# STUDY ON SPATIAL-TEMPORAL URBAN GROWTH AND LAND CONSUMPTION PATTERNS OF THIMPHU, BHUTAN USING MULTI-TEMPORAL SATELLITE IMAGES

Indra Bahadur Chhetri

Department of Civil Engineering and Surveying, Jigme Namgyel Engineering College, Dewathang

*indrachhetri.jnec@rub.edu.bt*

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***Abstract—*** *Like many other countries, Bhutan is also experiencing rapid trend of urban expansion mainly due to out-migration from rural to urban areas particularly in capital city, Thimphu. This study focuses on the dynamics of urban expansion, evaluating urban growth and land consumption pattern of Thimphu, using multi-temporal Landsat images during the year 1990-2018. The main aim of the study is to perform supervised classification to classify built-up area, green area, bare-land and others (water bodies, agricultural lands, etc…) and to perform a change analysis from the viewpoint of increasing the built-up areas (man-made structures) and decreasing in green and open spaces. Moreover, the study also highlights how has the land consumption pattern of the region changed over the years. The findings of the study confirmed that the Thimphu city has its built-up areas increased during 1990-2018 with net growth of 4.63 km2 (106.19%). The urban area was 4.36 km2 in 1990, 5.80 km2 in 2000 (33.03% growth), which increased to 7.24 km2 in 2013 (24.83% growth) and 8.99 km2 (24.17% growth) in 2018. The study also showed that there is decrease in land consumption between 1990-2018. In 1990, land consumption was 155.65 m2 per person which decreased to 78.48 m2 per person in 2018. This decrease in land consumption indicate that the city is experiencing increased densification between the years 1990-2018. The classifier performance evaluation was done using overall accuracy and kappa coefficient. The classification produced an overall accuracies ranging between 78.74% to 90.46 % and overall kappa statistics between 0.72 to 0.87 for all years indicating classification accuracy of moderate to substantial accuracy.*

***Keywords— Land Consumption Pattern (LCP), out-migration, landsat images, Thimphu city, urban growt***

## 1. INTRODUCTION

Urbanization and shape of the surrounding regions are always an important factor in the developmental progress. Due to the dynamic, complex and multifunctional nature of the urbanized areas, the comprehensive study on landscape conditions and alteration patterns are significantly vital to obtain reliable information during decision making processes [1], [2]. Urban growth is the extension of new developments from an urban region to the surrounding countryside. Urbanization-related land transformation demands significant consideration and prioritization, particularly in a developing nation like Bhutan [3]. In general, there are two components of land use - land use planning and land use regulation/ monitoring. The purpose of land use planning is to avoid land use conflict between government, commercial, and citizen stakeholders, the result of which can be legal entanglements or environmental degradation. Land use regulation, of which remote sensing monitoring is a component, conducted to ensure that real land use matches planned land use and that instances of deviation are recorded.

The actual changes of landscapes are induced by urbanization processes such as residential or industrial land development and new communication infrastructures. Due to this developmental process, population in urban cities are growing more rapidly than in rural areas worldwide, particularly in developing countries [4]. Additionally, urbanization process also result in loss of fertile land which is a severe violation of the country's limited agricultural land [5]. The sprawling nature of urban development in the areas of big cities in developming nations is the widely seen phenomenon of all urban population growth [6], [7]. With no exception, Bhutan is also experiencing a similar trend of urban expansion mainly due to internal migration from rural to urban areas especially in capital city, Thimphu. Thimphu city has seen its major development in the recent years where in the past the valley mostly consisted of terraced fields mostly used for rice cultivation. The year 1990s marked the consolidation of traditional architecture using modern technologies employing trained engineers and architects in T¬himphu and towns in other districts [8]. Thimphu city has also seen a significant transformation of its landscapes in the last four decades resulting in substantial land use and land cover (LULC) change; however, no major systematic analysis of the urbanization trend and LULC has been conducted on this valley over the years explicitly. Remote sensing data of urban environments are predominantly being used by many researchers and decision makers as an effective procedures for mapping land use/land cover, building density, climatic conditions, socio-economic characteristics and their inter-relationship in the area of interest over a long period without an in situ observations [9]–[11]. Land use/cover information plays a significant role in timely, accurately and effectively monitoring land use changes which enable the policy makers in city regions to make a reasonable decision on managing urban land resources effectively [12]–[14]. Therefore, to fill this gap, a change analysis is performed from the viewpoint of increasing the built-up areas (man-made structures) and decreasing in green and open spaces. Among the various available data source, many other studies that relates land cover observations have used Landsat images as a primary data source. Since 1972, numerous studies have used data from the Landsat Multispectral Scanner (MSS), Thematic Mapper (TM), and Enhanced Thematic Mapper Plus (ETM+) to determine land cover [9], [15]–[17].

## 2. STUDY AREA

The study area, Thimphu is the largest city and the capital of Bhutan. It lies in the Western part of the country (27°8' to 27°59' latitude and 89°13' to 89°46' longitude). Fig. 1 shows an official boundary of Thimphu city, which is the study area. Its approximate altitude ranges from 2,240 to 2,648 msl with the surrounding hills rising over 3800 msl. The city part of the valley enjoys a warm, temperate climatic condition with warm summer and cold and dry winter. The annual rainfall varies between 500 mm and 1000 mm. The average daily winter temperature varies between 5–15°C and the average daily temperature during summer varies between 15– 30°C. Thimphu is accessible by road, from India through the southern town of Phuentsholing, which is about 175 km away. It is also accessible by air from Paro, which is about 55 km.

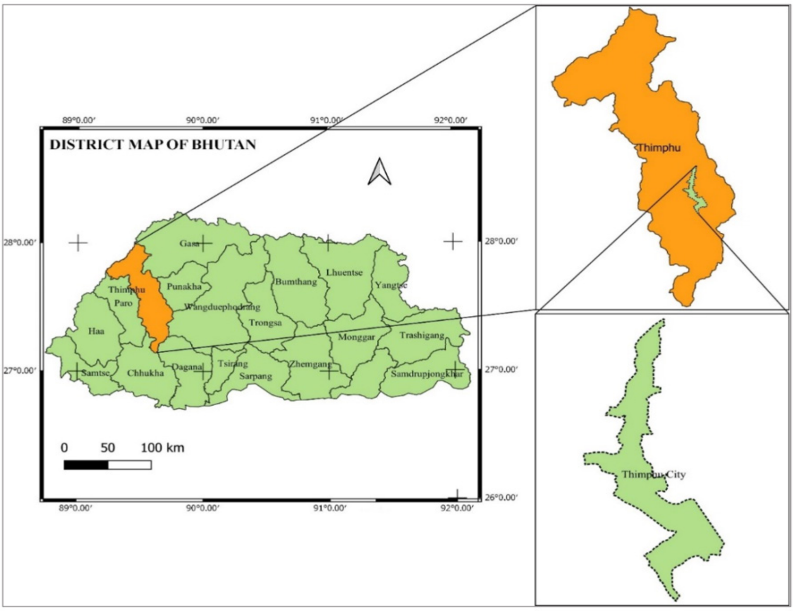


**Fig. 1.** Location of Thimphu (Study area), the capital city of Bhutan

In the short span of time, drastic urbanization and development is observed in Thimphu city with the initiation of planned development program in the region as late as 1985 i.e. Thimphu Urban Development Plan (1986-2000). According to the National Housing and Population Census Report (2005), the Thimphu city population was 79,185 (or 15,728 households) with a total area of about 26 km2 implying a population density of 3,046 people per km2. Thimphu city contributes 40% of the nation's urban population and 12.5% of the national population of the total urban population of 196,111 in 2005 [8]. The total population of the city was 16000 in 1986, 43479 in 2000, 79185 in 2005, and 114551 in 2017 (Fig. 3). The city's population increased by 2.72 times in 1986-2000 period and 2.64 times from 2000-2017. The population density of the city was 616 persons/km2 in 1986, 1672 persons/km2 in 2000, 3046 persons/km2 in 2005 and 4406 persons/km2 in 2017. The increase in population was mainly due to the increasing rate of out-migration from rural to urban areas as a result of increase in unemployment youths in search of better opportunities in the urban centers. Moreover, various ministries and departments of Royal Government of Bhutan, private sector enterprises, trade, transport and tertiary services are present in the city which attracted most immigrants to Thimphu. As a result, the increase in physical population density has significantly narrowed the open and green spaces in the city and had led to a rapid increase in commercial and residential areas.

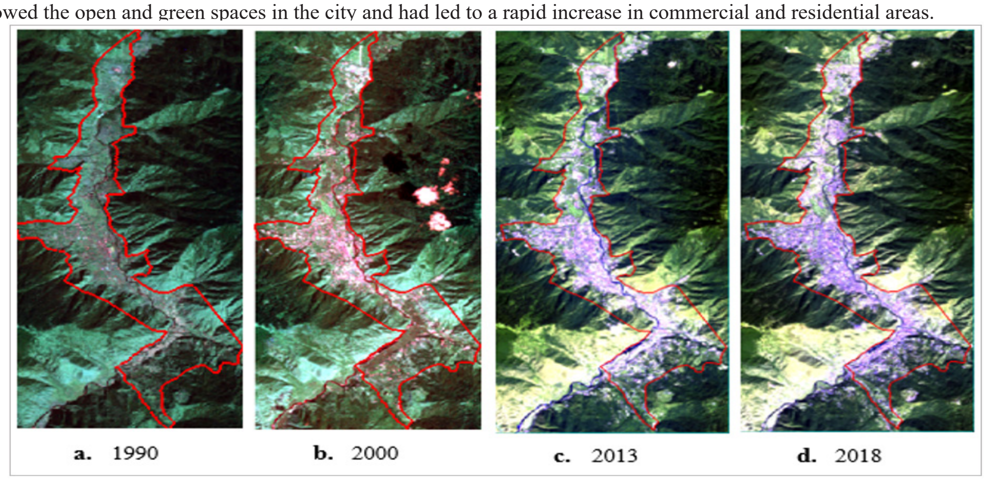


**Fig. 2.** Landsat 5 (TM), Landsat 7 (ETM+) and Landsat 8 (OLI) Satellite images of Thimphu City (False colour composite images)

## 3. DATA USED

In this study, the multi-temporal Landsat data series of 1990 (Landsat 5-Thematic Mapper (TM)), 2000 (Landsat 7 – Enhanced Thematic Mapper Plus (ETM+), 2013 and 2018 (Landsat 8 – Operational Land Surface Imager (OLI)) were used. The remote-sensing data, were downloaded from freely available Landsat archive of National Institute of Advanced Industrial Science and Technology (hereinafter referred to as "AIST"), Geological Survey of Japan and freely available Landsat archive of United States Geological Survey (USGS) (http://earthexplorer.usgs.gov/). The Landsat 8 images data (2013 and 2018 images) used in this study being processed by AIST is originally from US Geological Survey. Table 1 show the characteristics of the Landsat data and the information of the images used to produce the final classified map. Fig. 3 shows the change in population of the Thimphu city over the years.

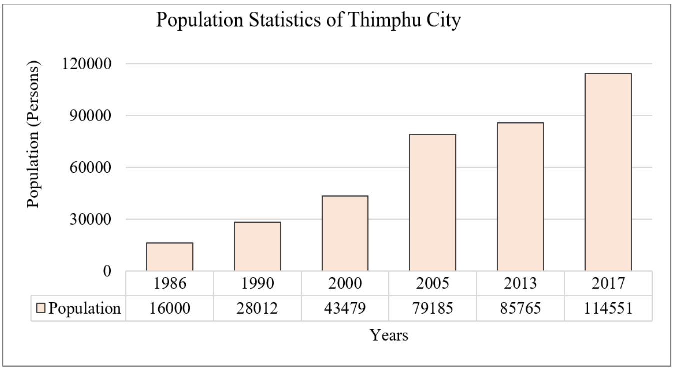


**Fig. 3**. Population statistics of Thimphu City in selected years

**Table 1**. Detailed description of the satellite imageries.

| Satellite | Landsat 5 | Landsat 7 | Landsat 8 | Landsat 8 |
|---|---|---|---|---|
| Sensor ID | TM | ETM+ | OLI TIRS | OLI TIRS |
| Acquisition Date | 16 Dec. 1990 | 30 Sept. 2000 | 12 Sept. 2013 | 27 Oct. 2018 |
| Cloud Coverage (%) | 0 | 0 | 0 | 0 |
| Pixel Size (m) | 30 | 30 | 30 | 30 |
| Band Combination | 1-5-7 | 1-5-7 | 7-6-2 | 7-6-2 |
| Path/Row | 138/041 | 138/041 | 138/041 | 138/041 |

## 4. METHODOLOGY

Deep learning (DL) techniques have recently been widely incorporated for the classification of remote sensing images, but fewer research have used them for land consumption (LC) i.e the land transformation process which results into the loss of agricultural, natural and semi-natural areas due to the construction of new buildings, the expansion of cities, and the infrastructure in the city [18], [19]. In this study, multi-temporal Landsat images were acquired for the years 1990, 2000, 2013 and 2018. In the first step, layer staking was carried out followed by clipping the study area using an official boundary of Thimphu municipal boundary shape-file. Secondly, different band combination was performed in order to better visualize the Landsat images. The sensors present in the Landsat satellite has different bands in different wavelengths. The OLI sensor aboard Landsat 8 has nine bands for capturing the spectral response of the earth's surface at discrete wavelengths along the electromagnetic spectrum. Landsat 7 (ETM+) images consist of eight spectral bands with a spatial resolution of 30 meters for Bands 1 to 7 and 15 meters for Band 8 (panchromatic). Landsat 5 (TM) images consist of seven spectral bands with a spatial resolution of 30 meters for Bands 1 to 5 and 7. Spatial resolution for Band 6 (thermal infrared) is 120 meters, but is resampled to 30-meter pixels. The Table 2 shows various bands from Landsat 8 OLI TIRS sensor and how these bands from Landsat 8 OLI multi-spectral bands line up with Landsat 7 (ETM+) and Landsat 5 (TM) sensors. From the literature, different band combinations are available with varying capabilities to distinguish various features in a Landsat images [15], [17], [20]. For the purpose of this study, bands 1, 5 and 7 were chosen for Landsat 5 and 7 (1990 and 2000 images) and band combinations of 2, 6 and 7 were chosen for Landsat 8 (2013 and 2018 images). After successful band combinations different land use/land cover classes was mapped for each year of the select city using supervised classification technique. The successful classification primarily depends on selection of suitable classification method [21]. Currently, there are various techniques available for change detection [22], [23]. The supervised classification technique employing Maximum Likelihood Classifier algorithm is the most commonly and widely used algorithm with higher classification accuracies [24].

In this algorithm the pixel-based approach was used to assign the pixel to each classes with the highest matching probability. Therefore, Maximum Likelihood Classifier classification procedure was used to classify the region into at least four major land use classes for each image. This include-urban/built-up areas, green areas, bare land and others (water bodies, agricultural land etc…) for each images. The image classification consisted of carefully selecting training samples and testing samples to produce an accurate classification. LULC maps published by forest resource management division under ministry of agriculture and forest, Bhutan, Google Earth images, expert knowledge from local land owners and visual interpretation of colour composite images were utilized as a reference data for selecting the training and testing samples. The Table 3 shows the number of training pixels and testing pixels generated for each classes.

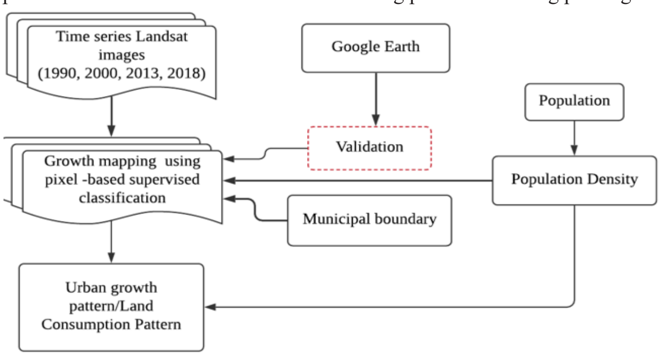


**Fig. 4.** The flowchart of the proposed method for LULC mapping

**Table 2.** Landsat multi-spectral bands and how the bands from Landsat 8 line up with Landsat 7 (ETM+) and Landsat 5 (TM)

| Landsat 8 OLI | | | Landsat 7 ETM+ | | | Landsat 5 TM | | |
|---|---|---|---|---|---|---|---|---|
| Band Name | Wavelength (µm) | Resolutions (m) | Band Name | Wavelength (µm) | Resolutions (m) | Band Name | Wavelength (µm) | Resolutions (m) |
| Band 1 Coastal/Aerosol | 0.43 – 0.45 | 30 | | | | | | |
| Band 2 Blue | 0.45 – 0.51 | 30 | Band 1 Blue | 0.45-0.52 | 30 | Band 1 Blue | 0.45-0.52 | 30 |
| Band 3 Green | 0.53 – 0.59 | 30 | Band 2 Green | 0.52-0.60 | 30 | Band 2 Green | 0.52-0.60 | 30 |
| Band 4 Red | 0.64 – 0.67 | 30 | Band 3 Red | 0.63-0.69 | 30 | Band 3 Red | 0.63-0.69 | 30 |
| Band 5 NIR | 0.85 – 0.88 | 30 | Band 4 NIR | 0.77-0.90 | 30 | Band 4 NIR | 0.77-0.90 | 30 |
| Band 6 SWIR 1 | 1.57 – 1.65 | 30 | Band 5 SWIR 1 | 1.55-1.75 | 30 | Band 5 SWIR 1 | 1.55-1.75 | 30 |
| Band 7 SWIR 2 | 2.11 – 2.29 | 30 | Band 7 SWIR 2 | 2.09-2.35 | 30 | Band 7 SWIR 2 | 2.09-2.35 | 30 |
| Band 8 - Pan | 0.50-0.68 | 15 | Band 8 Pan | 0.52-0.90 | 15 | | | |
| Band 9 - Cirrus | 1.36-1.38 | 30 | | | | | | |
| Band 10 TIRS 1 | 10.6 – 11.19 | 100 | Band 6 TIR | 10.40-12.50 | 60 (30) | Band 6 TIR | 10.40-12.50 | 120 (30) |
| Band 11 TIRS 2 | 11.5 – 12.51 | 100 | | | | | | |

**Table 3.** Number of pixels of training samples and testing samples for each classes

| Classes/ Year | Training Pixels | | | | Testing Pixels | | | |
|---|---|---|---|---|---|---|---|---|
| | Built up areas (no. of pixels) | Green areas (no. of pixels) | Bare Land (no. of pixels) | Others (no. of pixels) | Built up areas (no. of pixels) | Green areas (no. of pixels) | Bare Land (no. of pixels) | Others (no. of pixels) |
| 1990 | 388 | 4556 | 183 | 155 | 110 | 115 | 100 | 101 |
| 2000 | 429 | 2025 | 115 | 651 | 131 | 154 | 102 | 100 |
| 2013 | 411 | 2215 | 242 | 255 | 118 | 120 | 107 | 120 |
| 2018 | 2523 | 2993 | 131 | 349 | 148 | 161 | 100 | 113 |

## 5. RESULTS

In order to evaluate the percentage of changes in land consumption pattern, various satellites images (Table 1) is being explored to map the urban growth of Thimphu city from the given years in 1990, 2000, 2013, and 2018. Supervised classification using Maximum Likelihood Classifier algorithm was applied using ENVI 5.5. The classification was carried out by carefully selecting the training samples of four classes as shown in Table 3. Since some of the features such as water bodies, man-made structures, barren land and others under the study area are found smaller in size and also due to medium resolution of Landsat images, some patches of areas might have been misclassified. The classification results exhibited that the percentage of man-made structures has increased over the years. However, there is significant decrease in percentage of green area coverage. The number of pixels count on each classes in each year is shown in Table 4, while the percentage change of each classes are depicted in Table 5 which can be further visualized in Fig. 5. From the result it is shown that the built-up areas have expanded by about 17.64% over the period from 1990 to 2018, while there was decrease in green areas by around 19.16%. The increase in man-made structures have been observed significantly between the years 1990 to 2000 (5.49%) and 2013 to 2018 (6.68%). There was a significant increase in the percentage (14.78%) of land areas in 2013 than in other years. This is mainly due to a boom in the construction sectors along Olakha and Babesa areas. The Fig. 6 shows the land cover map of Thimphu city divided into four classes in the years 1990, 2000, 2013 and 2018. The images show an increase in the built-up areas and decrease in green areas over the years.

The result also confirmed that the Thimphu city has its built-up areas increased during 1990-2018 with net growth of 4.63 km2 (106.19%). The urban area was 4.36 km2 in 1990, 5.80 km2 in 2000 (33.03% growth), which increased to 7.24 km2 in 2013 (24.83% growth) and 8.99 km2 (24.17% growth) in 2018 as shown in Table 6. There is also decrease in land consumption between 1990-2018. In 1990, land consumption was 155.65 m2 per person which decreased to 78.48 m2 per person in 2018 that deduces the correlation between urban growth and population growth of the city. Therefore, this periodic decrease of land consumption indicate that the city experienced a decreasing trend indicating increased densification between the years 1990-2018.

**Table 4.** The four classes and the number of pixels in the images for each year

| Classes | Years (No. of pixels) | | | |
|---|---|---|---|---|
| | 1990 | 2000 | 2013 | 2018 |
| Built up Area | 4842 | 6446 | 8043 | 9994 |
| Green Area | 16659 | 13392 | 12913 | 11064 |
| Bare Land | 1000 | 1153 | 4314 | 1998 |
| Others | 6693 | 8203 | 3924 | 6138 |
| Total | 29194 | 29194 | 29194 | 29194 |

**Table 5.** The four classes and their percentages in the images by years

| Classes (%) | Years | | | |
|---|---|---|---|---|
| | 1990 | 2000 | 2013 | 2018 |
| Built up Area | 16.59 | 22.08 | 27.55 | 34.23 |
| Green Area | 57.06 | 45.87 | 44.23 | 37.90 |
| Bare Land | 3.43 | 3.95 | 14.78 | 6.84 |
| Others | 22.93 | 28.10 | 13.44 | 21.02 |
| Total | 100 | 100 | 100 | 100 |

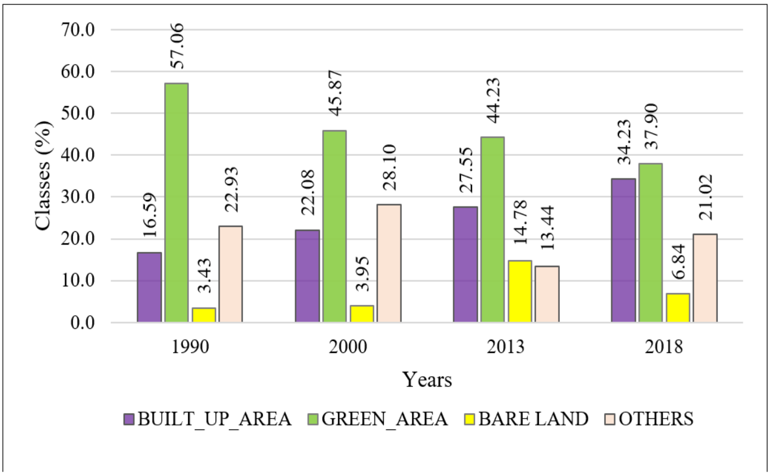


**Fig 5**. Percentage changes in the four classes by years

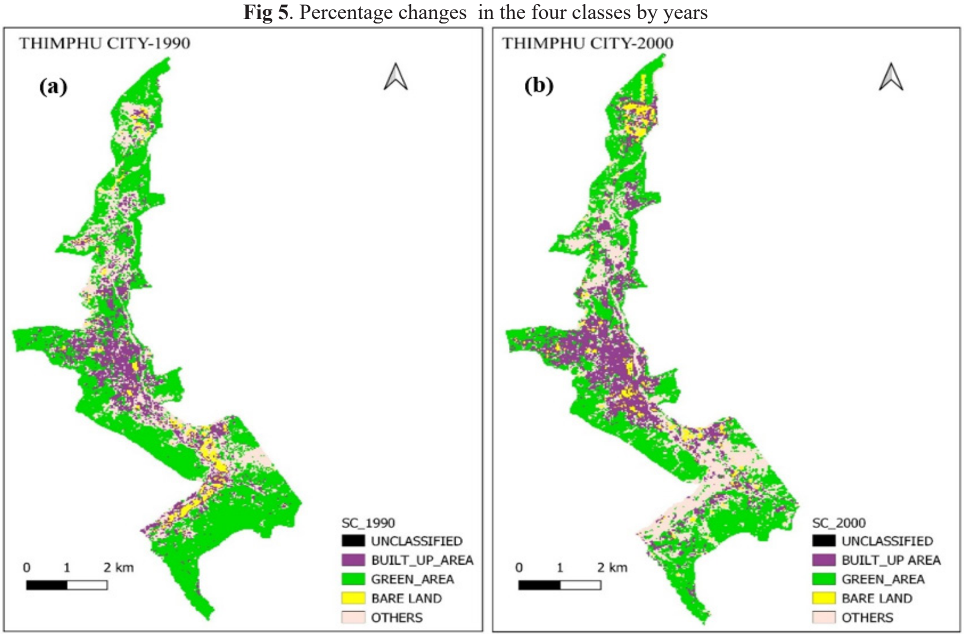


**Fig. (6).** Land cover map of Thimphu City in the years (a) 1990, (b) 2000, (c) 2013 and (d) 2018)

**Table 6.** Urban Growth and Land Consumption Patterns (LPC) of Thimphu City during 1990-2018

| Year | Population (Persons) | Built-Up-Area ($km^2$) | Urban Growth (%) | LCP ($m^2$/person) |
|---|---|---|---|---|
| 1990 | [a] 28012 | 4.36 | ------- | 155.65 |
| 2000 | [b] 43479 | 5.80 | 33.03 | 133.40 |
| 2013 | [c] 85765 | 7.24 | 24.83 | 84.42 |
| 2018 | [d] 114551 | 8.99 | 24.17 | 78.48 |

[a] Estimated [16]
[b] Estimated [8]
[c] Estimated-Data Collection Survey on Urban Development and Environment in the Kingdom of Bhutan [25]
[d] Population and Housing Census of Bhutan 2017 (PHCB, 2017)

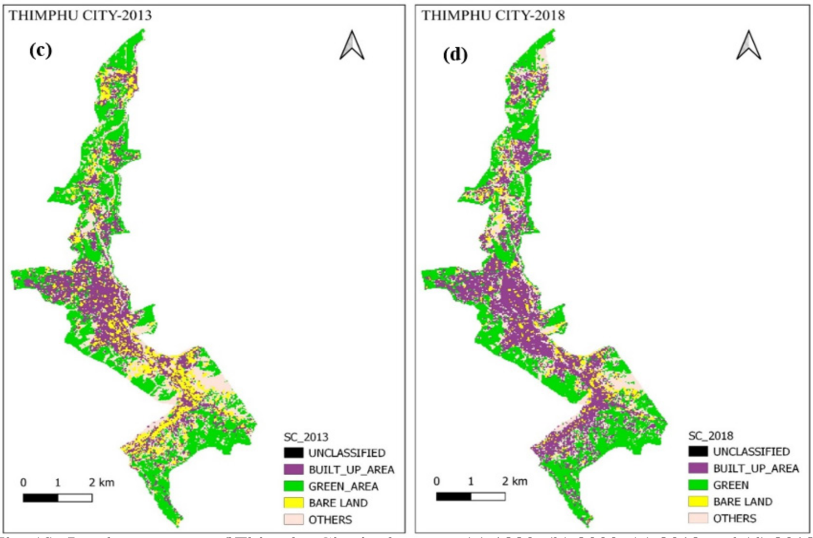


**Fig. (6).** Land cover map of Thimphu City in the years (a) 1990, (b) 2000, (c) 2013 and (d) 2018)

## 6. ACCURACY ASSESSMENT

When using remotely sensed data in thematic map creation, the accuracy assessment of thematic maps to determine its classification accuracy or map correctness remains a fundamental process. It is the quantitative assessment of image classification accuracy. The most commonly used metric for evaluation is overall accuracy [21]. Therefore, in this study the confusion matrix method was applied to all the classes using ENVI 5.5 software for all the images. The quantitative control was applied to evaluate producer's and user's accuracy, overall accuracy and kappa statistics. Using random sampling process, a minimum of 100 testing samples (in pixels) (Table 3) were utilized for each classes. The result showed that the classification produced an overall accuracies greater than 78.74 % and overall kappa statistics greater than 0.72 for all classes across all years as shown in Table 7 with moderate to substantial accuracy.

**Table 7.** Accuracy Assessment of the Classifications results for all classes of each year

| Years | Accuracy/Classes | Built-Up-Area | Green Area | Bare Land | Others |
|---|---|---|---|---|---|
| 1990 | Producer's Accuracy (%) | 91.82 | 99.13 | 79.03 | 86.14 |
| | User's Accuracy (%) | 99.02 | 86.36 | 98.00 | 83.65 |
| | Overall Accuracy (%) = 90.46 | | Kappa Coefficient = 0.87 | | |
| 2000 | Producer's Accuracy (%) | 97.00 | 99.00 | 76.47 | 77.10 |
| | User's Accuracy (%) | 84.35 | 83.7 | 97.5 | 93.52 |
| | Overall Accuracy (%) = 88.29 | | Kappa Coefficient = 0.87 | | |
| 2013 | Producer's Accuracy (%) | 84.75 | 100 | 88.79 | 83.33 |
| | User's Accuracy (%) | 91.74 | 97.56 | 73.08 | 97.09 |
| | Overall Accuracy (%) = 89.24 | | Kappa Coefficient = 0.85 | | |
| 2018 | Producer's Accuracy (%) | 76.35 | 93.79 | 88.00 | 52.21 |
| | User's Accuracy (%) | 86.92 | 91.52 | 64.71 | 64.84 |
| | Overall Accuracy (%) = 78.74 | | Kappa Coefficient = 0.72 | | |

## 7. DISCUSSION AND CONCLUSION

In this study, urban growth and land consumption patterns of Thimphu city was evaluated using multi-temporal Landsat images. The classification results were compared to evaluate the land cover changes in the selected years (1990-2018). This change is the quantitative difference between geo-referenced, digital image values obtained in multi-temporal images over time. The reference data such as LULC maps, Google Earth images, expert knowledge and visual interpretation of color composite images were used for selecting classification training samples and accuracy assessment. While not error free, the result showed that the built-up areas increased by 17.64 % during 1990-2018. In contrast there was a decrease of 19.16 % green areas within the same period. The fact that this change is mainly due to the rapid population growth as a result of out-migration from rural to urban areas, urbanization and commercial development in the region.

Due to the lack of training data of the period and non-heterogeneity of the terrain the classification process remained challenging. Also, in this study freely available Landsat images were used for change analysis with 30 m spatial resolution. Due to the medium-resolution of image and as most of the man-made structures being generally shorter than 30 m in length their might have been some possible errors in the classification processes since the resolution of image dataset effects the classification accuracies. It is therefore recommended to use images of higher resolution if possible, to increase the classification accuracies by the future researchers. It is also recommended that all the multispectral bands of images be fused with a panchromatic band to produce high-resolution images.

## REFERENCES

[1] L. Sharma, P. C. Pandey, and M. S. Nathawat, "Assessment of land consumption rate with urban dynamics change using geospatial techniques," J. Land Use Sci., vol. 7, no. 2, pp. 135–148, 2012, doi: 10.1080/1747423X.2010.537790.

[2] M. Antrop, "Landscape change and the urbanization process in Europe," Landsc. Urban Plan., vol. 67, no. 1–4, pp. 9–26, 2004, doi: 10.1016/S0169-2046(03)00026-4.

[3] P. N. Dadhich and S. Hanaoka, “Spatio-temporal Urban Growth Modeling of Jaipur, India,” J. Urban Technol., vol. 18, no. 3, pp. 45–65, 2011, doi: 10.1080/10630732.2011.615567.

[4] E. F. Lambin, H. J. Geist, and E. Lepers, “Dynamics of Land-Use and Land-Cover Change in Tropical Regions,” Annu. Rev. Environ. Resour., vol. 28, no. 1, pp. 205–241, 2003, doi: 10.1146/annurev.energy.28.050302.105459.

[5] O. R. Abd EL-kawy, H. A. Ismail, H. M. Yehia, and M. A. Allam, “Temporal detection and prediction of agricultural land consumption by urbanization using remote sensing,” Egypt. J. Remote Sens. Sp. Sci., vol. 22, no. 3, pp. 237–246, 2019, doi: 10.1016/j.ejrs.2019.05.001.

[6] M. Dadras, H. Z. M. Shafri, N. Ahmad, B. Pradhan, and S. Safarpour, “Spatio-temporal analysis of urban growth from remote sensing data in Bandar Abbas city, Iran,” Egypt. J. Remote Sens. Sp. Sci., vol. 18, no. 1, pp. 35–52, 2015, doi: 10.1016/j.ejrs.2015.03.005.

[7] A. S. Aguda and S. A. Adegboyega, “Evaluation of Spatio-Temporal Dynamics of Urban Sprawl in Osogbo, Nigeria using Satellite Imagery & GIS Techniques,” Int. J. Multidiscip. Curr. Res., vol. 1, pp. 60–73, 2013.

[8] R. Chand, “Social ecology of immigrant population and changing urban landscape of Thimphu, Bhutan,” J. Urban Reg. Stud. Contemp. India, vol. 4, no. 1, pp. 1–12, 2017, [Online]. Available: http://home.hiroshima-u.ac.jp/hindas/index.html

[9] S. Canaz, Y. Aliefendioğlu, and H. Tanrıvermiş, “Change detection using Landsat images and an analysis of the linkages between the change and property tax values in the Istanbul Province of Turkey,” J. Environ. Manage., vol. 200, no. November, pp. 446–455, 2017, doi: 10.1016/j.jenvman.2017.06.008.

[10] A. F. Alqurashi and L. Kumar, “Investigating the Use of Remote Sensing and GIS Techniques to Detect Land Use and Land Cover Change: A Review,” Adv. Remote Sens., vol. 02, no. 02, pp. 193–204, 2013, doi: 10.4236/ars.2013.22022.

[11] K. Green, D. Kempka, and L. Lackey, “and Remote to Detect Using Sensing Ghange Monitor and Land-Use,” Photogramm. Eng. Remote Sens., vol. 60, no. 3, pp. 331–337, 1994.

[12] J. Rogan and D. M. Chen, “Remote sensing technology for mapping and monitoring land-cover and land-use change,” Prog. Plann., vol. 61, no. 4, pp. 301–325, 2004, doi: 10.1016/S0305-9006(03)00066-7.

[13] S. Reis, “Analyzing land use/land cover changes using remote sensing and GIS in Rize, North-East Turkey,” Sensors, vol. 8, no. 10, pp. 6188–6202, 2008, doi: 10.3390/s8106188.

[14] R. K. Jaiswal, R. Saxena, and S. Mukherjee, “Application of remote sensing technology for land use/land cover change analysis,” J. Indian Soc. Remote Sens., vol. 27, no. 2, pp. 123–128, 1999, doi: 10.1007/BF02990808.

[15] Z. Deng, X. Zhu, Q. He, and L. Tang, “Land use/land cover classification using time series Landsat 8 images in a heavily urbanized area,” Adv. Sp. Res., vol. 63, no. 7, pp. 2144–2154, 2019, doi: 10.1016/j.asr.2018.12.005.

[16] Diksha and A. Kumar, “Analysing urban sprawl and land consumption patterns in major capital cities in the Himalayan region using geoinformatics,” Appl. Geogr., vol. 89, no. October, pp. 112–123, 2017, doi: 10.1016/j.apgeog.2017.10.010.

[17] N. S. N. Shaharum, H. Z. M. Shafri, J. Gambo, and F. A. Z. Abidin, “Mapping of Krau Wildlife Reserve (KWR) protected area using Landsat 8 and supervised classification algorithms,” Remote Sens. Appl. Soc. Environ., vol. 10, pp. 24–35, 2018, doi: 10.1016/j.rsase.2018.01.002.

[18] B. Calka, A. Orych, E. Bielecka, and S. Mozuriunaite, “The Ratio of the Land Consumption Rate to the Population Growth Rate: A Framework for the Achievement of the Spatiotemporal Pattern in Poland and Lithuania,” Remote Sens., vol. 14, no. 5, 2022, doi: 10.3390/rs14051074.

[19] G. Cecili, P. De Fioravante, L. Congedo, M. Marchetti, and M. Munafò, “Land Consumption Mapping with Convolutional Neural Network: Case Study in Italy,” Land, vol. 11, no. 11, 2022, doi: 10.3390/land11111919.

[20] N. Currit, “Development of a remotely sensed, historical land-cover change database for rural Chihuahua, Mexico,” Int. J. Appl. Earth Obs. Geoinf., vol. 7, no. 3, pp. 232–247, 2005, doi: 10.1016/j.jag.2005.05.001.

[21] S. S. Heydari and G. Mountrakis, “Effect of classifier selection, reference sample size, reference class distribution and scene heterogeneity in per-pixel classification accuracy using 26 Landsat sites,” Remote Sens. Environ., vol. 204, no. February 2017, pp. 648–658, 2018, doi: 10.1016/j.rse.2017.09.035.

[22] D. Lu, P. Mausel, E. Brondízio, and E. Moran, “Change detection techniques,” Int. J. Remote Sens., vol. 25, no. 12, pp. 2365–2401, 2004, doi: 10.1080/0143116031000139863.

[23] S. S. Nath, G. Mishra, J. Kar, S. Chakraborty, and N. Dey, “A survey of image classification methods and techniques,” 2014 Int. Conf. Control. Instrumentation, Commun. Comput. Technol. ICCICCT 2014, pp. 554–557, 2014, doi: 10.1109/ICCICCT.2014.6993023.

[24] J. . Benediktsson, P. . Swain, and O. . Ersoy, “Neural network approaches versus statistical methods in classification of multisource remote sensing data,” 1990.

[25] JICA, “Data Collection Survey on Urban Development and Environment in the Kingdom of Bhutan Final Report,” 2014.