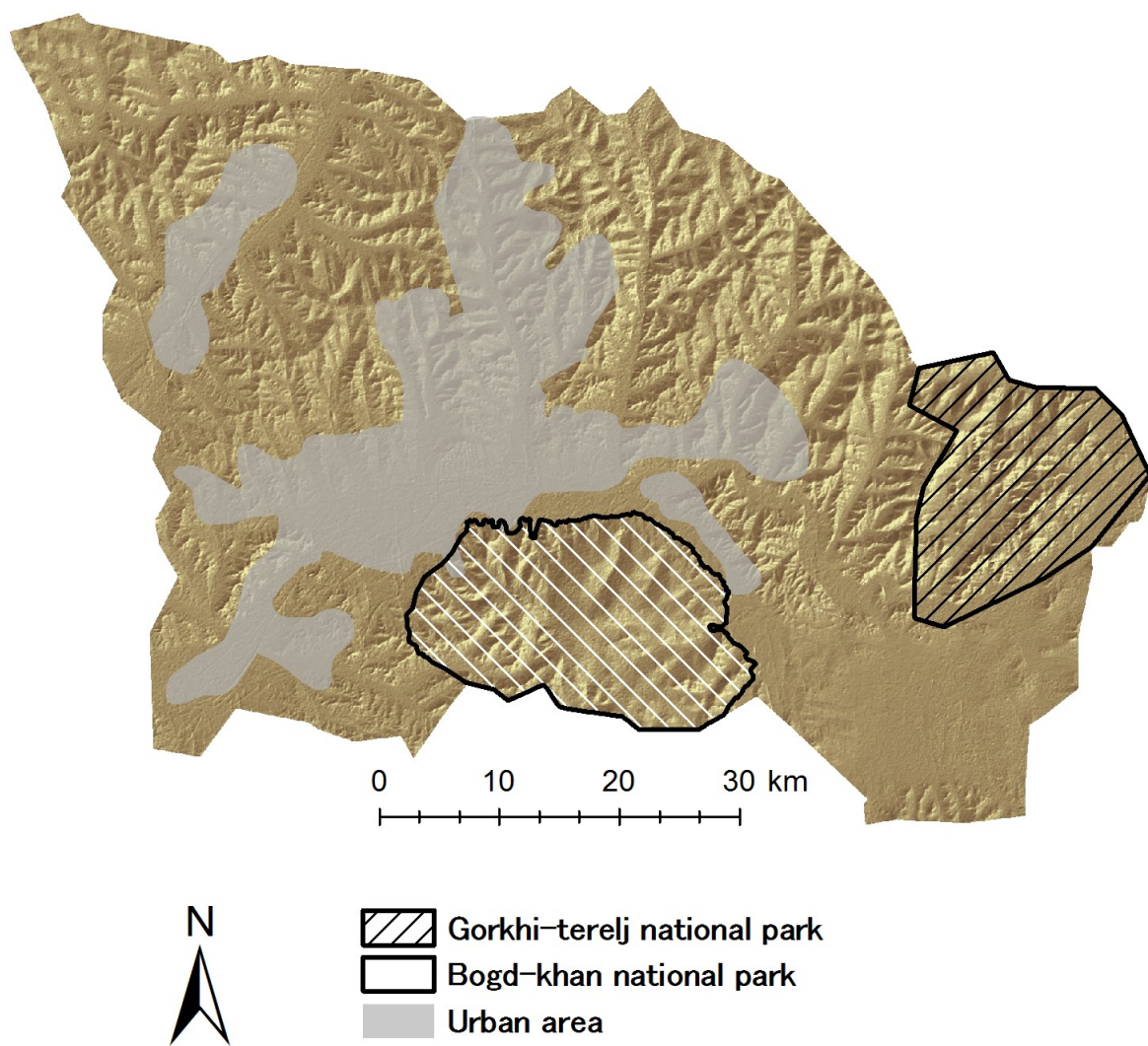


Figure 1. Study area.

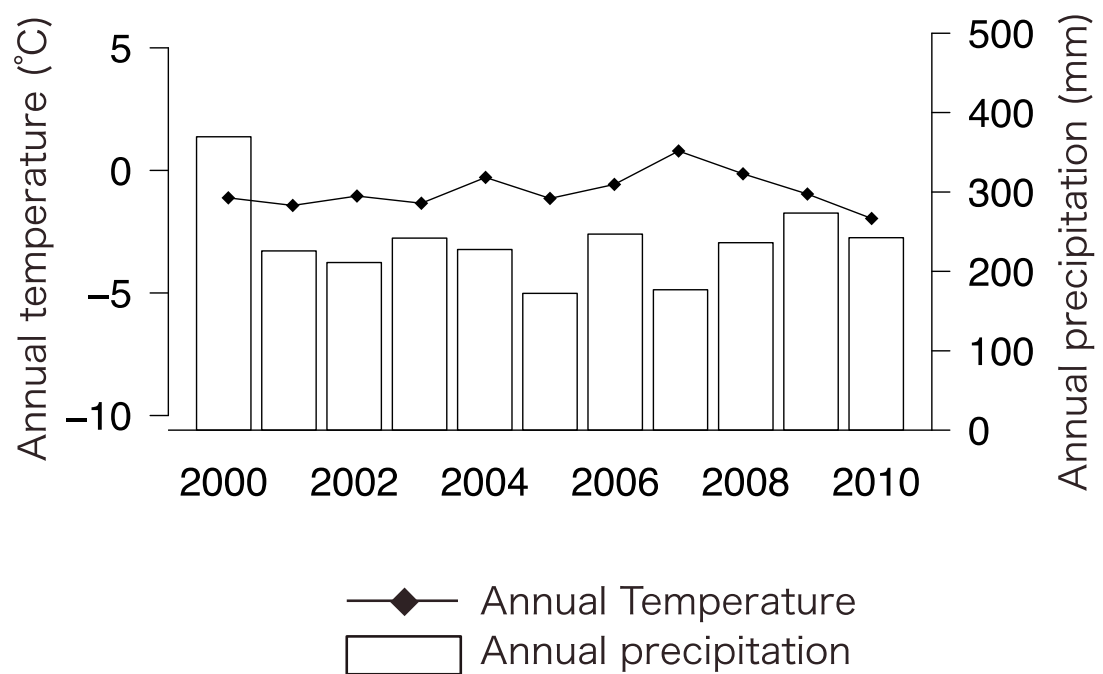


Figure 2. Annual temperature and precipitation in study area.

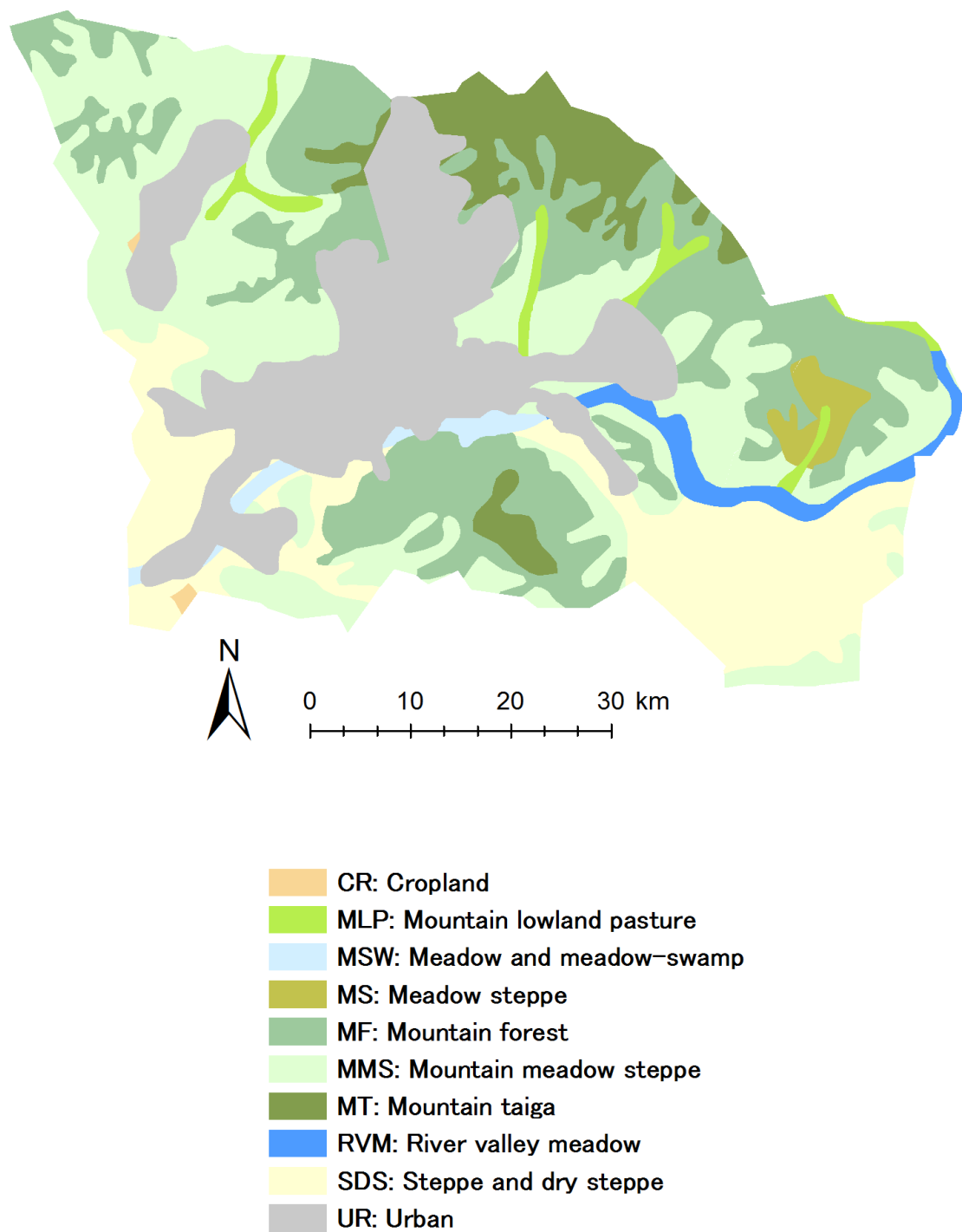


Figure 3. Land cover types in study area.
(Source: Saanda and Sugita, 2004)

Table 1. Land cover types and percentage of each area in the study area.

(Source: Saanda and Sugita, 2004)

Code	Land cover	Description	Percentage of the area (%)
CR	Cropland	Cropland	0.3
MLP	Mountain lowland pasture	Sedge-rush-bent, bent-herb with participation of willow's grove	1.9
MSW	Meadow and meadow-swamp	Complex marsh: Lymegrass-sedge, grass-herb, achnatherum's grove with Russian thistle-herb	2.3
MS	Meadow steppe	Stony needlegrass-wormwood-herb	1.3
MF	Mountain forest	Herb-grass, needlegrass-herb, fescue-herb, stand on larch and larch-birch forest	23.0
MMS	Mountain meadow steppe	Needlegrass-herb, blue grass-sedge-herb, little soddygrass-herb needlegrass-sedge-herb, fescue-herb in herbaceous larch-birch forest	25.8
MT	Mountain taiga	Mountain taiga forest	6.4
RVM	River valley meadow	Herb-grass in combination with grove of willow and marshy sedge-bent-herb	2.1
SDS	Steppe and dry steppe	Needlegrass-little soddygrass-lymegrass	14.7
UR	Urban	Khoroo areas	22.2
Total			100.0

The urban area is divided into three main areas: the city center area; ger areas; and others (Figure 4) (The World Bank, 2009b). The center of the city is located around Sukhbaatar Square, in front of the governmental palace, and has been extensively developed with high-rise offices and apartment buildings. Ger areas have developed mainly in suburban areas, and over recent years have rapidly expanded (Figure 5). Migrants typically relocate to the city by disassembling its *ger* (traditional Mongolian dwellings designed for a nomadic lifestyle, built easily from wood, and covered with felt), loading it and its contents on a truck, and reassembling it in Ulaanbaatar (Figure 6) (Badarch, Batsukh, & Batmunkh, 2003). They claim open land, build *khashaas* – wooden fences – at the property boundary, and finally build a *ger* or a detached house on the enclosed land (Kamata et al., 2010). Today, migrants from rural areas continue to arrive in the city to claim their own land and build *gers* and *khashaas* (Figure 7). Ger areas are also found in the northern part of the study area, where developments mainly comprise summer camps, known as “*zulsans*”. These areas originally contained summer houses and second homes for city residents, but the area is now being exploited by new residents, and a large number of settlement clusters have now been established (Badamdorj, 2004). Although residential plots are found both in the city center and ger areas, those in the city center have experienced a gradual conversion to apartment blocks (Figure 8) (Kamata et al., 2010). Other areas of note within the study area include: parts of the forest, the riverside, grasslands, and industrial areas such as electronic plants, factories, and the airport. The Tuul River, one of the largest rivers in

Mongolia, runs to the south of the study area, and divides Ulaanbaatar north and south.

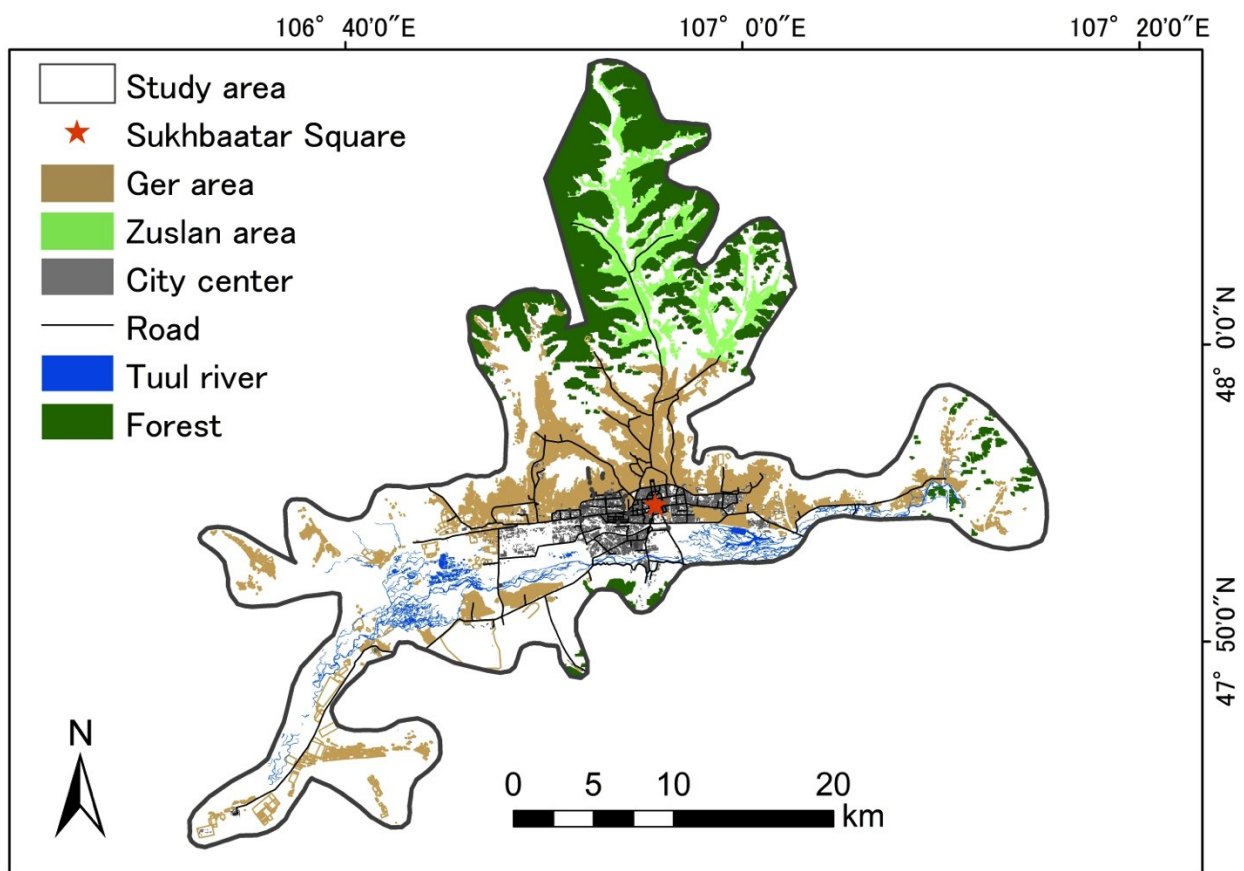


Figure 4. Land cover in urban areas.

Two khoros in the Songinokhanirkhan district and the Bayansurkh district are excluded because of their remote and disparate locations.



Figure 5. Typical landscape in ger areas.



Figure 6. *Ger* in the city center.



Figure 7. Residential plots in a fringe area of Ulaanbaatar.



Figure 8. Apartment construction in the city center.

Although Mongolia has abundant natural land resources, its population has been increasingly concentrated in the Municipality of Ulaanbaatar since the dramatic transition from a planned economy to a free-market economy in 1992, leading to a severely unbalanced population distribution in the country. In 2011, Ulaanbaatar contained 44% of the Mongolian population with an annual rate of increase of 4.6%, mainly because of internal migrations from rural areas (The data was obtained from National Statistical Office, Mongolia.) (Figure 9). During the period 2001–2004, the number of in-migrants to Ulaanbaatar increased rapidly because of a revision of land policy implemented in 2003 (see below). During 2010–2011, the number of in-migrants living in Ulaanbaatar increased a little because of a natural disaster, called a “*dzud*,” affecting the whole of Mongolia. A *dzud* is a combination of a summer drought followed by heavy winter snows and low temperatures, during which livestock die of starvation due to an inability to find grass and fodder (UNFPA Mongolia, 2010). Following the loss of their livestock, many herders abandoned their homeland and migrated to Ulaanbaatar, lured by the opportunity of finding a job.

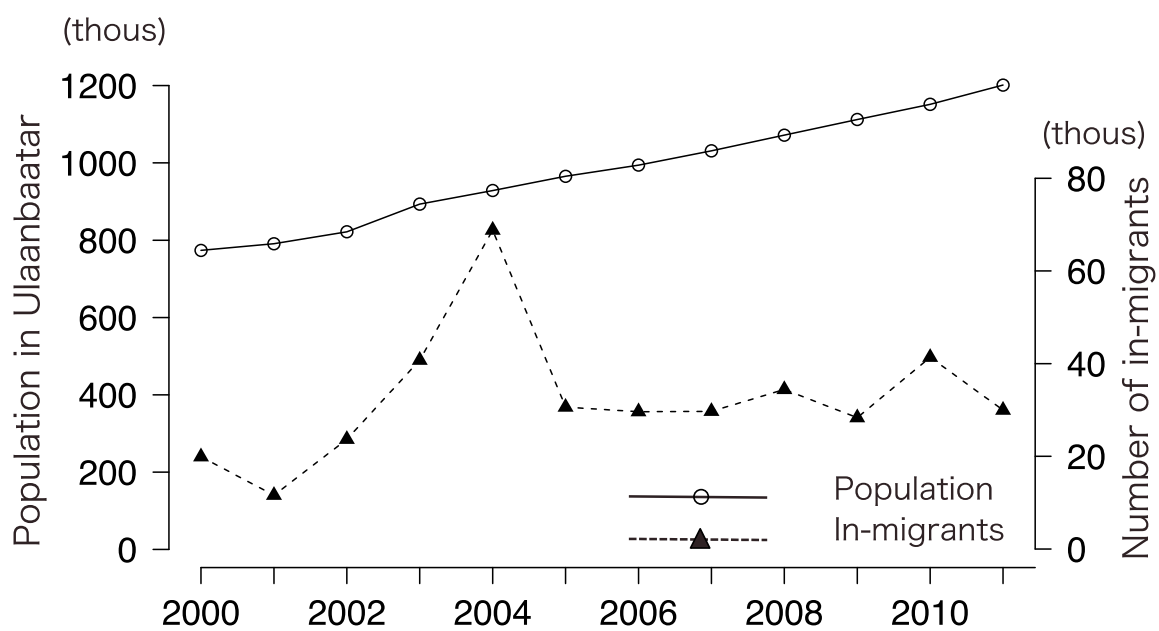


Figure 9. The population and in-migrants to Ulaanbaatar during the period 2000–2011.

(The data was obtained from National Statistical Office, Mongolia.)

The Mongolian government has implemented land law reforms in the form of the “Law on Allocation of Land to Mongolian Citizens for Ownership” in 2003 to accelerate the development of a free market economy (Bruun & Odgaard, 1996; Byambadorj et al., 2011; K. C. Cheng, 2003; Kamata et al., 2010). This law has allowed Mongolians to own land for the first time in Mongolia’s history (Asian Development Bank, 2003; Batbileg, 2007; Kamata et al., 2010). The new land tenure system introduced Mongolians to a combination of three land rights: “ownership,” for Mongolian citizens only; “possession rights” for up to 60 years, with possible extension, available to Mongolian citizens and joint ventures; and “land use rights,” valid for up to five years with possible extension, for which foreigners are also eligible (Kamata et al., 2010).

Land ownership is tied to the land fee system, which the government introduced in 1997 under the “Law of Mongolia on Land Fees” (Kamata et al., 2010). However, the “Law on Allocation of Land to Mongolian Citizens for Ownership” stipulates that each household is entitled to own up to 700 m² in Ulaanbaatar; up to 3,500 m² in aimags (administrative units at prefectural level); or up to 5,000 m² in soums (administrative units at county level). The associated land fee was set low: about 90% of the land fee up to 700 m² was originally exempt in Ulaanbaatar (Kamata et al., 2010). After some minor revisions, the land reform policy eventually came to stipulate that each citizen of Mongolia is allowed to privatize and possess one plot of land at no cost until 2018.

In general, a proper urban plan based on up-to-date and reliable spatial information is essential when dealing with urban expansion (Novack & Kux, 2010). Four urban plans formulated at a Russian urban planning institute were enforced between 1954 and 1986, while the current urban plan for Ulaanbaatar was developed by Mongolians in 2002; this was the first time that Mongolians had developed their own plan for Ulaanbaatar. However, the current urban plan has not helped control urban expansion owing to the lack of regulation and the loose association between the plan and land reform policy (Byambadorj et al., 2011).

The main reason for the unrestricted development of ger areas is the clash of two different legislation frameworks for land management: between the current master plan and the land reform policy. The current urban plan of Ulaanbaatar seeks to challenge the legitimacy and permanency of these regions, which are viewed as being available only for temporary land use, while the land reform seeks to give ger areas formal, permanent, and legal status (Byambadorj et al., 2011). As a result, residential plots have become prevalent, particularly in the city's fringes (Byambadorj et al., 2011; Kamata et al., 2010; The World Bank, 2009b).

To remedy this situation, policy directions, such as the "Compact City" concept of the UB Master Plan 2030, which is the revision of the current urban plan under the assistance of Japan International Cooperation Agency (JICA) in 2002 (Japan International Cooperation Agency, 2009), have emerged more clearly in recent years to control spatial expansion and

promote high-density development for ger areas (Kamata et al., 2010). This new plan is expected to restructure and improve the situation in ger areas (Japan International Cooperation Agency, 2009). For example, the project proposes a land use zoning which controls development in land unsustainable for urbanization and conserves existing natural networks of forests, waterways, and green areas (Japan International Cooperation Agency, 2009). Although the activities of the project contain new attempts to reduce urban expansion that the conversion of ger areas into apartment buildings and the gradual improvement of urban services for existing ger areas are addressed in plan (Japan International Cooperation Agency, 2009; Kamata et al., 2010), the scientific understanding concerning urban expansion in Ulaanbaatar is essential because it is still vague about spatial dynamics of urban expansion. The government needs to monitor the urban expansion because it is still progressing by encroaching the land in the peripheral areas.

3-2 DATA ACQUISITION

For identifying time-series changes in urban surface, it is quite difficult to obtain the official governmental spatial data which represent the boundary and ownership of each residential plot on a GIS system in the Administration of Land Affairs, Geodesy, Cartography (ALAGaC) because of the security and privacy. Additionally, the ALAGaC suffers from the limited

availability of its database because of unsatisfactory or insufficient cadastral surveys and mapping, and inadequate registration of land owners (Kamata et al., 2010). This database is updated when people register their own land, while not a few residential plots remain unregistered. According to the study by Batbileg (2007), only 28.76% of household in Ulaanbaatar registered their own land to ALAGaC due to the inability to pay the registration fee or the insufficient advantage of the registration. Accordingly, GIS data for urban objects are derived from VHR imagery.

All the remotely sensed imagery and GIS data for this study are listed in Table 2. VHR images from IKONOS for the year 2000 and from Quickbird for 2006 and 2008, ASTER data are acquired. For the implementation of pixel-based change analysis in land cover and the estimation of the environmental changes, MOD09A1 data for the period 2000–2010 are prepared. Regarding MOD09A1 data, seven data that were lacking, due to the pre-observation of MODIS between 1 January and 25 February 2000, were set to NA, to complete the full time-series datasets during the study period (i.e. $46 \text{ data} \times 11 \text{ years} = 506 \text{ data}$).

While the main data source is remotely sensed imagery, GIS data are supplementary obtained from JICA –The Study on City Master Plan and Urban Development Program of Ulaanbaatar City–. The GIS data on the boundary for the Municipality of Ulaanbaatar and *khoroos*, and the location of water kiosks were constructed by the Second Ulaanbaatar Services Improvement Project (USIP2), one of the key activities in Ulaanbaatar by the

World bank, to understand the urban structures in Ulaanbaatar in 2007 (Japan International Cooperation Agency, 2009; The World Bank, 2012).

Land cover data shown in Figure 3 and listed in Table 1 are obtained from Saanda and Sugita (2004). This data are utilized in Chapter 6 to estimate the environmental changes. Although the original source of this data is old (investigated in 1981), this is solely useful database which summarize the vegetation on the land in 1981 into GIS data.

Table 2. Data acquired in this research.

Data	Period	Frequency	Spatial resolution
IKONOS	2000	–	3.3 m
Quickbird	2006, 2008	–	2.4 m
ASTER	2007	–	26 m
MOD09A1	2000–2010	8 days	500 m
Location of water kiosk	2007	-	-
Administrative boundary	-	-	-
Land cover	1981	-	-

CHAPTER 4 RESIDENTIAL-SCALE MONITORING AND MODELING OF URBAN EXPANSION IN A FRINGE AREA

4-1 INTRODUCTION

Since residential plots have become prevalent especially in the urban fringe, it is quite important to monitor the detailed process of urban expansion. However, its obstacle is a lack of useful spatial data for land use have remained because the availability of this official data is not straightforward. The approach for extracting object-based spatial data from VHR imagery is an alternative way to build spatial database. Owing to the development of VHR satellite sensors in recent years, each urban object can be individually identified. Therefore, the aim of this chapter is to monitor the urban expansion by identifying time-series land cover changes at a residential-scale level in the fringe of Ulaanbaatar. In addition, an attempt is made to clarify the spatial characteristics of the urban expansion by constructing a spatial model and to predict the distribution of settlements in near future. Evaluation of spatial characteristics and prediction of a future's pattern of the distribution of settlements would be important for use in urban planning applications to deal with urban expansion.

4-2 STUDY AREA

A fringe of the urbanized area of Ulaanbaatar where the ger area has been expanding during the last decade is selected. The study area is located in the western part of Ulaanbaatar between $106^{\circ}43'$ E and $106^{\circ}52'$ E, and $47^{\circ}54'$ N and $47^{\circ}56'$ N, with a total area of approximately 33 km² (Figure 10). One of the main roads, named Enkhtaivan Avenue, runs in an east-west direction along the southern edge of the study area. Residential plots are mainly found on flat land and hillsides located on the north side of Enkhtaivan Avenue. The south side of the road is a part of the city center where some apartments and commercial facilities are found. The other type of land uses is constitutes by factories, schools, and governmental facilities. The rest parts of land are open land constituted by grasslands and bare lands. There are highly affected and degraded by anthropogenic activities.

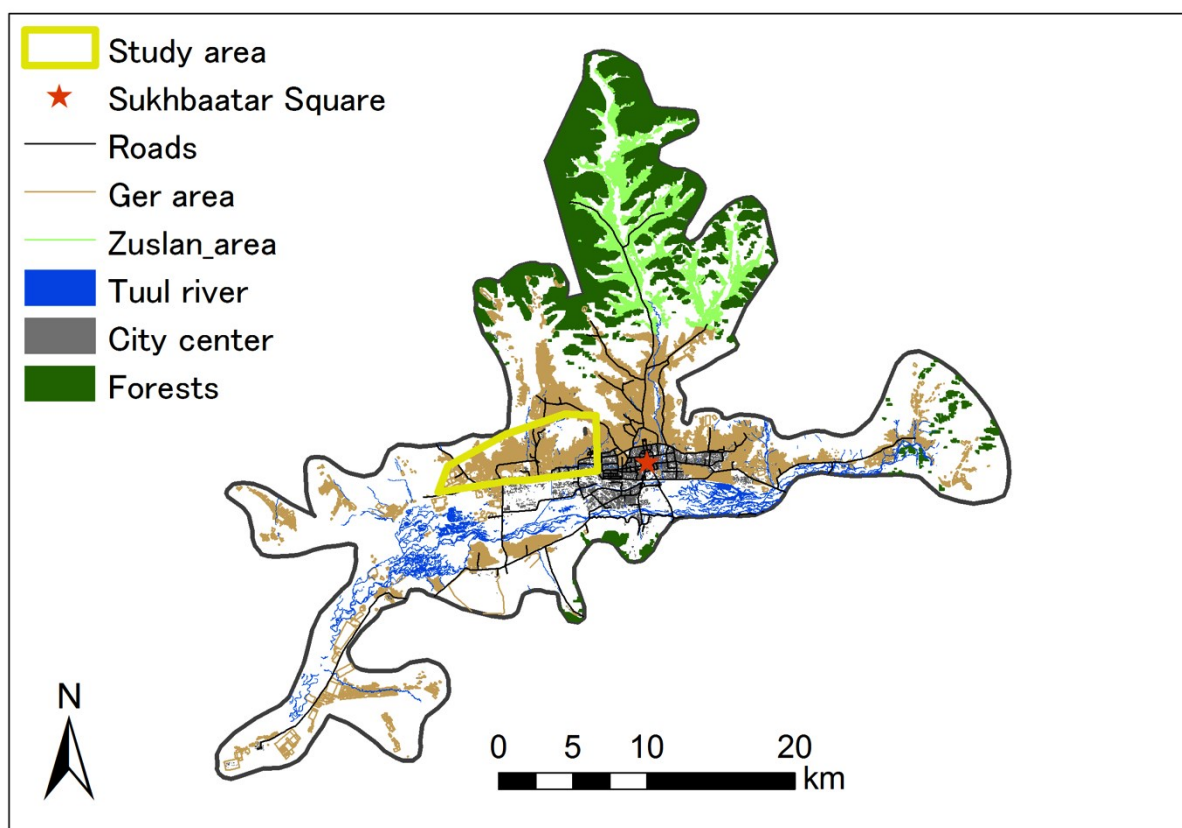


Figure 10. Location of the study area.

4-3 METHODOLOGY

Logistic regression models are of great utility when evaluating spatial characteristics relating to urban expansion (J. Cheng & Masser, 2003; Dubovyk et al., 2011; Fang et al., 2005; Hu & Lo, 2007; Huang, Zhang, & Wu, 2009; Petrucci, Salvati, & Seghieri, 2004; Sudhira et al., 2004; Zeng, Wu, Zhan, & Zhang, 2008). A wide variety of spatial modeling techniques has been employed to determine the spatial characteristics of urban expansion processes, including cellular automata (Fang et al., 2005; Li, Sato, & Zhu, 2003), agent-based modeling (Augustijn-Beckers et al., 2011; Matthews, Gilbert, Roach, Polhill, & Gotts, 2007), and artificial neural networks (Dai, Wu, Shi, Cheung, & Shaker, 2005; Pijanowski, Tayyebi, Delavar, & Yazdanpanah, 2009). However, logistic regression models have been shown to be particularly effective in the analysis of land use change owing to their explanatory power and spatial explicitness (J. Cheng & Masser, 2003; Dubovyk et al., 2011; Poelmans & Van Rompaey, 2010). For example, Cheng and Masser (2003) applied a logistic regression model to find and compare determinants of urban growth patterns for Wuhan City, China, for the period 1993–2000. They found the major determinants to be urban road infrastructure and pre-existing developed areas and suggested that the role of master planning was diminishing. Similarly, Dubovyk et al. (2011) applied a logistic regression model to analyze the driving forces of informal development in Istanbul, Turkey, and were able to identify probable locations of new informal settlements.

Although such models are known to be effective for the analysis of urban expansion, problems can arise if spatial autocorrelation is found in the residuals of models (J. Cheng & Masser, 2003; Dubovyk et al., 2011; Huang et al., 2009), because such models do not typically consider spatial dependence (J. Cheng & Masser, 2003). Thus, spatial autocorrelation, which violates the assumption of independent residuals, is often ignored when logistic regression models are used because the statistical methodology typically adopted to assess autocorrelation is not well developed for logistic regression models (Hu & Lo, 2007). Such models should not be considered appropriate for use if spatial dependence is detected in the residuals because this dependence suggests that the models are unable to capture all of the spatial features expressed in the data (Overmars, de Koning, & Veldkamp, 2003). Improper model use in this manner can lead to unreliable estimation of model parameters and incorrect conclusions (J. Cheng & Masser, 2003; Dubovyk et al., 2011).

To overcome this problem, autologistic regression models and random sampling schemes have been developed (J. Cheng & Masser, 2003; Hu & Lo, 2007; Petrucci et al., 2004; Poelmans & Van Rompaey, 2010; Zeng et al., 2008). An autologistic regression model incorporates components describing spatial autocorrelation into an existing logistic regression model. However, as noted by Dormann (2007), such models consistently underestimate the effects of environmental variables in the model and produce biased estimates compared to non-spatial logistic regression.

Random sampling has been proposed as an alternative means of minimizing spatial autocorrelation in model residuals, where sampled pixel points are selected randomly to utilize the model while maintaining spatial independence among points (Hu & Lo, 2007). Thus, in the present study, a random sampling scheme was employed in the analysis of a logistic regression model and reduced the number of samples until no spatial autocorrelation remained in the residuals statistically. In total, 500 points were sampled randomly in the study area.

A logistic regression model is a multivariate analysis model where there is a nonlinear relationship between the dependent variable and independent variables. A logistic regression model is expressed as follows:

$$y = \log_e \left(\frac{P(z)}{1-P(z)} \right) = a + b_1x_1 + b_2x_2 + \dots + b_mx_m + \varepsilon \quad (4-1)$$

where $P(z)$ is the probability of the dependent variable z ; $x_1, x_2, \dots, x_m$ are independent variables; the parameter a is an intercept; $b_1, b_2, \dots, b_m$ are regression coefficients; and ε is a binomially distributed error. The variable z is binary (0 or 1) and represents the existence of a land use. $P(z)$ represents the probability of the occurrence of a land use and its value is between 0 and 1. Regression coefficients represent the contribution of each independent variable on $P(z)$. A positive regression coefficient indicates that the independent variable supports an increase in the

probability of change, whereas a negative indicates the opposite effect (J. Cheng & Masser, 2003).

This logistic regression model was evaluated in terms of spatial dependency and performance. Spatial dependency was tested by calculating Moran's I for residuals under a normality assumption, such that each value represents an independent data point drawn from a single normal distribution. The null hypothesis states that the spatial distribution of residuals is not influenced by spatial autocorrelation. The performances of this model was evaluated according to the area under the receiver operating characteristics (ROC) curve method, also known as the area under curve (AUC) method (Gimblett et al., 2001; Muñoz & Felicísimo, 2004; Overmars et al., 2003; Park, Jeon, Kim, & Choi, 2011). The AUC method has been used widely in image-based studies and represents the performance of diagnosis and event occurrence by plotting true- and false-positive proportions (Fang et al., 2005; Swets, 1988). In this context, true-positive, plotted on the vertical axis, is the ratio of the number of pixels correctly classified as positive in the diagnosis to the total number of pixels classified as positive. Conversely, false-positive, plotted on the horizontal axis, refers to the ratio of the number of pixels incorrectly classified as positive in the diagnosis to the total number of pixels classified as negative (Fang et al., 2005; Park et al., 2011; Swets, 1988). The AUC value can range from 0.5 (no discrimination) to 1 (perfect correspondence) (Swets, 1988), where the true- and false-positive proportions are equal at 0.5.

4-4 DATA PROCESSING

In the present study, feature-oriented GIS data of urban components were constructed from VHR satellite imagery to explore processes of urban expansion. GIS data relating to residential plots, buildings, roads, main roads, and other land uses (i.e., factories, schools, governmental facilities, and others) were constructed from IKONOS images for 2000 and Quickbird images for 2006 and 2008. Images for 2000 and 2006 were compared with the characteristics of the study area before and after implementation of the land reform policy in 2003, whereas the image for 2008 was selected to monitor the characteristics achieved under continuation of the policy. Individual packages of residential plots were identified based on the enclosing khashaas and digitized them manually in a vector format along with other land use types (e.g., buildings including apartments and commercial facilities, roads) based on the images for each observed year (Figure 11). Main roads that were paved and had one or more lanes in 2000 were digitized separately using IKONOS imagery.

For the implementation of the logistic regression model, distances from roads, main roads, and water kiosks were calculated and combined with binary data representing the existence of private land in 2000 and 2008. In addition, elevation and slope were calculated based on ASTER GDEM data. The variables of this logistic regression model are listed in Table 3 and Figure

12. All independent variables were standardized according to the following formula: $(x - \text{mean}(x))/\text{Std}(x)$. This enabled comparison of the quantitative effects of regression coefficients between variables. The calculation and evaluation of the model were conducted in the R software package.



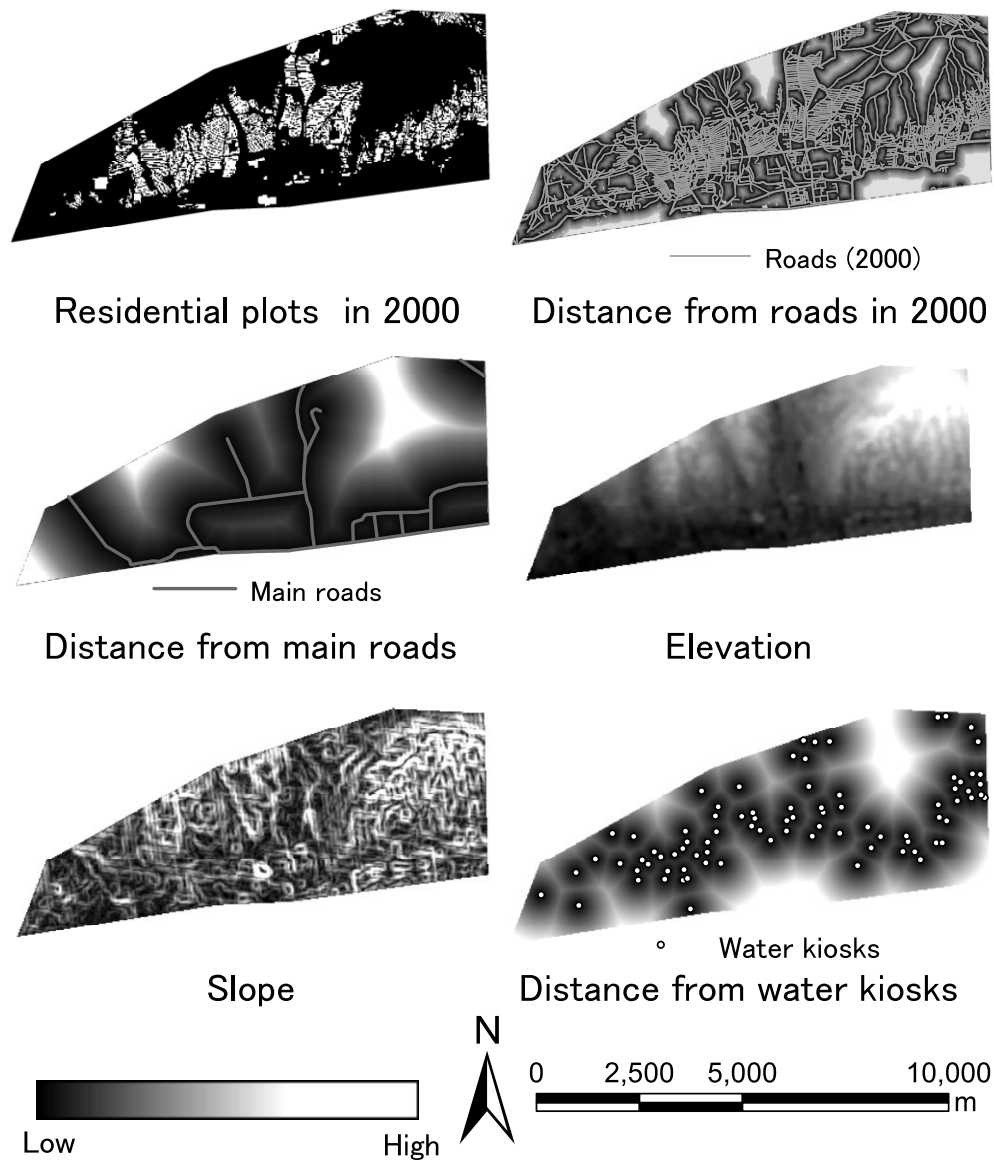
Figure 11. Examples of GIS data digitized from VHR imagery.

Left: A main road (green line) and other roads (purple lines)

Right: Residential plots (green polygons) enclosed by *khashaas*

Table 3. Variables in logistic regression model.

Type of factor	Variable	Description	Nature of variable
Dependent	Residential plots in 2008	0 : No residential plots 1 : Existence of residential plots	Binary
Independent	Residential plots in 2000	0 : No residential plots 1 : Existence of residential plots	Binary
Independent	Distance from roads in 2000	Distance from roads in 2000 (m)	Continuous
Independent	Distance from main roads	Distance from main roads (m)	Continuous
Independent	Elevation	Elevation (m)	Continuous
Independent	Slope	Slope (°)	Continuous
Independent	Distance from water kiosks	Distance from water kiosks (m)	Continuous



All variables were standardized into mean of zero and standard deviation of 1.

Figure 12. Raster layers of independent variables in logistic regression model.

Residential plot in 2000 is excluded.

4-5 RESULTS

The spatial distributions of residential plots in 2000, 2006, and 2008 are illustrated in Figure 13. These time-series maps demonstrate significant expansion of areas occupied by residential plots. The expansion of residential plots and roads was particularly prominent during the period 2000–2006: residential plots were found primarily on flat terrain along main roads in 2000, whereas these plots had spread across hillsides and even into steep areas in the period leading up to 2006 and 2008. Road extension occurred primarily in mountainous areas, as residential plots spread along roads over the years. The number of plots of residential plots increased from 6,747 in 2000 to reach 12,656 in 2006 and 13,064 in 2008 (Table 4). Although the distribution of buildings remained mostly unchanged throughout the study period, the rate of change of the number of residential plots decreased from 87.58% during the period 2000–2006 to 6.05% during the period 2006–2008. Moreover, the proportion of residential plots in the study area increased from 17.69% in 2000 to 30.58% in 2006 and 32.00% in 2008. Road extension is also apparent in the time series, with road length increasing from 409.9 km in 2000 to reach 576.5 km in 2006 and 619.3 km in 2008. Thus, the rate of increase of road length was lower (higher) than that of private land during the period 2000–2006 (2006–2008).

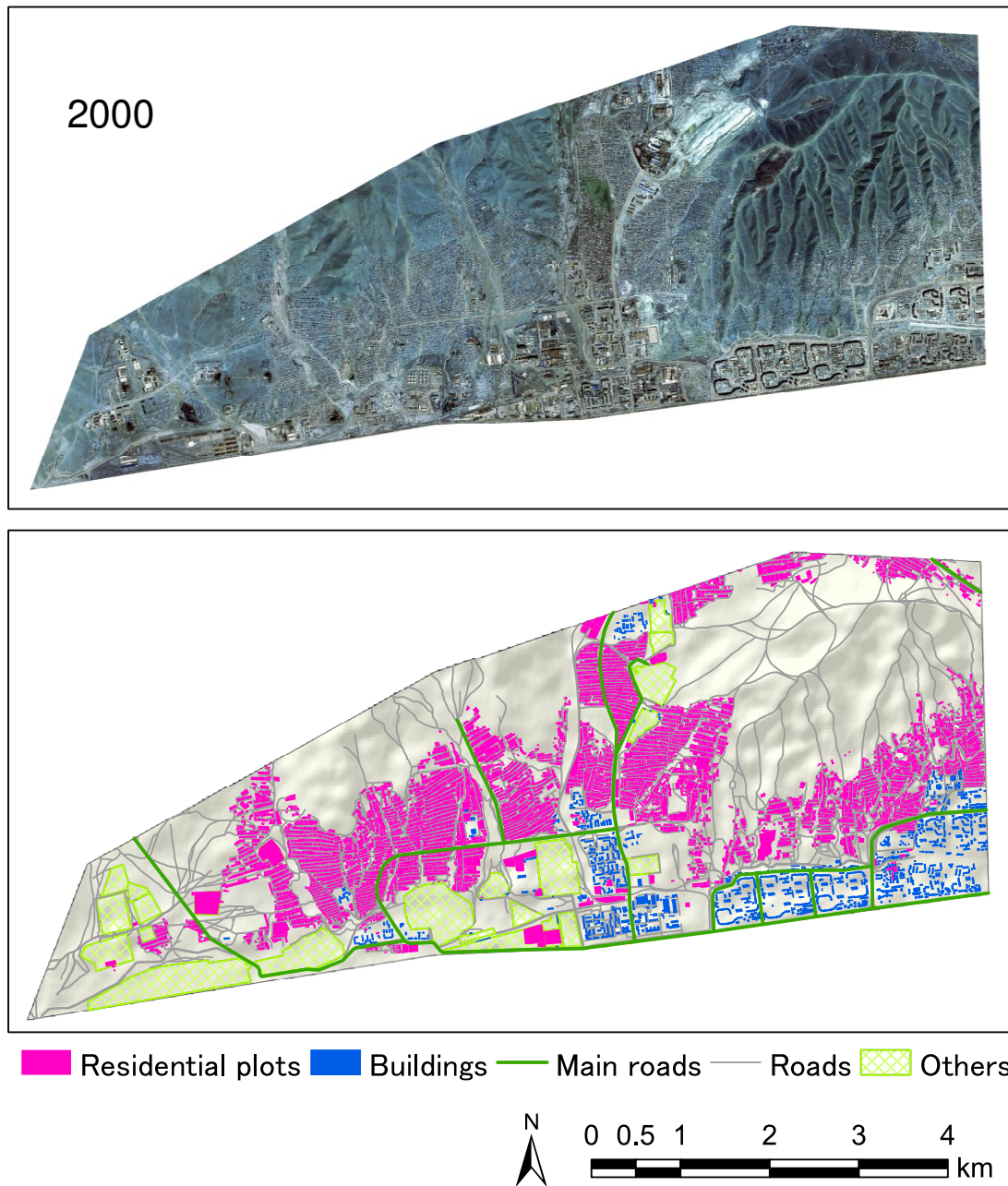


Figure 13. VHR images and maps detailing residential plots, buildings, roads, main roads, and other land uses in 2000, 2006, and 2008.

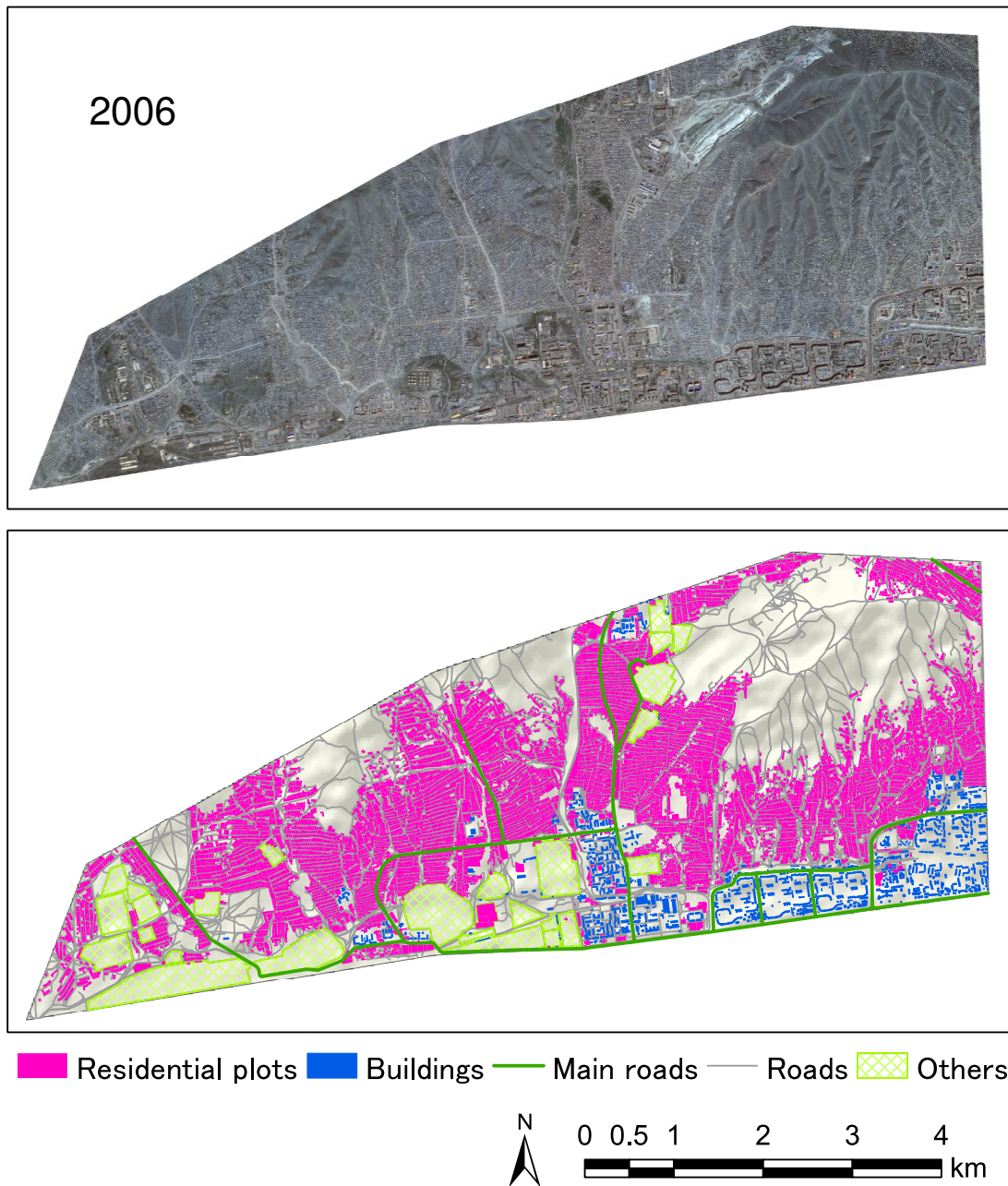


Figure 13. (Continued).

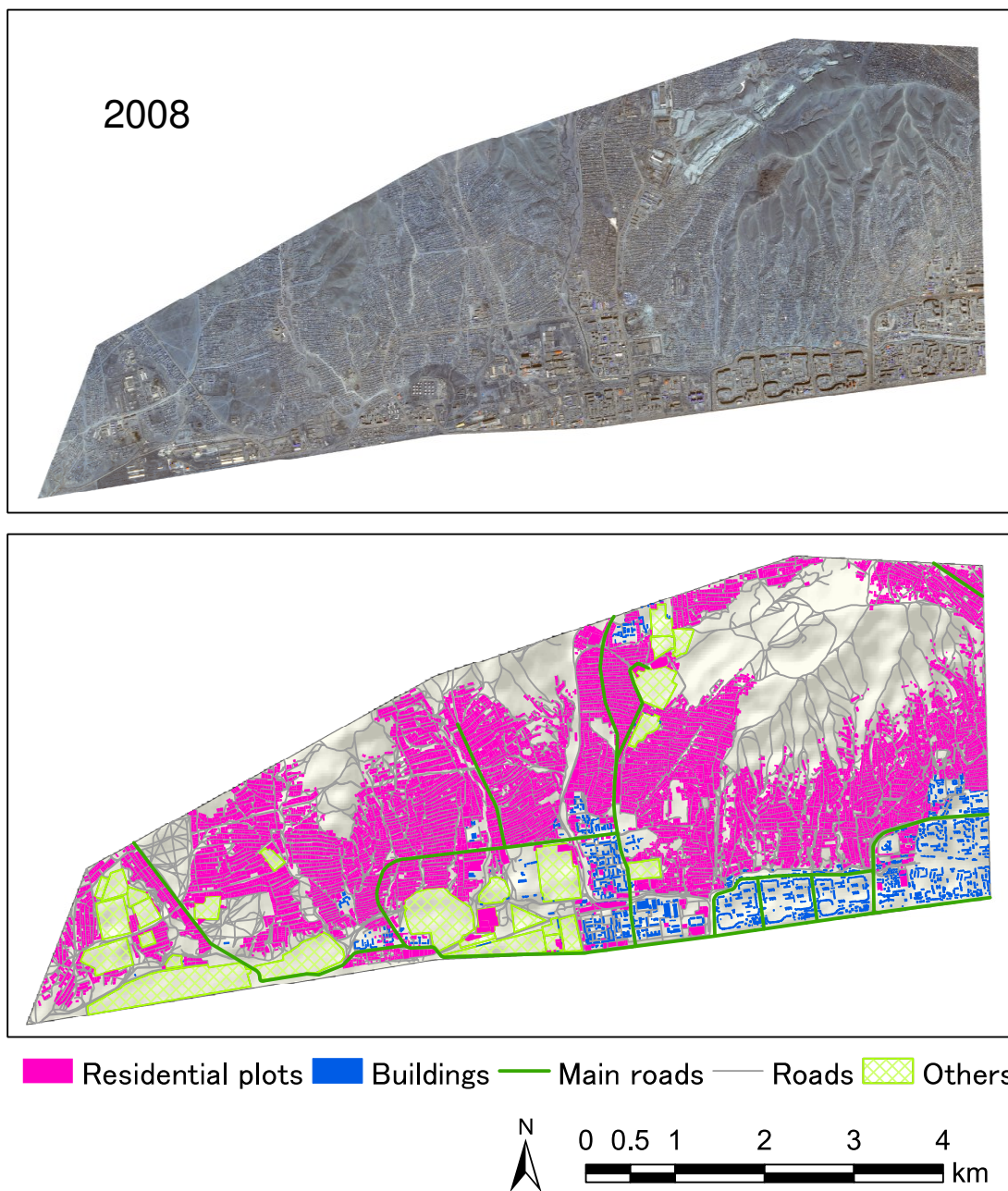


Figure 13. (Continued).

Table 4. Changes in the number of residential plots, proportion of residential plots and buildings within the study area, and the total length of roads.

	2000	2006	2008	Change from 2000 to 2006	Change from 2006 to 2008
Number of residential plots	6,747	12,656	13,064	5,909	408
(% change)	-	-	-	(87.58)	(6.05)
Proportion of residential plots in the study area (%)	17.69	30.58	32.00	12.89	1.42
(% change)	-	-	-	(72.82)	(5.88)
Proportion of buildings in the study area (%)	1.70	1.84	1.84		
(% change)	-	-	-	(0.14)	(0.00)
Total length of roads (km)	409.9	576.5	619.3	166.6	42.8
(% change)	-	-	-	(40.64)	(7.42)

The results obtained using the logistic regression model are presented in Table 5. The distribution of residential plots in 2008 were found to exhibit a statistically significant positive relationship with the distribution of residential plots in 2000. Conversely, a statistically significant negative relationship was found between the distribution of residential plots in 2008 and distance from roads and water kiosks. No statistically significant relationships were found between the distribution of residential plots and distance from main roads, elevation, or slope.

Values of Moran's I for the residuals of the model were found to be 0.025 and statistical testing of autocorrelation in the residuals indicated no statistical significance. Consequently, the model can be considered well developed in terms of spatial dependence. The AUC value in the model was 0.838, indicating a prediction accuracy of 83.8%.

Table 5. Statistical results for logistic regression model.

		Coefficients
Dependent variable	Residential plots in 2008	
	(Intercept)	-0.636 ***
Independent variables	Residential plots in 2000	1.060 ***
	Distance from main roads	0.053
	Distance from roads in 2000	-0.551 *
	Elevation	0.090
	Slope	-0.164
	Distance from water kiosks	-0.781 ***
AUC value		0.838
Moran's I in residuals		0.025

*: Statistically significant at the 5% level ($p\text{-value} \leq 0.05$)

***: Statistically significant at the 0.1% level ($p\text{-value} \leq 0.001$)

4-6 DISCUSSION

Until recently, studies concerning the spatial modeling of urban expansion have found it difficult to incorporate the effects of disaggregated human behaviors on urban surfaces. Land use changes in Ulaanbaatar have been analyzed at the metropolitan scale using MODIS, Landsat, and SPOT imagery in some previous studies (Amarsaikhan et al., 2009). However, residential-scale land use changes, which can depict urban expansion more precisely, have not been investigated in detail to date owing to the lack of time series of feature-oriented data reflecting urban components. In this context, one of the primary achievements of the present study is the construction of residential-scale GIS datasets and the use of these datasets to express urban expansion in detail. (Figure 13).

Habibi & Asadi (2011) noted that the most important factors driving urban expansion are as follows: population and income growth; the low price of land and access to appropriate housing, the low price of transportation systems; the promotion of a commuting network; new centers for jobs that are located in suburbs; and the use of infrastructure, subsidies, and public services. However, it is also important to understand the spatial dynamics and patterns of urban expansion when developing policies and implementing sustainable development policies for a given region (Habibi & Asadi, 2011; Sudhira et al., 2004). The results obtained using the logistic regression model demonstrate the spatial characteristics of the distribution of residential plots. The development of private land has a positive feedback effect,

fostering the development of further private land through the neighborhood effect. Moreover, our results confirm the aggregated (rather than scattered) formation of *ger*-areas. The distance from roads appears to be one of the primary forces governing the formation of *ger*-areas. Most of the roads in *ger*-areas began as informal tracks to private land in response to residents' demands for better access to social and public infrastructure. Subsequently, these tracks evolved in a haphazard manner to become earthen roads (Kamata et al., 2010). Based on these results, it is clear that road accessibility is important for migrants when selecting a location for their own private land. Water kiosks are also a key factor controlling the formation of *ger*-areas. To be able to survive in *ger*-areas, residents must purchase water at water kiosks when required (Kamata et al., 2010). No house or *ger* in any *ger* area has a private connection to a water distribution network, so residents have to purchase water at kiosks. In a blueprint of development strategy, water kiosks are located within 500 m such that each serves approximately 900–1,200 people (Kamata et al., 2010).

Although we found no significant relationship between distance from main roads and the distribution of private land, our model results indicate that land far from main roads has been developed most recently, likely because most of the land along or near main roads has already been occupied by private land, buildings, or other land cover types. Similarly, elevation and slope, which are indicators of landform, do not appear to have

impeded the recent development, although the newer development appears to occur primarily at higher elevations and in areas of flatter slope.

Potential “hot spots” for the future development of residential plots can be estimated spatially by comparing regression coefficients. These hot spots, which are typically closer to water kiosks and roads, exhibit much greater probability of being developed. Accordingly, residential plots are likely to become concentrated around these hot spots, exhibiting spatial characteristics consistent with the aggregated formation of ger-areas during the period 2000–2008. Figure 14 illustrates the predicted probabilities for future development of private land derived from the results of our logistic regression model during 2008–2016. These results suggest that development is most likely to occur in unoccupied land adjacent to existing private land. Although these predictions do not reflect patterns of private land development considering disaggregated human behaviors, our results may still provide valuable insight into the future development of ger-areas and their spatial relationships with geographical factors. In particular, our results demonstrate that social infrastructure exhibits a much closer relationship than natural geographical factors with the formation of ger-areas.

The models used in the present study are subject to data constraints, which is a universal problem in urban land use modeling (Huang et al., 2009). Accordingly, it can prove difficult to integrate all possible factors affecting the expansion of ger-areas. However, results obtained using more complex models that include most of the factors that could possibly affect

urban expansion are generally difficult to interpret accurately. Accordingly, such results do not highlight the advantages of mathematical models particularly well. Although the models applied in the present study are simple, they can reflect real situations to a considerable extent while avoiding spatial autocorrelation in the residuals.

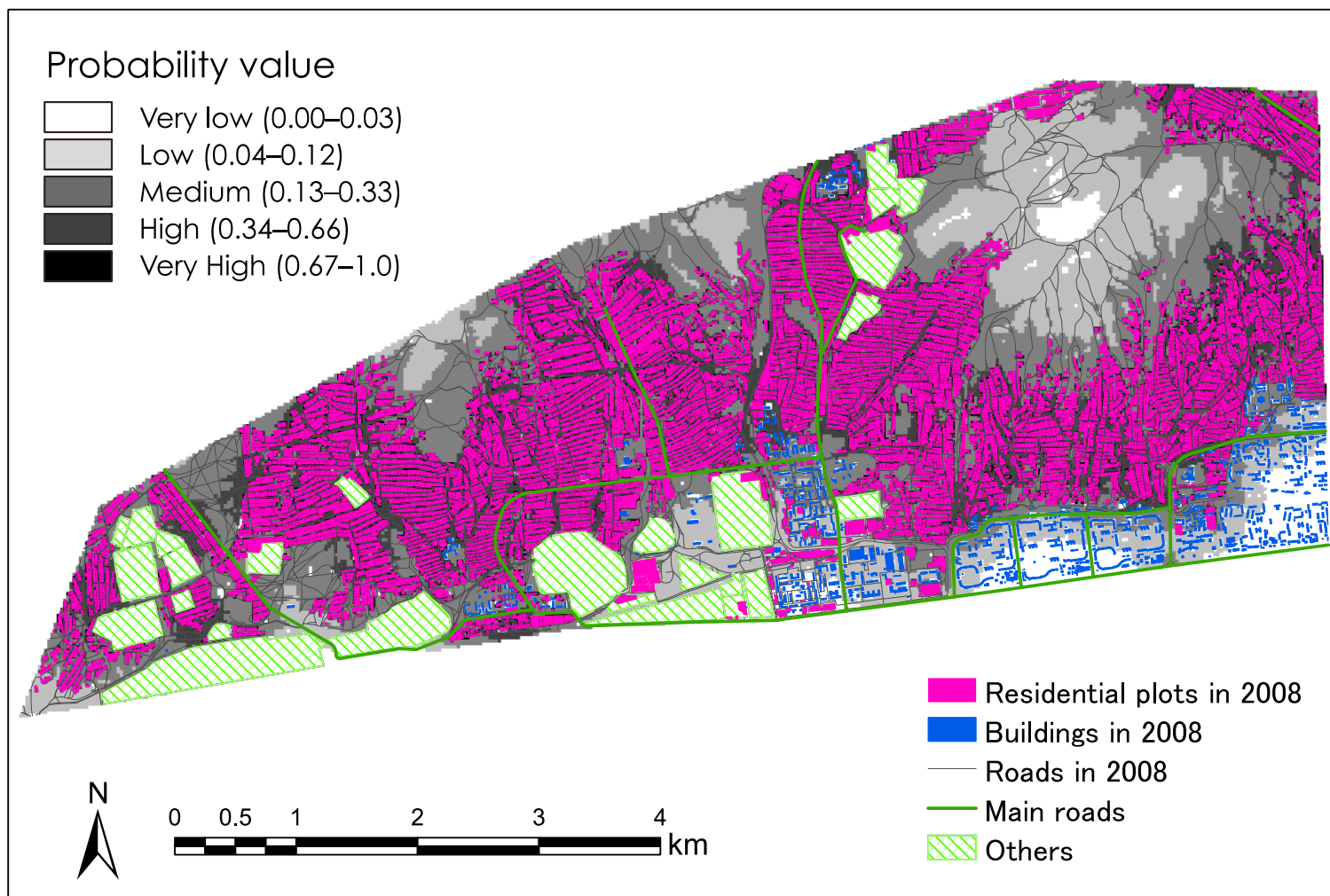


Figure 14. Predicted probabilities of development of residential plots based on the logistic regression mode, 2008–2016.

4-7 CONCLUSION

In this study, more realistic characterization of spatial expansion processes of ger areas has been achieved at the residential scale than was possible previously by utilizing VHR imagery to observe time-series changes of the formation of ger areas in the fringe of Ulaanbaatar. Furthermore, the application of the logistic regression model produced some fruitful quantitative insights regarding the patterns and possible controlling factors for the expansion of residential plots. Consequently, this study demonstrated that failures in land management resulted in the expansion of ger areas in the fringes of Ulaanbaatar. This expansion resulted in deterioration in living standards and induced a disordered spatial pattern of urban fringes from which it will be difficult to recover with the present urban plan. Most demand for land is associated with residential use; accordingly, the associated concentration of (and increase in) population is likely to give rise to an unprecedented land use situation. Urgent action by both urban planners and decision makers is necessary to mitigate the effects of urban expansion.

CHAPTER 5 PIXEL-BASED LAND COVER CHANGE

DETECTION IN URBAN AREAS

5-1 INTRODUCTION

Appropriate strategies for managing urban expansion must be identified and effectively employed (Angel et al., 2011). It is therefore obvious that an analysis of urban expansion would assist regional planners and decision-makers in understanding growth patterns, thereby allowing plans to be made that include certain essential infrastructures (Verbesselt, Hyndman, Newnham, et al., 2010). Detecting and characterizing changes in land cover is a natural first step towards identifying and understanding the drivers and mechanisms for such change (Verbesselt, Hyndman, Newnham, et al., 2010).

A new approach is proposed, using the Breaks For Additive Seasonal and Trend (BFAST) method, which is a type of wave decomposition technique developed to overcome the limitations of the methods described in section 2.2 (Verbesselt, Hyndman, Newnham, et al., 2010). It is much more useful in estimating land cover change than other techniques, because it is able to robustly and automatically derive both the time and location of land cover changes from NDVI time series, without needing to select a reference

period, set thresholds, or define a change trajectory (Verbesselt, Hyndman, Newnham, et al., 2010; Verbesselt, Hyndman, Zeileis, & Culvenor, 2010).

Although the BFAST method has been shown to be useful, it has not previously been used in an urban expansion analysis. It could be applied widely and should therefore be made more available, to allow it to be a practical tool for urban planners when monitoring urban expansion. A robust and feasible method is needed to estimate land cover change in Ulaanbaatar in particular, because urban expansion is rapidly accelerating in this developing city. Therefore, to estimate changes in land cover in the urban area of Ulaanbaatar, BFAST method is applied and explored to be a tool for urban expansion analysis.

5-2 STUDY AREA

This analysis is focused on the urban area, comprising 122 *khoroos* in seven districts of the Municipality of Ulaanbaatar, with a total area of approximately 756.25 km² (see Figure 4). Two *khoroos* in the Songinokhanir Khan district and the Bayansurkh district are excluded from the study area because of their remote and disparate locations.

Since natural land covers are not as affected by anthropogenic land cover changes, compared to urban surfaces (Lunetta et al., 2006), the forests and the Tuul River are masked from the analysis in order to focus on land cover changes caused only by anthropogenic disturbances.

5-3 METHODOLOGY

BFAST integrates the iterative decomposition of time series data into trend, seasonal, and remainder components, with methods for detecting changes (Figure 15) (Verbesselt, Hyndman, Newnham, et al., 2010). The model is used iteratively to fit a piecewise linear trend and a seasonal model, given by the equation:

$$Y_t = T_t + S_t + e_t \quad (t=1, \dots, n) \quad (5-1)$$

where Y_t is the observed data at time t , T_t is the trend component, S_t is the seasonal component, and e_t is the remainder component (Verbesselt, Hyndman, Newnham, et al., 2010). It is assumed that T_t is piecewise linear with segment-specific slopes and intercepts on the different

segments of $m + 1$ ($m \geq 0$). Thus, there are m breakpoints $\tau_1^*, \dots, \tau_m^*$, such that:

$$T_t = \alpha_i + \beta_i t \quad (\tau_{i-1}^* < t < \tau_i^*) \quad (5-2)$$

where $i = 1, \dots, m$ and we define $\tau_0^* = 0$ and $\tau_{m+1}^* = n$. S_t represents the piecewise phenological cycle on different $p + 1$ ($p \geq 0$) segments divided by the seasonal breakpoints, $\tau_1^\#, \dots, \tau_p^\#$ ($\tau_0^\# = 0$ and $\tau_{p+1}^\# = n$), shown as:

$$S_t = \sum_{k=1}^K \left[\gamma_{j,k} \sin\left(\frac{2\pi kt}{f}\right) + \theta_{j,k} \cos\left(\frac{2\pi kt}{f}\right) \right] \quad (\tau_{i-1}^\# < t < \tau_i^\#) \quad (5-3)$$

where the coefficients are $\gamma_{j,k}$ and $\theta_{j,k}$, K is the number of harmonic terms, and f is the frequency. We employed the harmonic model proposed by Verbesselt et al., (2010) which sets $K = 3$ in eq. 5-3. This model has a robust approach that avoids noise, and parameters that can be easily used to characterize phenological change (Verbesselt, Hyndman, Zeileis, et al., 2010). The frequency is set as $f = 46$ for annual observations of an 8-day time series in this study. The remainder component is the remaining variation in the data beyond that defined by the seasonal and trend components (Verbesselt, Hyndman, Zeileis, et al., 2010).

Breakpoints in trend and seasonal components are detected iteratively (Jong, Verbesselt, Schaepman, & Bruin, 2012; Verbesselt, Hyndman, Newnham, et al., 2010; Verbesselt, Hyndman, Zeileis, et al., 2010) as follows: 1) breakpoints $\tau_1^*, \dots, \tau_m^*$ are estimated using the residuals-based moving sum (MOSUM) test, and are assessed by minimizing Bayesian information criterion (BIC) from the seasonally adjusted data $Y_t - \hat{S}_t$, where $\hat{S}_t$ is first found by the STL method (R Development Core Team, 2011); 2) $\hat{T}_t$, $\hat{\alpha}$, and $\hat{\beta}$ are estimated using robust regression based on M-estimations; 3) breakpoints $\tau_1^\#, \dots, \tau_p^\#$ are similarly estimated by MOSUM and BIC from the de-trended data $Y_t - \hat{T}_t$; 4) revised $\hat{S}_t$ is estimated based on the M-estimation; 5) the estimation of parameters is iteratively performed until the number and position of breakpoints are unchanging.

All parameters above are determined automatically. BFAST requires only the parameterization of the minimal segment size between potentially detected breaks (Schucknecht, Erasmi, Niemeyer, & Matschullat, 2013); in this study, this was set to two years.

5-4 DATA PROCESSING AND IMPLEMENTATION

BFAST is implemented through the `ndvits` package in the R statistical software (Frelat & Gerard, 2011; R Development Core Team, 2011). Interpolated time-series images were clipped along the boundary of the study area, and datasets were then extracted in chronological order by the `ExtractFile` function within the R-`ndvits` package. In this study, a high frequency of breakpoints is found in the trend components during the period 2000–2010 (e.g. Figure 15). Since the trend component represents gradual changes due to interannual climate variability or land degradation (Jong et al., 2012; Verbesselt, Hyndman, Newnham, et al., 2010), its breakpoints do not assist in the detection of land cover changes on urban surfaces well. Instead, breakpoints in the seasonal component do indicate changes in seasonal trend patterns, and therefore we focus only on the breakpoints in these seasonal components, which could represent a change in land cover.

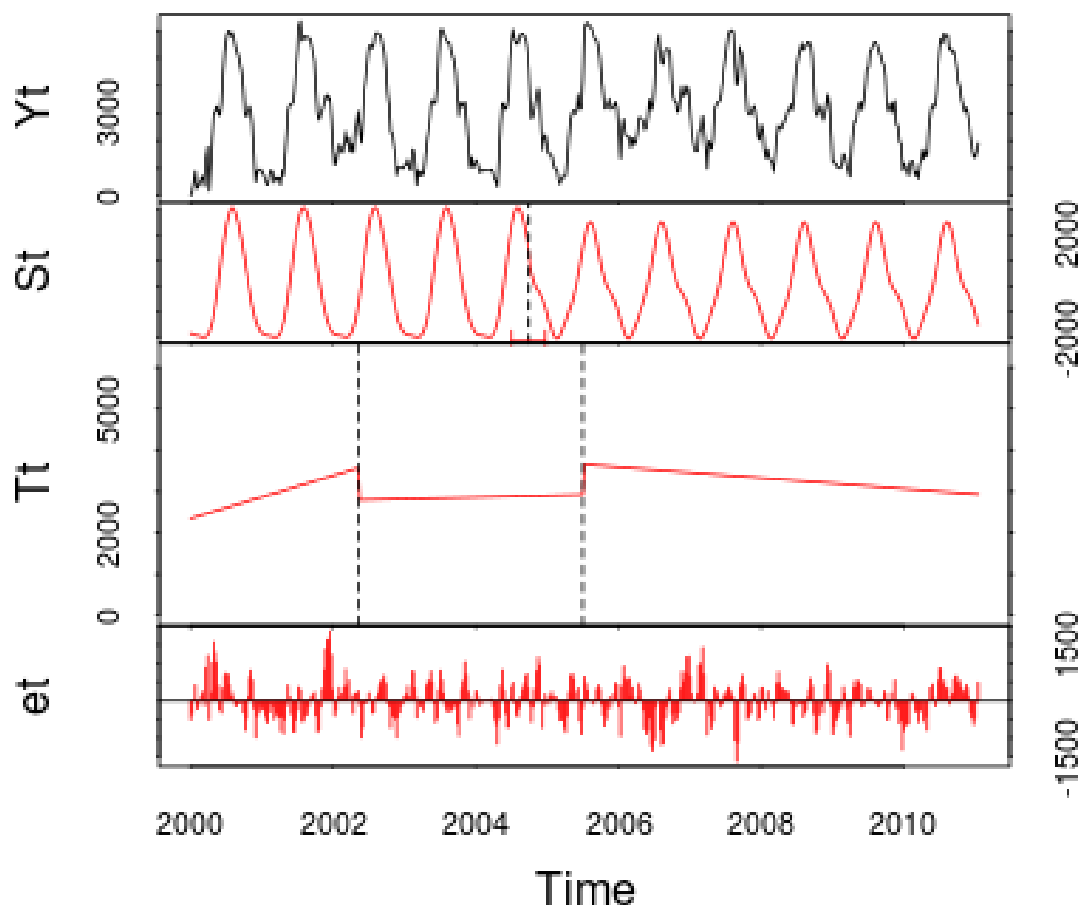


Figure 15. Fitted seasonal, trend, and remainder components for MODIS time series during the period 2000–2010, generated by BFAST method.

The dashed lines represent the dates of detected breakpoints, together with their confidential intervals (red).

5-5 RESULTS

The BFAST method was implemented in the study area to detect the number and timings of breakpoints in the seasonal components. The frequency of detection of seasonal components changes during the period 2000–2010 (Figure 16). Changes are detected in 22.51% of the study area, and are mostly seen just once during the 11-year period. Since the forest and Tuul River areas are masked, the changes are detected within the areas affected by anthropogenic disturbances. These areas are distributed spatially in locations governed by the extent of ger areas, the internal development of ger areas, and land degradation due to anthropogenic activities, such as the development of earthen roads. The main concentration of detected change is around the edge of the city center, corresponding to locations in and around ger areas. A smaller number of breakpoints are found in the *zuslan* areas in the northern part of the study area. The temporal periods of the detected seasonal component changes are shown in Figure 17, and the timing of the changes estimated by BFAST are summarized each year to facilitate a comparison, similar to that performed by Verbesselt et al. (2010). In the areas around the city center, change was mostly detected during 2004 and 2005, and it is clear that the later a change is detected, the further that area will be from the city center (see Figure 17). Most of the

change occurred within the suburban areas between the years 2005 and 2007.

Significant difficulties were encountered in evaluating the performance of change detection methods, and result from an inability to adequately characterize outcome accuracies (Lunetta et al., 2006). Therefore, in order to verify that our detected results are in accordance with actual land cover changes, the spatial distribution of detected areas in a sample area was compared with bi-temporal VHR images from IKONOS in 2000, and Quickbird in 2008 (Figure 18). Apartments are illustrated in the southern portion, ger areas in the central part, and mountainous areas in the northern part of the sample area. Each residential plot is colored to facilitate the identification of the extent of ger areas. An expansion of ger areas, shown by the increase of residential plots towards the northern mountainous area, was clearly observed in the bi-temporal VHR images. In comparison with the BFAST data, few breakpoints of seasonal component changes are found in the apartment areas, while many are found in ger areas, mostly corresponding to areas experiencing internal development of ger areas, or the conversion of open lands to ger areas. Although some pixels are false findings of land cover changes, it is evident here that the spatial distribution of detected changes corresponds well to the areas of expansion.

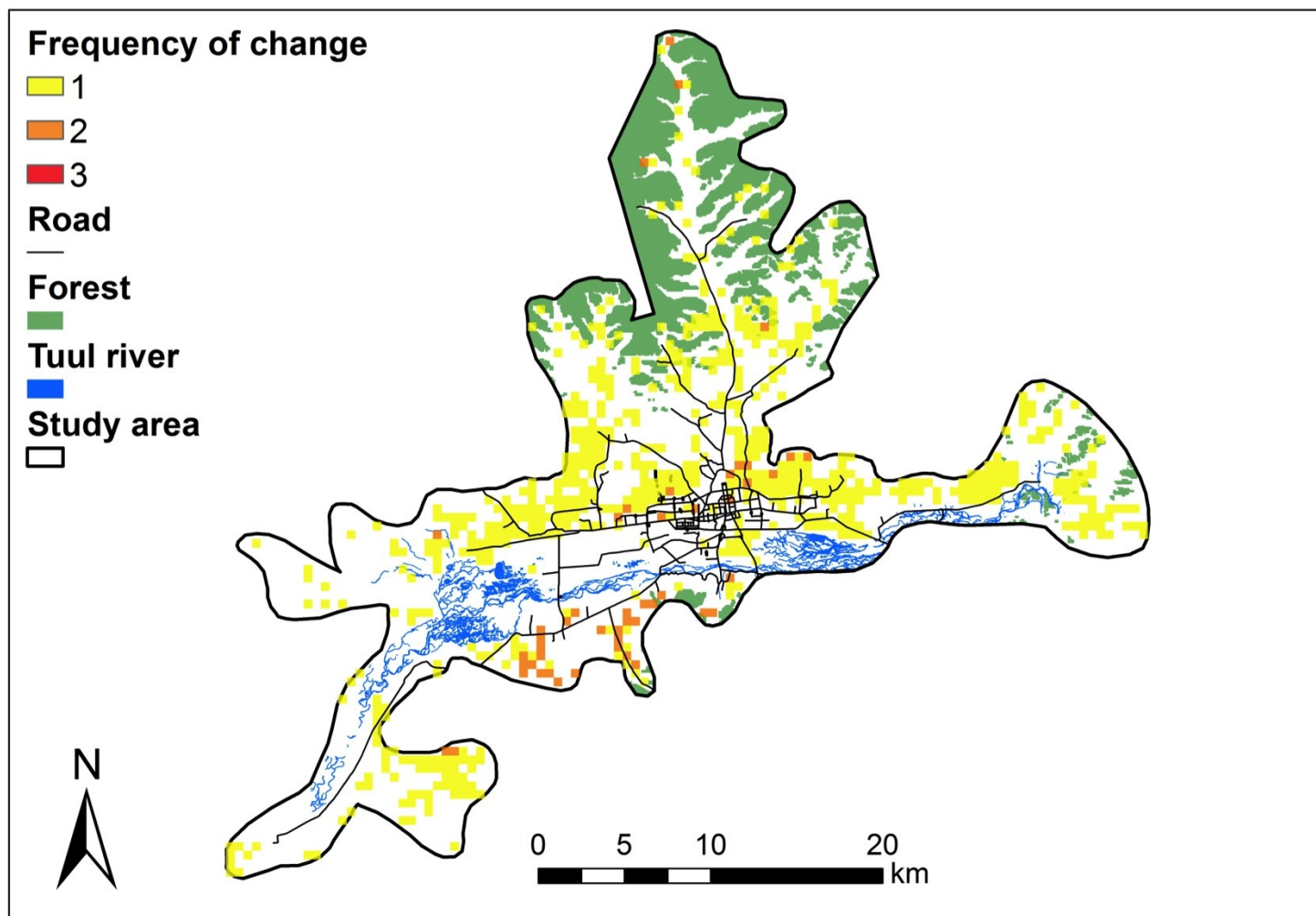


Figure 16. Spatial distribution of the frequency of seasonal component changes.

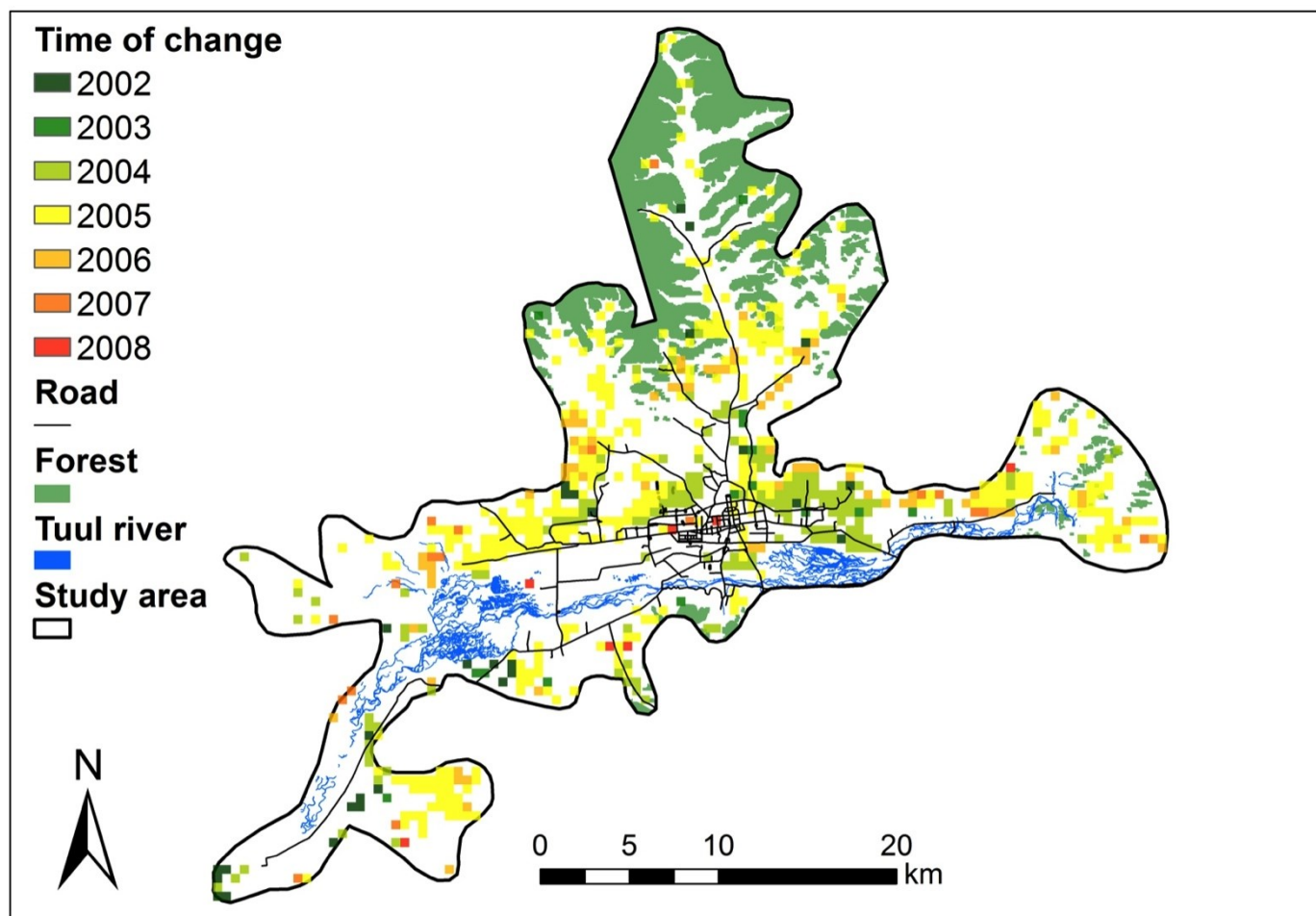


Figure 17. Spatial distribution of the timing of seasonal component change occurrences (showing only the first detected changes).

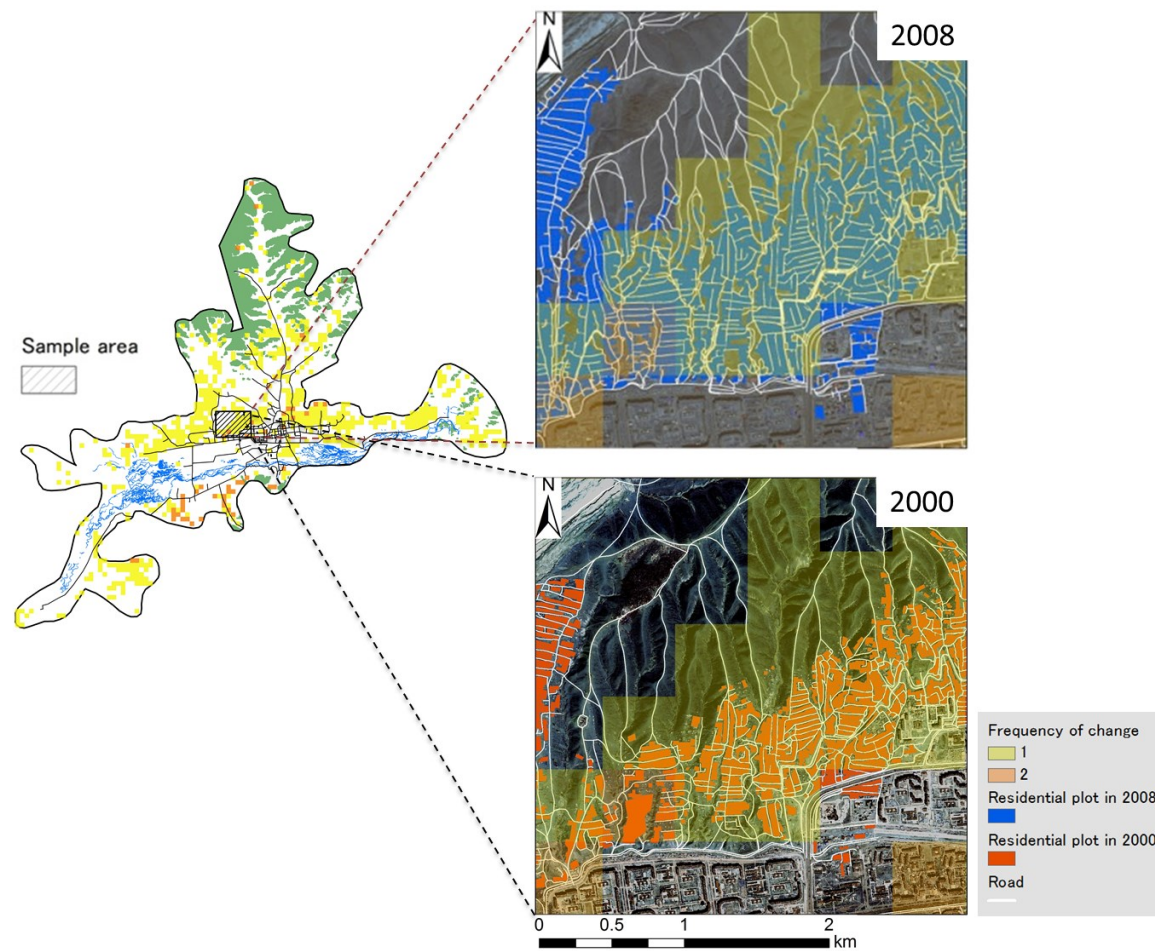


Figure 18. Spatial distribution of detected changes in the sample area and the expansion of the ger area observed by bi-temporal images in 2000 and 2008.

5-6 DISCUSSION

Until recently, the expansion of urban areas from the city center outwards to peripheral areas was often confirmed by observing an urban surface with satellite images (J. Cheng & Masser, 2003; Habibi & Asadi, 2011; Irwin, Bockstael, Hg, Puga, & Ma, 2007; Sexton et al., 2013; X. J. Yu & Ng, 2007). However, such an approach to understanding changes in land cover caused by urban expansion has been insufficient, because most studies have applied change detection techniques to less-frequently observed time-series images such as those from Landsat and SPOT (Deng et al., 2008; Dubovyk et al., 2011; Jat et al., 2008; Rojas et al., 2013; X. J. Yu & Ng, 2007; Zanganeh et al., 2011). These satellites could not capture ger areas precisely due to the insufficient spatial resolution. Furthermore, the patterns of change on urban surfaces are also not clear, especially in terms of their temporal characteristics. However, a MODIS satellite has the advantage of performing observations on a regular basis (although the images are of a lower resolution than those from Landsat and SPOT), and by using the break points detected by BFAST in the seasonal components, we were able to identify when and where the land cover changed.

Results from a BFAST calculation over sample areas of open land, an area converted from open lands to ger areas, and an area of apartment

buildings, indicate the different wavelet characteristics of each land cover type (Figure 19). Although it was difficult to interpret the differences between each type of land cover using the observed data and the trend component, the characteristics were captured well by the seasonal component. The ger area (after the breakpoint in Figure 19 (b)) and the apartment area (Figure 19 (c)) have a notably strong cyclic interannual variation with one peak in each year, while the hilly open areas (Figure 19 (a), and the period before the breakpoint in Figure 19 (b)) have a less obvious periodicity. The breakpoint shown in Figure 19 (b) indicates the structural change of the seasonal component and gives a profound insight into the changes of land cover from the NDVI time series. In this way, use of the NDVI time series, particularly by BFAST, is able to describe land cover changes.

The results show that land cover changes occurred at the edge of the city center region in Ulaanbaatar (Figure 16), and that the changes have tended to occur at a later time with increasing distance from the city center (Figure 17). Due to the land reform legislation, the expansion of urban areas in Ulaanbaatar has accelerated since 2003. In the first stage of policy implementation, only lands at that time under unadmitted possession were privatized to families who lived on land in ger areas (Batbileg, 2007), and only those who lived there had the right to possess land. After this first wave of privatization, open land around the city center became attractive to new

migrants, and ger areas developed rapidly. The first step to claiming private land in open areas was the building of *khashaas* to clarify the property boundary, as described above, and as a result a vast number have been erected in ger areas (Byambadorj et al., 2011). The expansion of ger areas has also occurred to the north and north-west of the city, which are predominantly mountainous areas with steep slopes (Badamdorj, 2004).

Previously, the BFAST method has only ever been applied in areas of rich vegetation, for instance, with the aim of distinguishing plantation land from grassland and detecting forest fires (Gitas, Katagis, & Toukiloglou, 2012; Lambert, Jacquin, Denux, & Chéret, 2012; Schucknecht et al., 2013; Verbesselt, Hyndman, Newnham, et al., 2010; Verbesselt, Hyndman, Zeileis, et al., 2010). We have here identified that the BFAST method is also able to monitor land cover changes caused by urban expansion, however we acknowledge that the following lessons may be learned from further study. Firstly, in this investigation, we focused only on the seasonal component changes of BFAST, instead of the trend component changes. It is known that the detection of the trend component change in BFAST is much more sensitive than that of the seasonal component change (Verbesselt, Hyndman, Newnham, et al., 2010), as illustrated by the larger number of breakpoints in the trend component (areas of detected change were found to comprise 39.17% of the study area by this method). However, the trend component

includes abrupt and gradual changes in the NDVI time series (Verbesselt, Hyndman, Newnham, et al., 2010), which are regarded as disturbances and noise against the seasonal component changes (Verbesselt, Hyndman, Zeileis, et al., 2010). Consequently, we were not able to capture any meaningful information relating to land cover changes from the trend component. Secondly, in any investigation, the study period should be of a sufficient length to grasp the target phenomenon. We set the study period to be 11 years, from 2000 to 2010, and were required to exclude the first two years (2000 and 2001) and last two years (2009 and 2010) in order to set the segment size as two years. When conducting an analysis of time-series satellite images, this limited period is still considered to be relatively short for the detection of long-term land cover change (Verbesselt, Hyndman, Newnham, et al., 2010; White et al., 2009). Urban expansion is still progressing in Ulaanbaatar and monitoring should be continued in order to manage it. Continuous long-term observations on a regular basis and the construction of a spatio-temporal database would be useful in further understanding interannual spatial phenomena (Sexton et al., 2013). Thirdly, it is essential to precisely distinguish land cover types. Forests and the Tuul river were masked to focus on the urbanized areas profoundly affected by anthropogenic disturbances, although many changes were also found in the masked areas covered by rich vegetation. The Tuul river and the forests have different characteristics in the NDVI time series, and are more highly affected

by natural disturbances than human ones. Although it is currently difficult to acquire precise land classification maps in rapidly developing urban areas, validation data for change detection need to be collected, to enable future analysis to provide sufficient documentation of change events (i.e., before and after) (Lunetta et al., 2006). Ground-based land cover maps also need to be developed to understand the detailed land use and land cover changes. Finally, an accurate assessment of the result has yet to be developed. An assessment of the identified areas in which land cover has changed could be carried out using traditional methodologies derived from a confusion or error matrix (Foody, 2002; Lunetta et al., 2006). However, as mentioned above, time-series spatial information of the entire land cover is insufficient for the assessment of land cover changes, especially in terms of temporal changes, and although IKONOS and Quickbird images give fully detailed land cover data, the frequency of observations and their spatial ranges are limited. New remote sensing instruments such as RapidEye, which has a spatial resolution of 5 m and was launched in 2008, would provide great opportunities for this large-scale assessment as it has wider spatial extents compared to IKONOS and Quickbird.

Although these approaches can be considered in further studies, we believe that the use of BFAST in this investigation has provided meaningful results that are applicable in the monitoring of urban expansion

over large geographic regions. In addition, the application of BFAST, developed alongside a maximum utilization of MODIS time series, which cover the globe, and is available free of charge, could facilitate easy analysis in other regions.

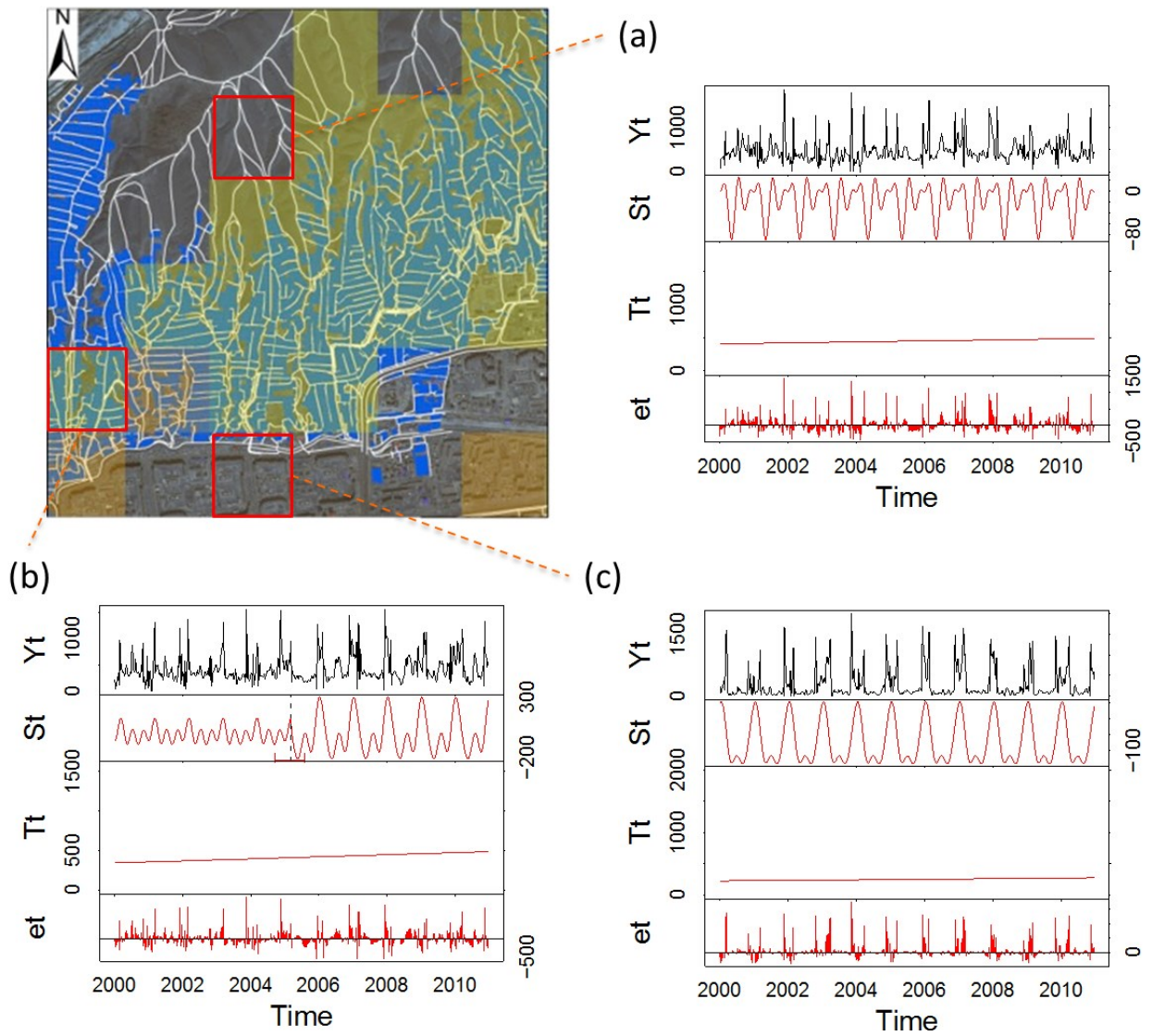


Figure 19. Results of applying BFAST method to sample sites.

(a) open land; (b) area converted from open land to ger-area; and (c) apartment.

5-7 CONCLUSIONS

Reliable information about land cover and land cover changes caused by urban expansion is clearly needed to enable informed planning decisions (Angel et al., 2011), because unplanned growth of ger areas and the unprecedented pace of urbanization in Ulaanbaatar have resulted in unemployment, traffic congestion, air pollution, and other negative environmental impacts (Kamata et al., 2010). The findings in this study could contribute to an understanding of the characteristics of urban expansion and consequently the countermeasures that must be taken to halt or minimize future haphazard urban expansion.

The BFAST method was applied for the first time to urban expansion analysis, and was able to estimate the time and location of land cover changes at the fringes of Ulaanbaatar, simultaneously and automatically. The results are verified by comparing bi-temporal VHR images, which show the actual land cover changes caused by anthropogenic disturbances, such as the development of residential plots. The areas of detected change are concentrated around the city center, indicating the high influence of anthropogenic effects. BFAST is shown to be a robust and applicable method for the monitoring of urban expansion, when carefully

applied and focused only on anthropogenic activities using a long observation period centered on the target phenomenon.

CHAPTER 6 ESTIMATING ENVIRONMENTAL CHANGES IN THE MUNICIPALITY OF ULAANBAATAR

6-1 INTRODUCTION

In this chapter, it is attempted to estimate the environmental changes through the vegetation trend analysis of vegetation biomass and vegetation cover in the Municipality of Ulaanbaatar. Degradation of vegetation biomass by anthropogenic activities such as overgrazing and deforestation has been a serious issue in Mongolia since the country's dramatic transition from a planned economy to a free-market economy in 1992 (Y. Cheng, Tsendeekhuu, Narantuya, & Nakamura, 2008; Tsogtbaatar, 2004). Although traditional nomadic pastoralism has supported a renewable and sustainable grassland ecosystem in Mongolia for more than 2000 years, excessive grazing pressure in recent times has been a major cause of vegetation degradation, as it depletes subsurface plant roots and inhibits re-growth after grazing (Research Institute for Humanity and Nature, 2013). The pasture usually recovers if it is free from grazing for a certain period; however, the resulting alkalization of the soil leads to the dominance of non-fodder plant species and further delays the recovery of the pasture when grazing continues (Research Institute for Humanity and Nature, 2013). The grazing pressure on grasslands was not significant during the socialist period,

because the livestock population was controlled by the authorities (Saizen, Maekawa, & Yamamura, 2010). However, since the transition to a market economy in 1992, the number of herders has more than doubled as a result of livestock privatization (Togtokh, 2008). Consequently, the number of livestock animals has also increased, especially goats for the export of cashmere (Saizen et al., 2010). This has caused degradation of vegetation biomass in the pastureland (Liu et al., 2013). In forested areas, deforestation, not only the degradation of vegetation biomass but also the diminishment of forest cover, has taken place due to anthropogenic activities (Allen, Barnes, & Barnest, 1985). Owing to the high demand for timber for fuel and industry, large parts of the forested areas have been destroyed by commercial and illegal logging in northern Mongolia and around Ulaanbaatar (Tsogtbaatar, 2004; UNDP Mongolia, 2009).

Decreases in vegetation biomass and changes in vegetation cover, such as conversions from forests to shrubs, or from grasslands to deserts, are markedly obvious in and around Ulaanbaatar (Hirano et al., 2006). Herders who have migrated into Ulaanbaatar usually bring their livestock, which consume fodder on the grasslands, resulting in the degradation of vegetation. Although the mechanisms by which vegetation biomass or vegetation cover changes as a result of overgrazing and deforestation have been presented by some researchers (Y. Cheng et al., 2008; Fujita et al.,

2009; Tsogtbaatar, 2004), the spatial distribution of this degradation is not yet well understood. Since decreases of vegetation biomass and changes in vegetation cover are caused by multiple driving forces on different scales, monitoring and understanding them is essential for preserving local vegetation resources.

6-2 STUDY AREA

The study area comprises the main part of the Municipality of Ulaanbaatar; around 4,000 km² in which the urbanized area is located in the central region between mountains (Figure 1).

6-3 INDICATORS FOR ENVIRONMENTAL CHANGES

NDVI is often examined as a proxy of vegetation biomass (Hirano & Batbileg, 2013; Kawamura et al., 2005; G.J. Roerink, Menenti, Soepboer, & Su, 2003). It has a great advantage for a wide range of monitoring of the vegetation biomass on land. Temporal observations from remote sensing instruments enable us to monitor the annual cycle of vegetation phenology (Pettorelli et al., 2005). Phenology is the study of the timing of recurrent

biological events, as well as the causes of such timing with regard to biotic and abiotic forces, and the interrelation among phases of the same or different species (Badeck et al., 2004; Lieth, 1974). By unpicking the greatest temporal increases in the NDVI, it is possible to retrieve phenological events from NDVI time series. For example, the start of the growing season (SOS), which is the onset day for the greening-up period within the annual cycle of vegetation phenology, can be estimated from NDVI time series and could be used as a proxy of vegetation cover (Alexander Buyantuyev & Wu, 2012; Jeong, Ho, Gim, & Brown, 2011; F. Yu, Price, Ellis, & Shi, 2003). Changes in vegetation cover are estimated from temporal changes in the SOS. For example, a degraded land surface as a result of overgrazing or a combination of overgrazing and climate stress may delay the SOS (F. Yu et al., 2003). Therefore, the NDVI and SOS are used as indicators of vegetation degradation and vegetation cover change, respectively.

6-4 METHODOLOGY

It is difficult to evaluate vegetation biomass by using NDVI during the winter seasons, due to the presence of snow in Mongolia (F. Yu et al., 2003). As such, annual vegetation biomass is estimated from the average of NDVI values collected only during the summer season each year. The

summer season is regarded as the period between the days of the year (DOY) 113 and 274 (or DOY 114–275, if it is a leap year). Then, NDVI_{avg} is calculated as the average of annual vegetation biomass during the study period. In order to detect significant changes in the annual vegetation biomass from the time series, NDVI_{slope} is calculated by time series regression, selecting only those pixels that were statistically significant according to their p-value ($p < 0.05$).

The calculation of SOS was conducted using the half-maximum method (Figure 20) (White, Nemani, Thornton, & Running, 2002). The satellite-derived SOS is determined as the day in which the NDVI lastly exceeds the threshold, which is half of the maximum NDVI in a year, in an upward direction between DOY 1 and 180 (Schwartz, Reed, & White, 2002; White et al., 2002; F. Yu et al., 2003). Similar to NDVI_{avg}, SOS_{avg} is calculated as the average of SOS days during the study period. In order to detect significant changes in vegetation cover from the time series, SOS_{slope} is calculated by time series regression, selecting only those pixels that were statistically significant, according to their p-value ($p < 0.05$). A field survey was conducted in September 2012, and it confirmed that the results from these remote sensing studies correspond to actual vegetation changes in the appropriate regions.

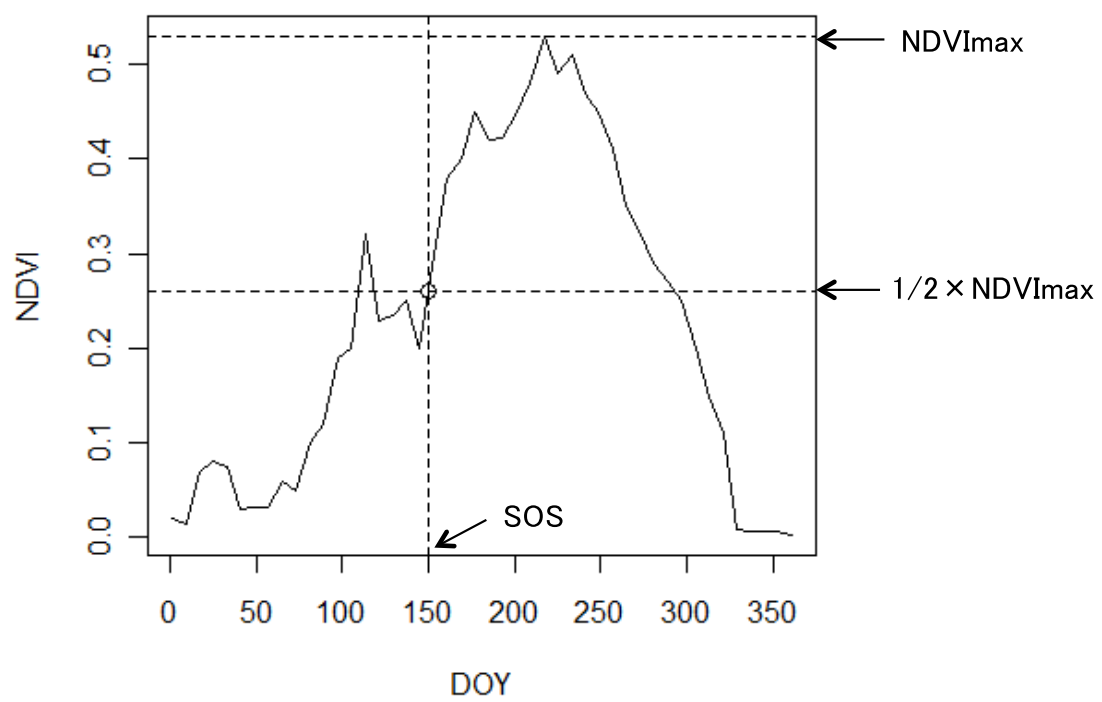


Figure 20. Calculation of SOS corresponding to half of NDVImax.

The SOS is determined only when the NDVI lastly exceeds the half of NDVImax in an upward direction between DOY 1–180.

6-5 RESULTS

The distributions of NDVI_{avg} and NDVI_{slope} are shown in Figure 21. NDVI_{slope} found the area with statistically significant positive/negative vegetation biomass to be 540.50 km². Most of the NDVI_{slope} values indicated negative trends, accounting for 527.25 km². The positive gain in vegetation biomass was seen in a *mountain taiga* region, across 13.25 km² of the Bogd-khan national park. The areas exhibiting negative trends in NDVI_{slope} were widely distributed across *mountain taiga*, *mountain forest*, and *mountain meadow steppe* in the northern part of the study area. Focusing on the Gorkhi-terelj national park, the majority of the negative trend is found in *meadow steppe* areas. The spatial average of NDVI_{avg} for each type of land cover (Figure 22) shows it to be highest in *mountain taiga* (0.6), followed by *mountain forest*, *meadow steppe*, and *mountain lowland pasture*. In contrast, *steppe and dry steppe* and *urban* areas have low values, of 0.30 and 0.36, respectively. Of those areas with negative trends in land cover (Figure 23), the percentage loss is highest in *mountain meadow* (43.3%), followed by *mountain lowland pasture*, *mountain forest*, and *mountain meadow steppe*. The distributions of SOS_{avg} and SOS_{slope} are shown in Figure 24. SOS_{slope} found the area with statistically significant positive/negative land cover changes to be 65.00 km². Most of the SOS_{slope} indicates positive (later SOS) trends, amounting for 62.75 km², and areas

having positive trends in SOSslope are distributed mainly in *mountain forest* and *mountain taiga* areas in the northwestern part of the study area, as well as being sparsely distributed in *mountain meadow steppe* and *urban* areas. The spatial average of SOSavg in different land cover types (Figure 25) shows it to be earliest in the *steppe and dry steppe* areas (134.1), followed by *mountain taiga* (134.5), and *urban* (138.1) areas. The latest SOSavg value is 145.4 in meadow steppe, and ranges 140–143 in the other land cover types. The percentage area with positive trends for each land cover type is highest in *mountain taiga* (4.3%), followed by *mountain forest* and *mountain meadow steppe* (Figure 26).

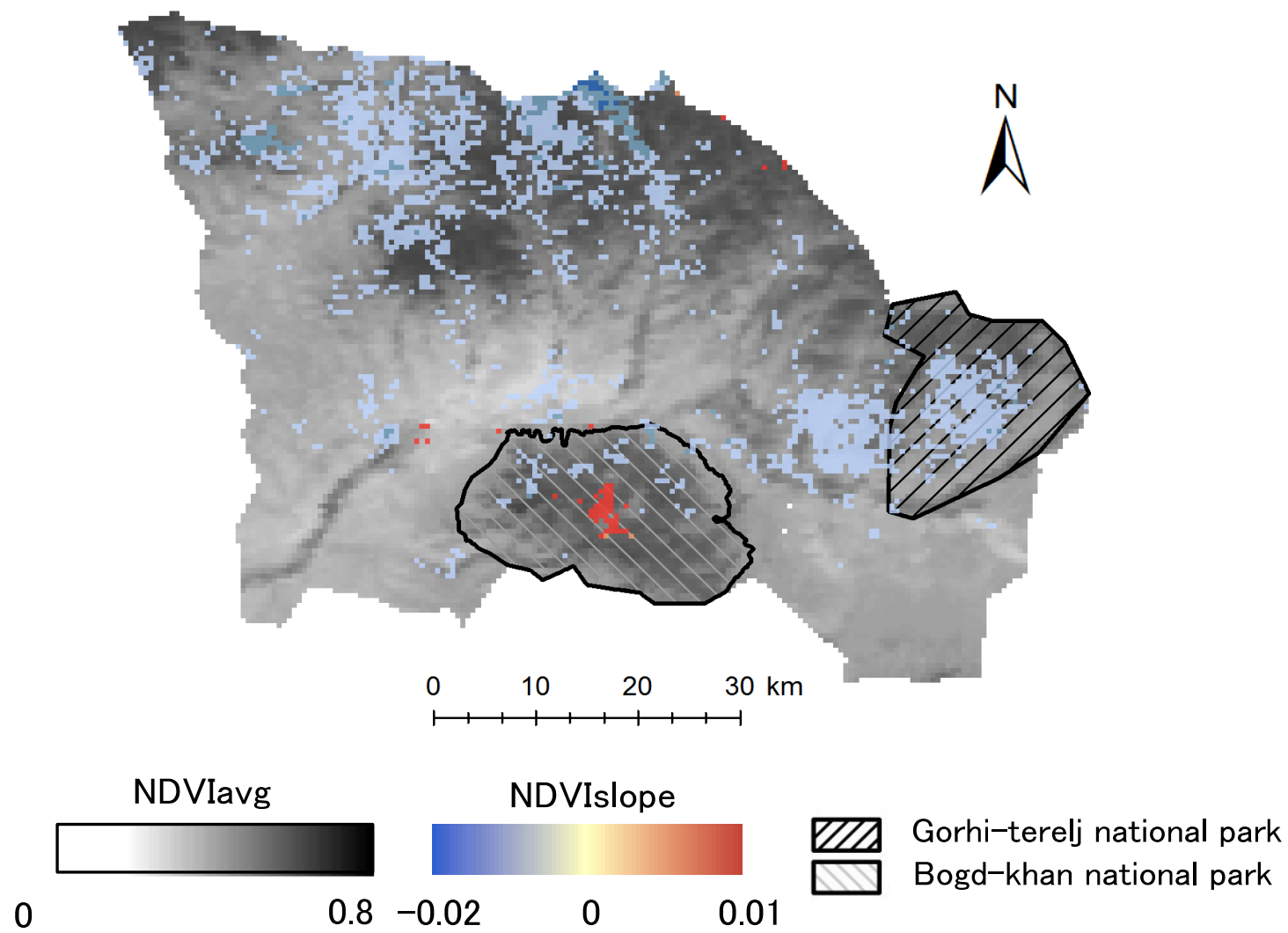


Figure 21. Spatial distributions of NDVIavg and NDVISlope.

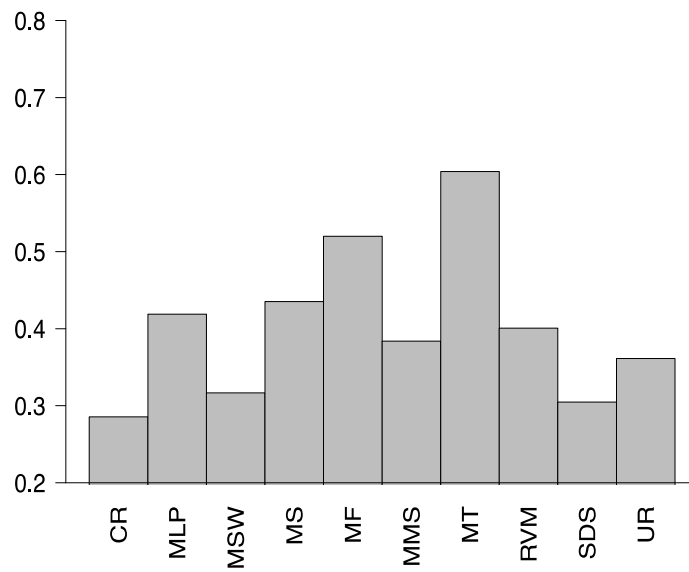


Figure 22. Spatial average of NDVIavg for each land cover type.

See land cover abbreviations in Table 1.

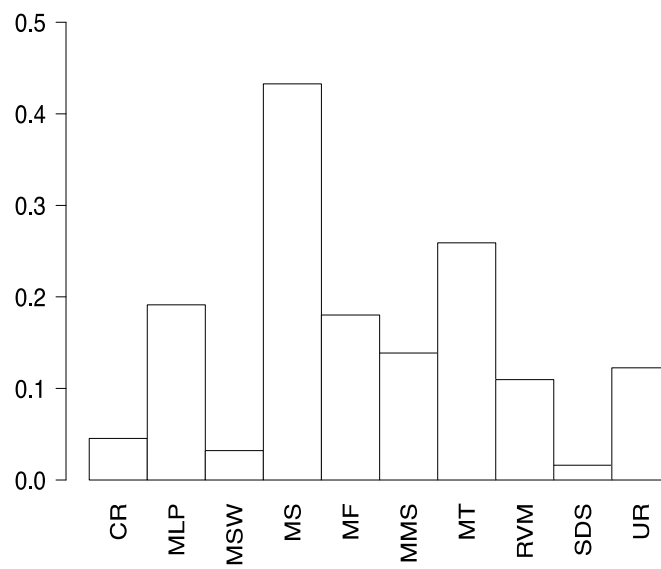


Figure 23. Ratio of the area showing a significant decreasing trend in NDVIslope to the total area, for each land cover type.

See land cover abbreviations in Table 1.

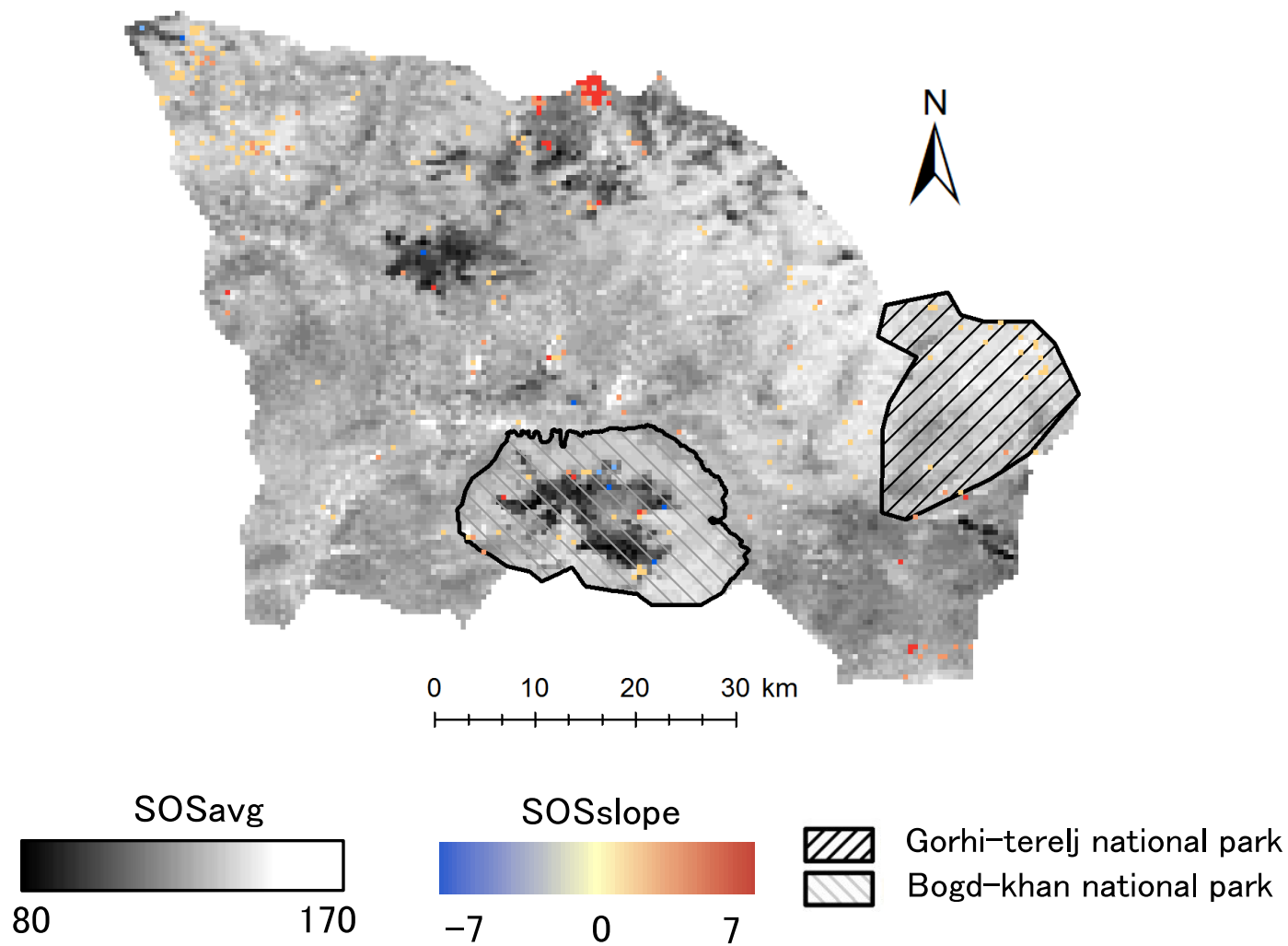


Figure 24. Spatial distribution of SOS_{avg} and SOS_{slope} .

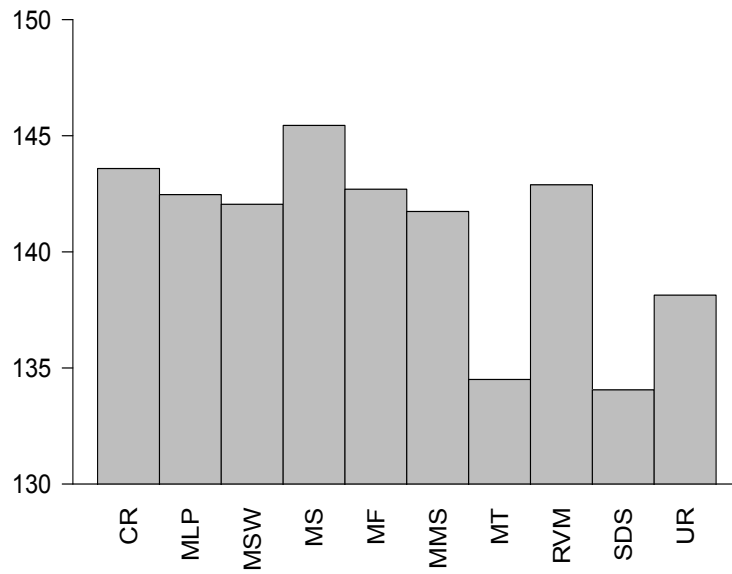


Figure 25. Spatial average of SOSavg for each land cover type.

See land cover abbreviations in Table 1.

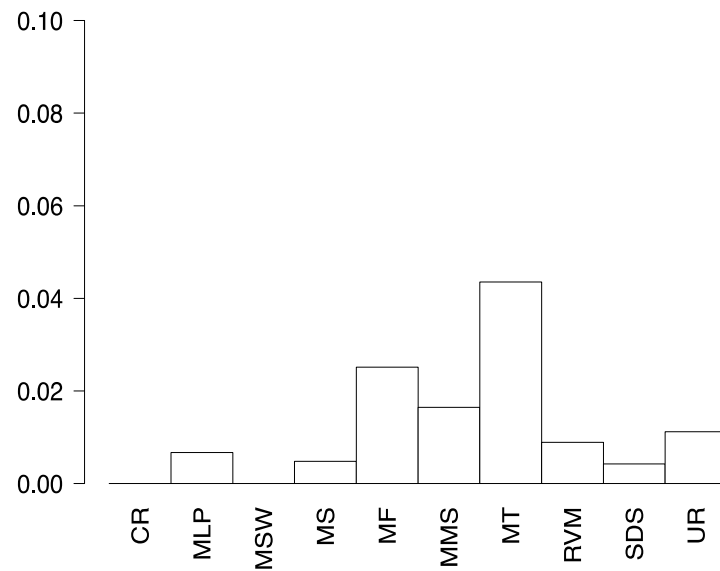


Figure 26. Ratio of the area showing a significant decreasing trend in SOSslope to the total area, for each land cover type.

See land cover abbreviations in Table 1.

6-6 DISCUSSION

The results show that the NDVIavg tends to be larger, the earlier the SOSavg is. For example, *mountain taiga* shows an early SOSavg and a large NDVIavg, while the inverse is seen in *meadow steppe*, as shown in Figure 21 and 24. Only *Steppe and dry steppe* has a different trend, showing an early SOSavg and a small NDVIavg. Since *Steppe and dry steppe* areas have sparse vegetation due to the high pressure of overgrazing (The World Bank, 2009a), this land cover tends to show a small NDVIavg. In addition, its earlier SOS compared to that of vegetated areas corresponds to the results of previous studies (Bradley, Jacob, Hermance, & Mustard, 2007; G J Roerink, Danes, Prieto, Wit, & Vliet, 2011). Focusing on the *mountain forest* and *mountain meadow steppe* areas, although there are not significant differences in SOSavg between the two land cover types, the NDVIavg in *mountain forest* is larger than in *mountain meadow steppe*. In this way, the characteristics of land covers can be summarized using NDVIavg and SOSavg values.

Negative trends in NDVIslope are found in the complex land covers that include forests and grasslands, while trends in SOSslope toward a later SOS are found mainly in forested areas. These areas detected by remote sensing are related to the degraded areas, which are affected by overgrazing

and deforestation. For example, a combination of decreasing trends in NDVIslope is found in *meadow steppe* areas in the Gorkhi-terelj national park (Figure 21). This corroborates the report by The World Bank (2009), which observes that the lands are significantly affected by intense use and resultant degradation of land resources. Permanent houses and dense settlements, including tourist camps, have been spreading here. Most herders living close to this park do not tend to move for richer fodders, instead causing land degradation through intense grazing of a single region (The World Bank, 2009). In the north-west part of the study area, decreasing trends in the NDVIslope as well as later trends in SOSslope are found. In particular, later trends in SOSslope are sparsely distributed around those areas that have a high vegetation biomass or early SOS. This result is in agreement with the report by UNDP Mongolia (2009) that documented illegal logging of a large area of forest for domestic purposes. The vegetation cover in these detected locations confirmed the conversion from larch trees to shrubs in the field survey. Although the SOSslope is not able to identify vegetation cover changes in grasslands, a change can be detected in forested areas. Positive trends in NDVIslope were found only in the central part of Bogd-khan national park, because this park is a strictly preserved area. However, the peripheral areas of the park show decreasing trends in NDVIslope, indicating that some settlements and tourist camps have been developed in these regions.

6-7 CONCLUSION

Changes in vegetation biomass and land cover are detected in Ulaanbaatar, using MODIS time series for the period 2000–2010. By analyzing temporal trends in NDVI over 11 years, results show that vegetation biomass has decreased across around 13% of the study area. This result corresponds to previous reports on land degradation caused by anthropogenic activities, especially in the Gorkhi-terelj national park and forested areas of the north-west part of the study area. In addition, by analyzing temporal trends of SOS in the 11-year study period, significant later trends in SOS are detected around areas with rich vegetation biomass. This result corresponds to the areas that have experienced vegetation cover changes, the conversion from larches to shrubs because of logging activity. Although the SOS does not contribute to the detection of land cover changes in grasslands, it is able to support estimations of drastic changes in forested areas.

CHAPTER 7 GENERAL CONCLUSION

An understanding of the spatio-temporal characteristics and changes in land cover, as well as the environmental impacts caused by urban expansion, are clearly required to enable informed planning decisions in the future (Angel et al., 2011). In the case of Mongolia, the unplanned growth of ger areas and the unprecedented pace of urbanization in Ulaanbaatar have resulted in poor living conditions, including unemployment, traffic congestion, and air pollution (Kamata et al., 2010). The findings of this research may contribute to the scientific understanding of the characteristics of urban expansion and its impacts on vegetation in a number of ways, detailed below.

In chapter 4, it was shown that residential plots have been expanding towards the outer boundary of Ulaanbaatar's city center. By using object-based GIS data, the residential-scale process of urban expansion in Ulaanbaatar was illustrated for the first time. In addition, a logistic regression model was applied, providing some valuable quantitative insights into the patterns and possible controlling factors of the ger area expansion. In chapter 5, the BFAST method was used to show pixel-based land cover changes in Ulaanbaatar, enabling simultaneous and automatic estimation of the timing and location of land cover changes. The areas undergoing land cover changes were found to concentrate around the city center, and expand

towards the outer boundary of the city center each year, indicating the significant effects of anthropogenic activity on land cover. Environmental changes were evaluated through vegetation trend analysis, and the results indicated that a decrease in vegetation biomass had occurred across 13% of the Municipality of Ulaanbaatar during the period 2000–2010. Within the major agglomeration, the decreasing trend of vegetation biomass corresponded to those areas where severe land degradation had been reported, as a result of anthropogenic activities. Changes in vegetation cover from larches to shrubs, as a result of logging activities, were seen around areas with a rich vegetation biomass.

The results in chapter 4 and 5 indicate that the land reform policy was a critical event in the social development of the region, accelerating the concentration of population and the expansion of ger areas in Ulaanbaatar. Considering the environmental problems caused by such an expansion, the encroachment into peripheral areas should be restricted by land use regulation, however it will be difficult to control the phenomenon without first solving the prevailing political issues. Although the government promoted the construction of high-rise apartments under the 40,000 housing units program around 2003, and the 100,000 housing project around 2008 (Byambadorj et al., 2011; Kamata et al., 2010), the low-income groups residing in ger areas are resistant to moving into apartments because of the large expenses

involved (Japan International Cooperation Agency, 2009). Thus, alternative countermeasures are needed for the poorer demographic, to improve their living conditions. Here, I would like to propose such a countermeasure, which is a conceptual strategy to prevent irrational encroachment of urban developments. Based on the fact that ger areas are undergoing continual expansion, as addressed in chapter 4 and 5, it is recommended that residents of ger areas who do not fully meet the living standards are preferentially given the right to migrate to new residential areas that are totally supported by both urban planning and land reform policy, which may be developed instead of improving infrastructure in existing ger areas (Figure 27). To implement this, the government would first prohibit extra settlement development in ger areas by land control, and strictly register all private land in a land management system. The government may then concentrate its budgets on the development of new residential zones with the minimum living infrastructure necessary, for the benefit of residents that are dissatisfied with their current living situation in ger areas. Although there may be residents who are not eager to leave, and wish to stay in the ger areas, the government should not make further developments there. In this way, the government can increase the extent of such residential zones gradually, by controlling land use, and halt the expansion of ger areas allowing their development to be more efficiently managed. This research has highlighted several environmental problems that, from a scientific viewpoint, are the result of

human activities and the failure of land-use policies. There is nothing to say that comprehensive legal system between the new master plan and land law should be stipulated clearly.

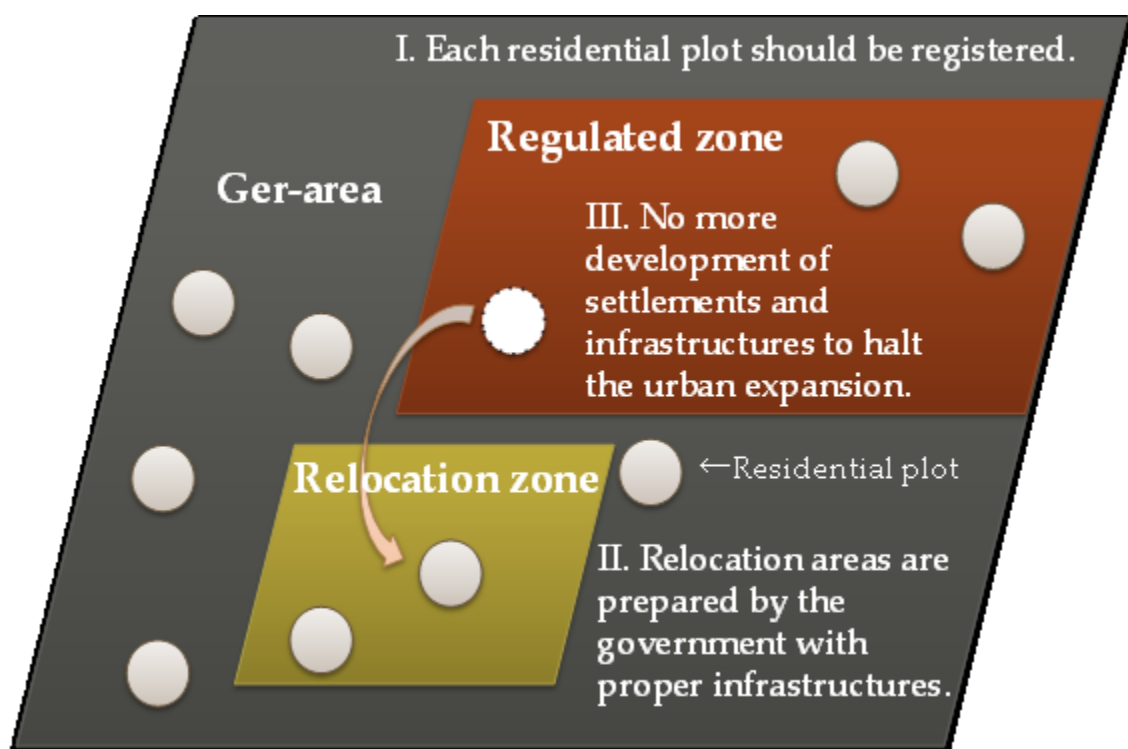


Figure 27. Conceptual strategy for preventing urban expansion in ger areas.

This study not only reinforces the necessity for an effective urban plan for Ulaanbaatar, but also provides operational information for planning purposes, including maps and GIS layers of the actual extent of ger areas, the patterns of development, and the locations of developed and degraded areas, through the use of remote sensing technologies. To manage the ongoing urban expansion, it is essential to continue further research and conduct continuous and real-time monitoring over a wider range of peripheral areas, as well as in the city center of Ulaanbaatar. For approaches using VHR imagery, there is still a lack of robust technology to extract the GIS data that characterizes urban objects. Thus, the data processing employed in Chapter 4 is time-consuming because the data are manually extracted from the VHR imagery. It will therefore be necessary to develop an automation scheme for data processing, which has been shown to be feasible in some cases through the integration of VHR imagery with machine learning technology (Hussain, Chen, Cheng, Wei, & Stanley, 2013; Myint et al., 2011; Taylor, Street, & Wt, 2010). Such a scheme will enable us to fulfill a large proportion of the monitoring requirement, because of the broad availability of such images. For approaches using MODIS time series, the results given by BFAST still lack information about real-time changes in land cover, as a result of the minimal segment size used in the analysis. To overcome this limitation, accurate and robust techniques would need to be developed in the near future, to detect real time changes in land cover using MODIS time

series. Developments in these types of rapid monitoring systems and related studies in the future would assist immediate decision-making and sustainable urban management.

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