

Assessing Spatiotemporal Built-up Dynamics in Chiang Mai City, Thailand using Entropy approach

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Abstract

The rates of urban dynamics affecting by industrialization, urban agglomeration, and large-scale migration turn its behaviour from monocentric to polycentric metropolitan resulting in unprecedented urban growth. Therefore, the present study incorporated an entropy-based approach to measure the degree of compactness and dispersiveness of urban development in Chiang Mai City. The Object-based machine learning was deployed for the image classifications with an overall accuracy above the minimum requirements (i.e., 90%) and kappa statistic of agreement above 0.85. The study reveals that Chiang Mai city has undergone urban development outskirts from the urban centre (CBD) and north and south-west direction from the CBD. A considerable increase in urban demographic and physical urban patches was observed in last 1998 to 2018. The research emphasized the significant role of Shannon Entropy to analyze the built-up growth supplemented by Remote Sensing and Geographic Information System (GIS) in respective zones and geographical directions.

1. Introduction

Migrating from rural to urban area is one of the primary sources of urban expansion, which reflects either increase in population and land size or urban patches (Maarseveen et al., 2019). Additionally, urban growth is considered as an indicator that characterized socio-economic development, whereas it also reveals the impacts of anthropogenic activities on the natural environment (Badlani et al., 2017b). Developing land use for different unique purposes or converting natural landscapes to impervious surfaces, for instance, creates a negative influence on the urban ecosystem (Hamedianfar & Shafri, 2015). In this context, monitoring urban sprawl, infrastructure growth, or planning and management for long term is necessary to involve a primary information on the amount of built-up and land use pattern. This enables planners to propose for maintaining smooth and to balance the developmental activities in the region (Jat et al., 2007). Hence, it supports for the decision maker and policymaker to prioritize on monitoring the land use and sustaining natural resources, biodiversity, and climate change from negative consequences.

Chiang Mai is the third largest city in North of Thailand with rapid socio-economics development and physical increase in urban growth was observed with ever increase in population and being center for business development in recent year (B. Setiawan B. & Rahmi, 2002). The primary factor of urban growth is service center for urban agglomeration, rural urban development, absorption of immigration toward the largest cities of Thailand and availability of social and public service facilities (Setiawan and Rahmi, 2002, Srinurak and Mishima, 2014). In this context, several studies have employed for modelling and monitoring of urban development under the aspects of engineering, economic and environment in Chiang Mai City (Brian McGrath et al., 2017; Sangawongse, 2006; Thitimakorn, 2013). Those studies used classification techniques [i.e. maximum likelihood classification, object based image classification, and other supervised classification (Brian McGrath et al., 2017) for examining urban sprawl studies. However, in the context of classification, Object Based Image Analysis (OBIA) used spatial and spectral informations for categorization of pixels in correlation with surrounding pixels based on shape, spectral

and texture, improving accuracy of the classification. Addition to the OBIA, Shannon Entropy Index (SEI) was used to calculate the diversity of land use pattern at local (Rahman, 2016) and regional levels (Maarseveen et al. 2019). In geographical concept, the entropy for spatial analysis is defined as spatial entropy that enable in partitioning the area into various zones for analyzing the geographical features (Cabral et al., 2013). Therefore, the built-up pattern in the Chiang Mai city was selected to implement based on the application of the OBIA and the SEI.

Remotely sensed data is an efficient database resource to extract a piece of various information's regarding urban management and sustainable planning (Kadhim et al., 2016) through space and time. It provides an enhancement in terms of spatial, temporal, radiometric, and spectral resolution (Hamedianfar & Shafri, 2015), large area coverage (Badlani et al., 2017a), cost effective, detection of landscape dynamics at subpixel level (Hamedianfar & Shafri, 2015; Raziq et al., 2016), and availability of multi-time series archival data. Previous study applied ASTER (Jianwen and Bagan, 2005), IKONOS (Zhang and Wang, 2003), SPOT 5 (Lu et al., 2012), RADARSAT-1 and ENVISAT SAR (Xu, 2007), Sentinel (Abdulhakim Mohamed, 2019) and Landsat (Alam et al., 2019) to monitor urban changes at separate regions. Among various sensors, Landsat was commonly used to analyze urban sprawl and performed built-up pattern at provincial level with considerable accuracy, because of free charge, a long temporal resolution from 1972, spatial resolution of 30 m, and large swath area (Bhatti and Tripathi, 2014; Nautiyal et al., 2019; Ramachandra et al., 2012). The Landsat series consists of sensor with a various spatial resolution that can be used for different applications such as Operation Land Imagery (OLI) with Multi Spectral Sensor (MSS) for land use monitoring (Amalisana and Hernina, 2017; Badlani et al., 2017b; Phiri and Morgenroth, 2017), ice flow mapping (Fahnestock et al., 2016) and the thermal infrared band (TIR) for active fire detections (Schroeder et al., 2016). In this study, Landsat imagery between 1988 and 2018 was applied for characterizing built-up changes in Chiang Mai city.

Overall, the study aimed at (i) classifying built-up and non-built-up using OBIA techniques from the Landsat imagery, (ii) computing Shannon Entropy Index for each zone, and (iii) understanding urban expansion in zone and geographical direction. The Chiang Mai city in Thailand was selected as a case study for examining the dynamics growth of built-up patches. This research also enables to support comprehensive development control strategy and policy documentation for future sustainable urban planning without haphazard urban sprawl.

2. Materials And Methods

2.1. Study site

Chiang Mai (18°47'N lat and 098°59'E long) is the largest city with an area of 22,800 km², comprises of seven administrative districts, named Muang, Mae Rim, Hang Dong, Saraphi, Sansai, Sankamphaeng and Doi Saket (Sangawongse, 2006) (presented in Figure 1). The city is situated on the flood plain of Ping Mai River Basin with Doi Suthep-Pui range to the west and the curvilinear ridge of Doi-lang Ka-Khun Tan mountain range toward East (Thitimakorn, 2013). The average annual temperature is 25.6°C with an

annual rainfall of 1,184 mm. The general elevation of the study area ranges from 280 m to 335 m above mean sea level. In the past decade, the study area observed with the rapid expansion in built-up area and population as per Official Statistics Registration Systems of Thailand in 2018 (Plecher, 2019; Prurapark and Asavaritikrai, 2020). According to Srinurak and Mishima (2014), the Thailand government had considered Chiang Mai City as the multicenter to the north of Thailand being center of Lan Na (independent state) before it merged to a part of Thailand. Chiang Mai is exacerbating toward Urban Heat Island (UHI) due to high construction activities, clustered impervious surfaces (Srivanit and Hokao, 2012) and juxtaposition for new incoming immigrants lead to formation of outward peri-urban (Tubtim, 2012). Therefore, this study may demonstrate the urban density information using SEI on impervious surface in respective zone and direction.

2.2. Data used

Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imagery (OLI) were selected to evaluate the long-term trend analysis of urban dynamics during 1998-2018 period. The classified land use land cover maps are geographically projected to the UTM 47 North zone with WGS84 datum. The satellite imagery was corrected radio-metrically, geometrically and atmospherically by removing the effects of sun angle, noise and atmospheric noise reproducing the actual surface reflectance values. The details of date of acquisition, rows and path of satellite imagery is shown in Table 1 and their band specification are stated more in details by (Gyeltshen et al., 2020).

2.3. Image Processing

The Object-Based Image Analysis (OBIA), also known as Object-oriented classification techniques, was applied widely to extract a variety of pixel information as well as to classify the spectral and spatial relationship of an identical object based on its contextual, tonal and shape (Gupta & Bhadauria, 2014). Several studies proved that the OBIA conveys a boundless potential in the classification and extraction of built-up patches for further analysis (Hamedianfar and Shafri 2015, Amalisana and Hernina 2017). It was widely used other than normal classification techniques such as: supervised or unsupervised classification namely, maximum likelihood classification, parallelepiped classification and minimum distance classification method (Ahadnejad et al., 2009). In this study, the object-based classification is followed by two steps (i.e., segmentation of image into discrete objects and assemblage of each object in different classes).

It is considered that multi-resolution segmentation is the pivotal component of Object-based image classification (Hossain and Chen, 2019). It groups the number of pixels into object or feature based on the spatial and spectral characteristics of an image (Blaschke et al., 2004). The current research maintains threshold scales values of 50 and classified the image into six classes; forest, urban, vegetation, barren land, fallow land, and waterbodies. Besides, the false color composite (FCC) band 4, 3, 2 for Landsat 5 TM and band 5, 4, 3 for Landsat 8 OLI color composite information were used to interpret features in the satellite imagery. Since the study emphasized on built-up and non-built-up growth, the six

classes have been further reclassified into built-up and non-built-up category by merging urban into built-up and rest of the land use into non-built-up areas.

Finally, the most profound and popular techniques for accessing the accuracy of the classification is Kappa Index of Agreement (KIA) which is based on confusion matrix. It requires ground truth data (training data) to determine the accuracy of classified map. Since, ground truth data are time consuming due to large extent and expansive, high-resolution satellite imagery, google image and existing classified imagery suit the requirement of field data collection. Hence, the current research picked up random training samples from the high resolution google earth image to compute confusion matrix and determine the kappa coefficient along with user and producer accuracy. Mathematically, the Kappa Coefficient can be computed using equation (4).

$$K = \frac{\text{Observed Accuracy} - \text{Chance Agreement}}{1 - \text{Chance Agreement}}$$

1

Overall, the methods encompass of (i) image preprocessing, (ii) image classification using OBIA (iii) Accuracy assessment in term of Kappa agreement of statistic for classified built-up and non-built-up of 1998, 2008 and 2018 (Figure 2), and (iv) analysis on built-up dynamic using Shannon Entropy by applying circular concentric buffering and spatial direction model.

2.4. Shannon Entropy

A technique was developed by Shannon in 1948 which measure the degree of compactness and divergence of any geographical feature. It plays a significant role in information theory measuring information, prefer ability, and uncertainty (Burgin, 2003). Das Chatterjee et al., (2016), has also demonstrated the effective used of entropy metric-based approach in integration with geographic information system for urban sprawl modelling and monitoring. Besides, it is suitable for the measurement of built-up spatially and temporally with the help of concentric buffering and spatial geographical direction approach (Shukla and Jain, 2019). The mathematical formula to compute the Shannon entropy is shown in Equation (2) below:

$$H_n = - \sum_{i=1}^n P_i \log(P_i)$$

2

The above equation can be further restructured using the following equation by removing (-)_{ve} values:

$$H_n = \sum_{i=1}^n P_i \log\left(\frac{1}{P_i}\right)$$

Where H_n represent the Shannon Entropy, n for number of zones in the concentric buffering or directional pattern and P_i for ratio of built-up within the zone to total built-up within the zone. The values of Shannon entropy ranges from 0 to $\log(n)$, (i.e., for concentric buffering, $n=10$ and for directional approach, $n=8$ was identified). Furthermore, H_n approaching toward $\log(n)$, determine the high rate of dispersion or divergence with less density of built-up in the area whereas, H_n tending toward zero indicate urban haphazard due to compact built-up and less urban growth (Aburas et al., 2018; Shukla and Jain, 2019). In this study, a spatial distribution and variability of geographical features in respective geographical direction and zone was implemented with the assistance of Shannon entropy under the approaches of concentric buffering and geographical direction. An analysis of 5 km interval from CBD (loop) toward edge of the study area (i.e. Zone 1-Zone 10) was employed based on compactness and depressiveness following the Burgess Theorem in 1924 (Aburas et al., 2018). In addition, 8 different directions (i.e., E, NE, N, NW, W, SW, S, and SE) were divided to determine the built-up growth in respective geographical direction.

2.5. Relative Entropy

The normalization of SEI values in between 0 to 1 is called relative entropy (Thomas, 1981) which can be calculated using equation (4).

$$R(H_n) = \frac{\sum_{i=1}^n P_i \log\left(\frac{1}{P_i}\right)}{\log(n)}$$

Where $R(H_n)$, represents relative entropy, and $\log(n)$ shows the upper limit of the entropy values. Values from 0 to 0.5 indicate high compactness of geographical feature (patches) and 0.5-1 indicate high degree of dispersion in urban growth.

3. Result And Discussions

3.1. Applicability of Remote Sensing in Built-up change mapping

Remote Sensing Earth Observation Satellite Imagery with series of Landsat imagery launched by NASA from Vandenberg Air Force Base with their temporal archival dataset provide high temporal built-up analysis with large swath area coverages. With the application of Object Based Image Classification (OBIA) techniques in built-up classification, considerable accuracy was obtained and demonstrated in Table 2 with Kappa co-efficient of three years, respectively. From the explored result, a strong agreement of statistic between the raster was observed that OBIA can be used for the classification of imagery for

dynamical assessment of urban built-up. As indicated in (Deka et al., 2011), the overall accuracy of the classification above 85% is acceptable. Therefore, the current adopted classification using OBIA obtained above the minimum accuracy requirement.

3.2. Spatiotemporal pattern of built-up dynamic based on concentric circle

The main principle behinds subdividing the area in concentric circle is to evaluate the degree of urban growth within the zone according to Burgess theorem which state that the urban expansion start from centre of business district (loop) toward edges (Aburas et al., 2018). Multi-ring concentric circle with equal distance in whole direction, therefore, facilitate an analysis of spatial distributions of built-up from centre toward edge of the study area. The study area, hence, was subdivided into 10 sub-zone to compute the entropy values of each zone for analysing the degree of built-up compactness and divergence for the respective zones. The 5 km intervals were maintained for creating concentric buffer from the loop (CBD) stretching outskirts of 50 km toward the edge of study area. The location of CBD was collected using handle GPS from Chiang Mai City. Additionally, the built-up feature of each zone was further extracted to compute the Shannon entropy values.

In comparison with 1998, the built-up pattern mostly occurred in the centre loop under zone 1, while the built-up in corresponding two years (i.e., 2008 and 2018) speeded a development toward the edges of the study area (Figure 3).

Based on zonal statistic (Figure 4), zone 2, 3, 4, and 5 observed a drastic increase in built-up patches. Under zone 1, the small changes in urban development were taken place due to compactness of urban patches. Whereas, under zone 2, the area of built-up increased from 9.05 km² in 1998 to 30.11 km² in 2008, and further to 55.56 km² with an annual average growth rate of 3% and 5.14% during the period of 1998-2008 and 2008-2018, respectively. Similarly, under zone 3, the built-up area rose from 7.83 km² in 1998 to 23.90 km² in 2008 and further to 40.27 km² in 2018 with 3.27% growth rate annually from 1998 to 2008 and 4.34% from 2008 to 2018 respectively. Besides, under zone 4, there was an increase in the built-up area patterns from 5.88 km² in 1998 to 23.90 km² in 2008 and further to 40.27 km² with an annual growth rate of 3.34% from 1998 – 2008 and 4.36% in 2008 - 2018 period. Additionally, the gradual increase in area (zone 6-10) was also noticed during the study period with an average annual increment of 54.97 km² in 1998 to 144.48 km² in 2008 and 274.67 km² in 2018, respectively.

In addition to the change analysis based on area statistic, the Shannon entropy values were computed in each zone for further evaluation under the application of concentric circle buffering technique. The entropy values of each zone were also tabulated in Table 3. According to (Aburas et al., 2018; Deka et al., 2011; Shukla and Jain, 2019), the values of Shannon entropy range from $0 - \log(n)$, where n represents the number of concentric circle (i.e. $\log(10) = 2.3026$). The H_n values, therefore, range from $0 - 2.3026$.

From Table 4, the Shannon entropy values tending toward the upper limits (i.e., 2.3026) during the three-study period demonstrate with a dispersive nature of urban growth in the Chiang Mai City. The H_n values for the entire study area show the unitless figures of 1.662, 2.002, and 2.053 in 1998, 2008, and 2018, respectively. The Shannon entropy was further converted into the relative entropy, demonstrate that the $R(H_n)$ values are greater than 0.5 (i.e., 0.722, 0.87, and 0.892, respectively). This revealed that the city experienced with scattered impervious surface and distributed with diversified economic development (Jat et al., 2008; Ozturk, 2017). It also indicates that the development in patches (building footprints) on the landscape had been observed with an increase in entropy values for the last 20 years in the study area (Shukla and Jain, 2019). In addition, the urban growth patches in 1998 were less dispersed than the patterns of 2008 and 2018 as a demonstration to uniform developmental activities in whole direction. However, the growth pattern in different geographical directions was further discussed in next section using geographical direction technique for urban growth analysis.

Regression analysis was performed between the driving factor (population) and Entropy values of the patches. A high correlation between population and Shannon entropy was observed with strong correlation coefficient of 0.9. The archival population data of Chiang Mai City was retrieved from macro trends website (United Nations, 2020).

3.3. Quantification of built-up at different geographical direction

Built-up analysis on spatial and geographical direction were evaluated and quantified based on concentric circular buffering technique surrounding the Centre Business District (CBD) serving as a centre point of developmental activities (Aburas et al., 2018). Hence, the Chiang Mai City was divided into 8 major geographical directions (Figure 5) to further quantify the spatial distribution of urban patches into realistic evaluation which support circular buffering analysis. Table 5 demonstrate that the area of impervious footprint of built-up reveal a vertical distribution throughout the study area. Based on the directional approach, the dispersed patches obtained from concentric buffering approach are mostly occurs along the north direction with 115.3 km² in three consecutive years followed by S-W direction with an area of 79 km².

The area and entropy values in each direction is computed in Table 5. Most of the developmental activities were occurred from 1998 to 2008 followed by 2018 in north direction, where least developmental activities are observed in W and N-W directions. Furthermore, it was also demonstrated that Chiang Mai City experienced hefty developmental activities, which indicate rapid increase in population density (Brian McGrath et al., 2017; B. B. Setiawan and Rahmi, 2002)

From Table 6, a high $R(H_n)$ was observed in the case of geographical directional analysis in addition to the concentric buffering approach. The rate of dispersion is high as most of the entropy values tend toward upper limits (i.e., 0.5). However, small entropy value was observed at the Centre Loop, West and North-West directions where least development activities were occurred in the beginning of 1998's (Figure

6). In addition, along West and North-West direction, the developmental activities were interrupted due to topographical and geological phenomena. The observed values are mostly above the threshold of built-up patches for depressiveness in three years (i.e., 0.5). From this analysis, patches at W and N-W geographical direction shown to be lower values since least development activities was occurred in 1998 in core area (i.e., loop). On the contrary, due to topographical and geological reason, which composed of mountain ridges and fault line, least development activities are happened in that W and N-W direction.

According to Setiawan and Rahmi, (2002), the author emphasized on statistical measure with other contributing factors such as population, land values and economic scale in Chiang Mai City for land-use change. In addition, Brain McGrath et al., (2017) has analysed the built-up dynamic using area statistics to demonstrate the land use change, patch dynamic and type of landform existed in Chiang Mai City. They also employed SLEUTH model for determining the urban growth and land use dynamics. However, these researches have not demonstrated the level of urban growth or sprawl happen in which zones and geographic directions, respectively. Therefore, the emphasisization on entropy-based approach provide in-depth understanding on the level of urban growths in respective zones and geographical directions in terms of compactness and dispersive nature of urban patches which gives the clear picture on how and where to implement the developmental activities in equitable and sustainable manner. Hence, the research enable to provide the fundamental information's on built-up pattern in Chiang Mai which support the urban planner, designer and local authorities to propose accordingly to implement based on the innovative approach indicated above for future developmental activities.

4. Conclusions

The study emphasized OBIA based GIS approach for classification of remote sensing data and statistical model to monitor the time series analysis on built-up growth in the Chiang Mai city. The study discovered that the study area was experienced with built-up expansion with 54.97 km² in 1998 to 144.48 km² in 2008 and further 274.67 km² in 2018. In addition, there was a significant increase in in patches with 8.95 km² built-up from 1998 to 2008 and 13.019 km² from 2008 to 2018 annually.

The study employed Shannon entropy model through concentric buffering and geographical directional techniques for computing the entropy values at different geographical directions and zones as demonstrated above. Through concentric multi-ring buffering approach, it was noticed with diverge and distributed built-up patches in Chiang Mai city with Shannon entropy values greater than 1.662 and relative entropy values greater than 0.72. The observed relative entropy for three consecutive year is; 0.72, 0.87 and 0.89 in 1998, 2008 and 2018 respectively. The logistic regression was performed with the driving factor (population) and Shannon entropy which is dependent on population. It was observed with high positive correlation of 0.9 between the entropy and population data.

Through directional approach, it was observed with high dispersive developmental activities mostly occurs in north direction followed by S-W direction and less entropy values with compact development were observed in W and N-W direction since the clustered developmental activities was mostly happen

before 1998 in the loop of Chiang Mai city. The study concludes that Chiang Mai City is diverging toward the edge of the study area with diversified built-up growth increasing every year. Thus, this study will enable an individual, working under government sector, NGO and other related focal person under planning and strategy section to come up with innovative policies and development control strategy for sustaining the developmental activities in all direction without urban sprawl. Since the classification of land use using OBIA in this paper obtained considerable accuracy above the minimum requirement, the future land use/built-up prediction will be carried out using Markov Chain (MC) Analysis or any method that best suit the requirement of the study.

Declarations

Conflict of Interests

The author declares no conflict of interests for this publication.

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Tables

Table 1
 Details of Landsat satellite imagery acquired and other ancillary data.

Satellite/Sensor	Resolution	Date of Acquisition	Sources
Landsat 5 TM	30 m	19-Jan-98 30-Nov-08	USGS Earth Explorer
Landsat 8 OLI	30 m	30-Nov-08	
Digital Elevation model (DEM)	30 m		SRTM DEM

Table 2
 Accuracy assessment on LULC for the respective year

Year	Overall Accuracy (%)	Kappa Statistics
1998	90.24	0.86
2008	90.00	0.88
2018	90.91	0.88

Table 3
Shannon Entropy values of each zone based on
circular buffering approach between the 1998-2018
period

Zone	Year	1998	2008	2018
Zone 1		0.36	0.34	0.28
Zone 2		0.30	0.33	0.32
Zone 3		0.28	0.30	0.32
Zone 4		0.24	0.26	0.28
Zone 5		0.15	0.23	0.24
Zone 6		0.06	0.18	0.20
Zone 7		0.08	0.09	0.14
Zone 8		0.11	0.12	0.13
Zone 9		0.06	0.09	0.09
Zone 10		0.02	0.07	0.04
Shannon Entropy (H_n)		1.66	2.00	2.05
Relative Entropy $R(H_n)$		0.72	0.87	0.89

Table 4
Correlation of Shannon, relative and Population of Chiang Mai
City

Year	Shannon Entropy	Relative Entropy	Population
1998	1.66	0.72	353,000
2008	2.00	0.87	804,000
2018	2.05	0.89	1,135,000

Table 5
Area statistic distribution on different geographical direction.

Direction	S-W	S	S-E	E	W	N-E	N	N-W
Year								
1998	7.7	5.5	9.9	10.9	4.0	5.4	8.7	2.8
2008	46.4	33.0	29.0	44.7	5.9	29.6	73.1	13.0
2018	24.9	17.4	16.8	21.6	4.9	15.8	33.5	9.6
Total	79.0	55.9	55.7	77.3	14.8	50.8	115.3	25.4

Table 6
Shannon Entropy values of Spatial distribution of impervious patches in different geographical direction.

Direction	E	N-E	N	N-W	S	S-E	W	S-W	$R(H_n)$
Year									
1998	0.32	0.23	0.29	0.15	0.23	0.31	0.19	0.27	0.96
2008	0.28	0.24	0.34	0.18	0.25	0.25	0.12	0.30	0.94
2018	0.30	0.24	0.35	0.14	0.25	0.24	0.08	0.30	0.91
Total (H_n)	0.9	0.71	0.98	0.47	0.73	0.8	0.39	0.87	

Figures

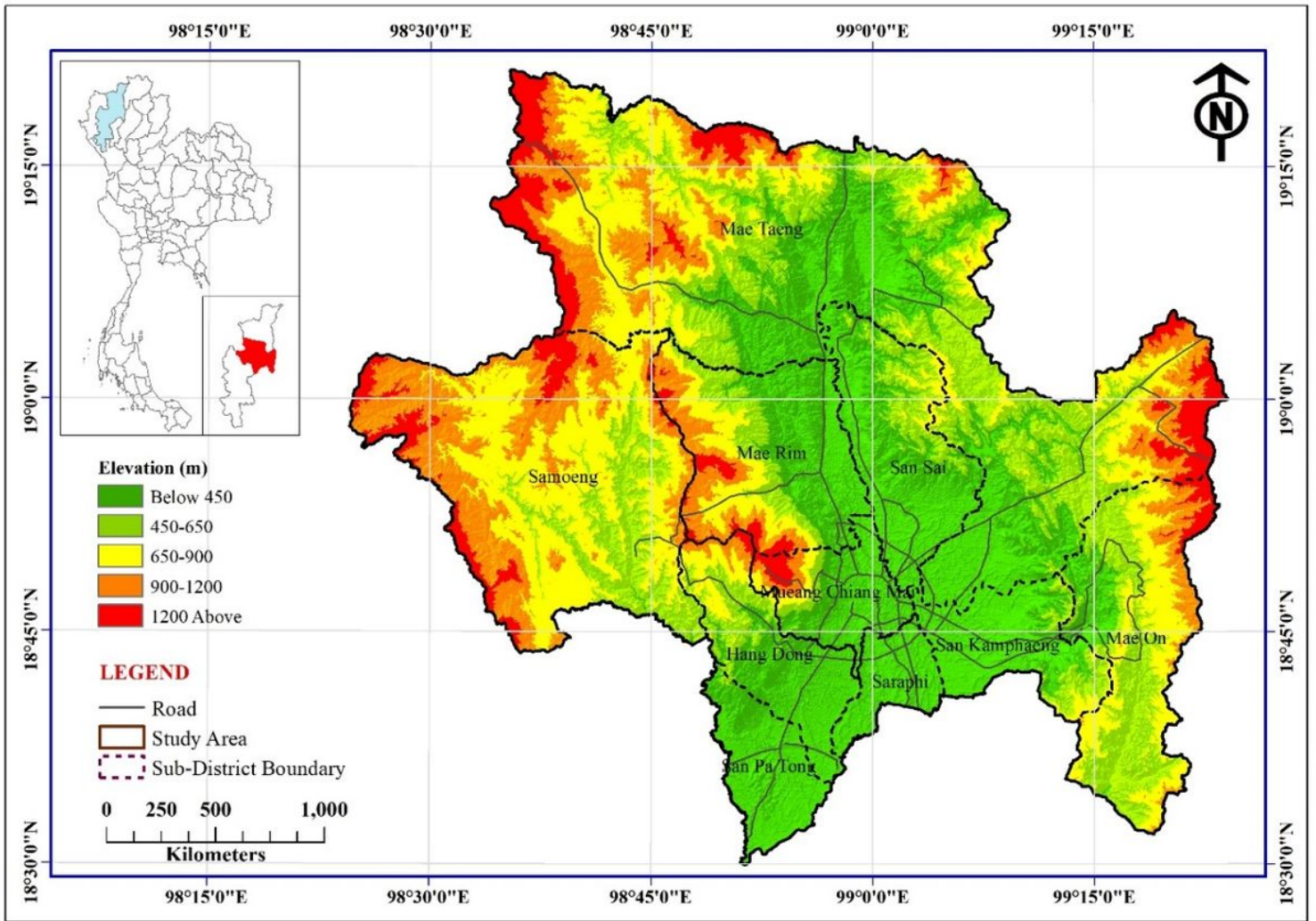


Figure 1

Location with sub-district and general elevation of the study area.

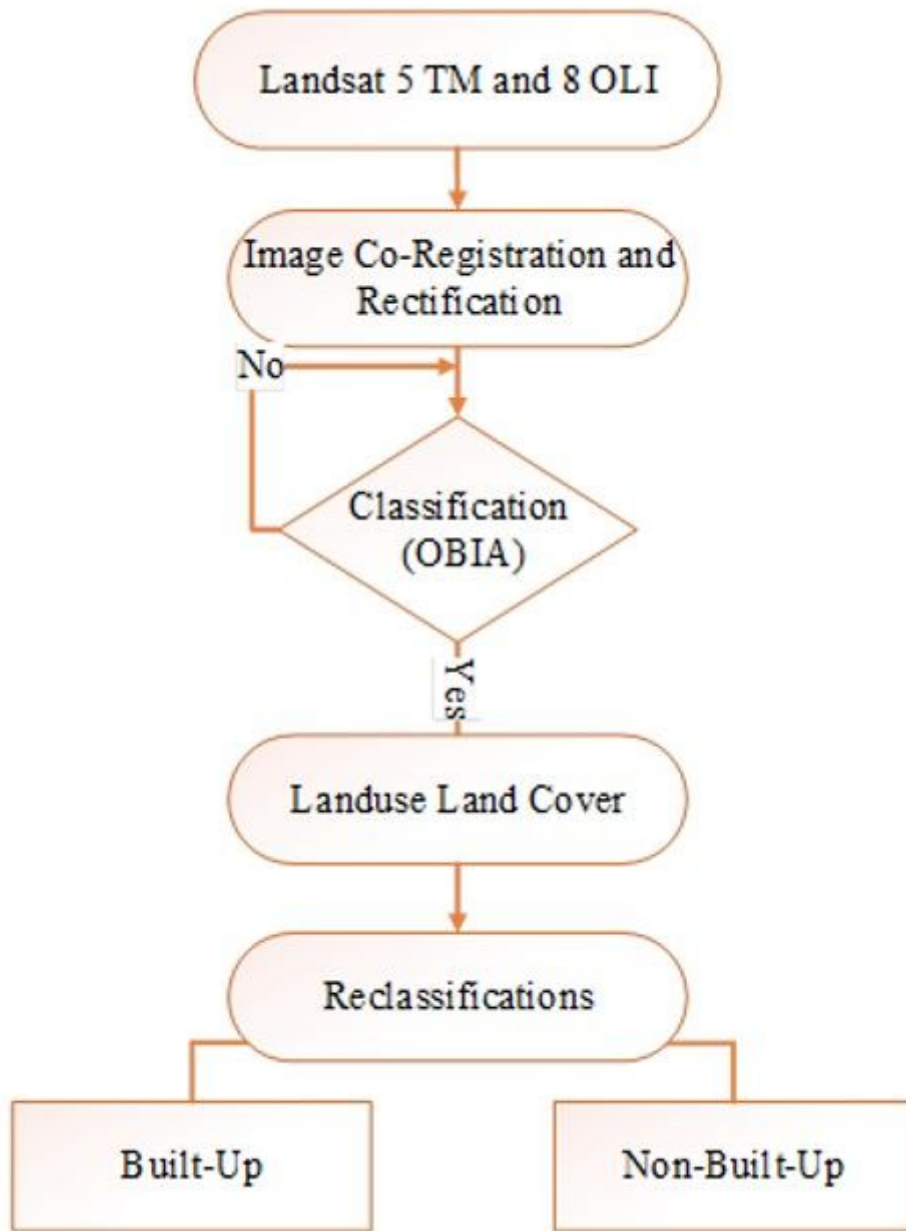


Figure 2

Flow chart for classification of Landsat 5 TM and Landsat 8 OLI.

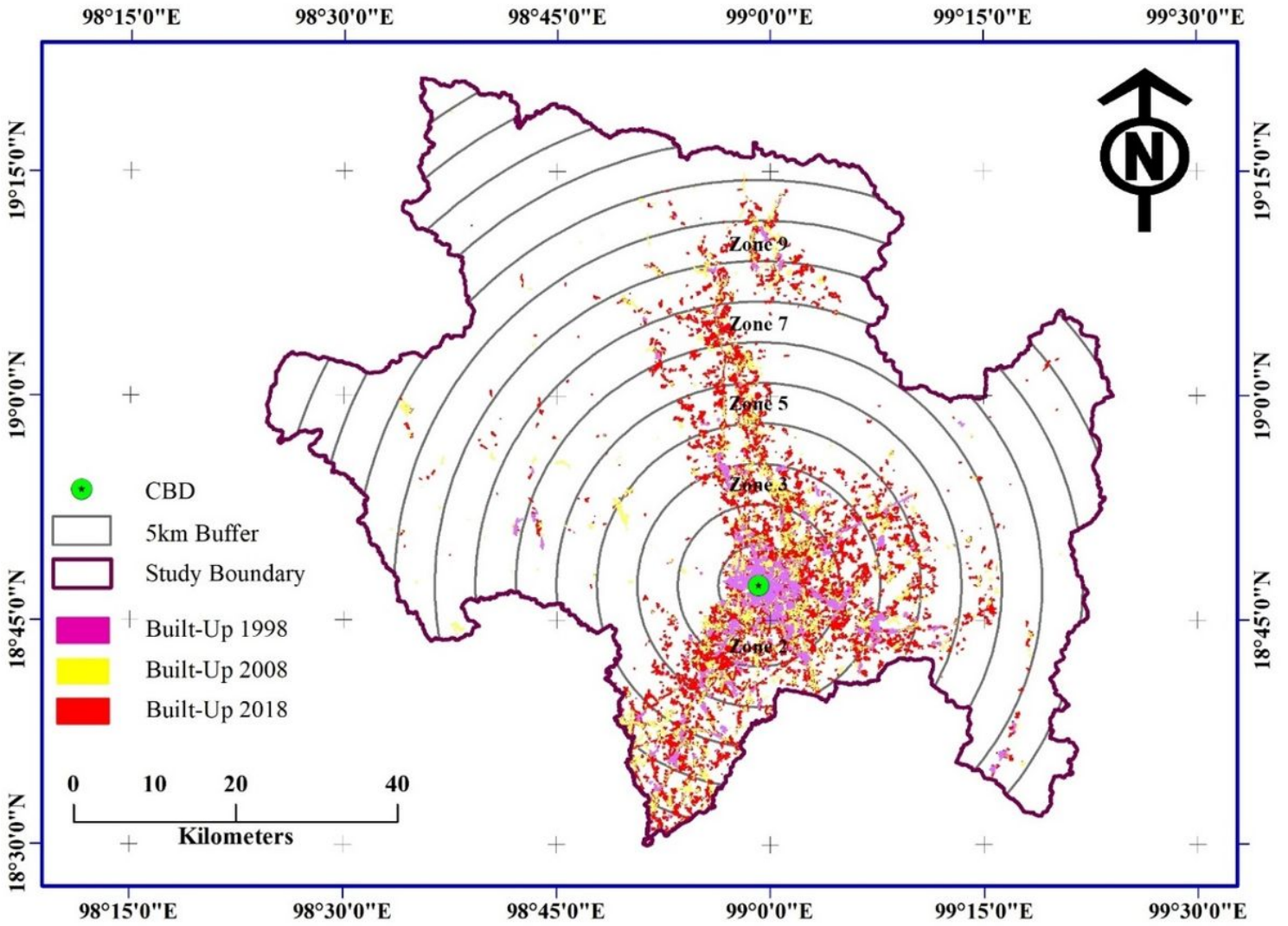


Figure 3

Superimposed built-up for three temporal years using concentric buffer ring

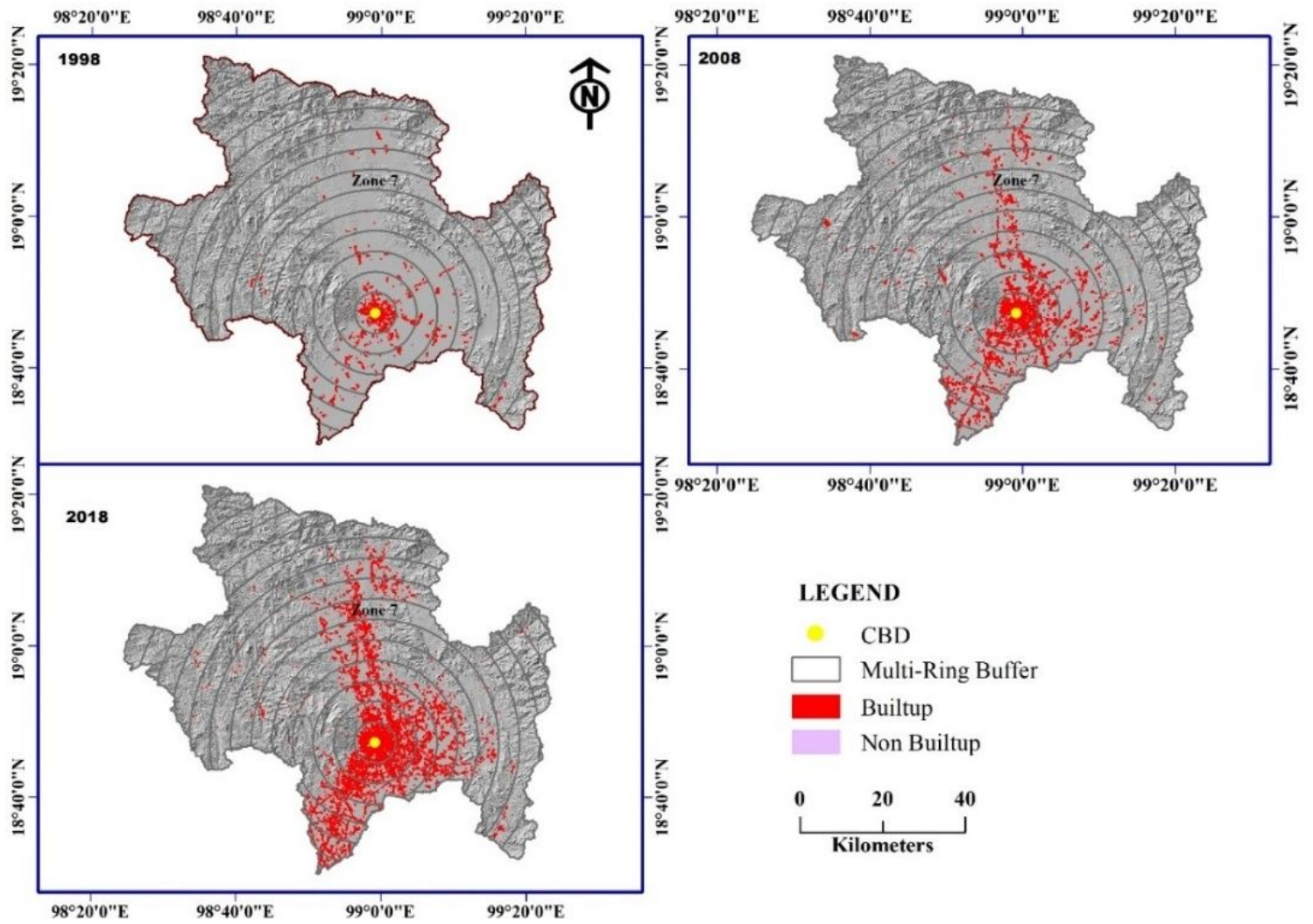


Figure 4

Spatial Distribution of urban patches in the three spatiotemporal year (a). 1998, (b). 2008, and (c). 2018 respectively.

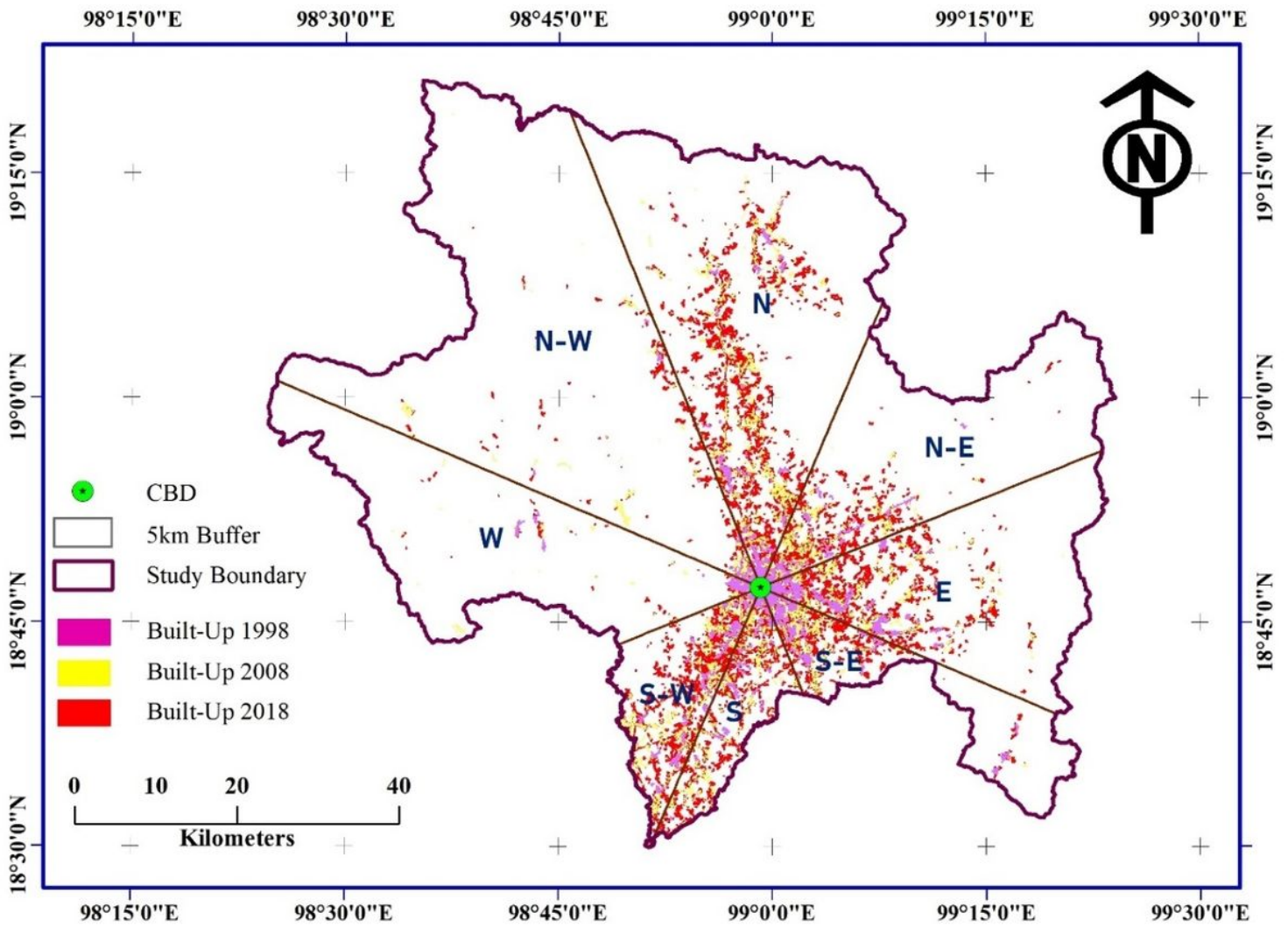


Figure 5

Superimposed built-up for the 3 respective years on 8 common geographical directions

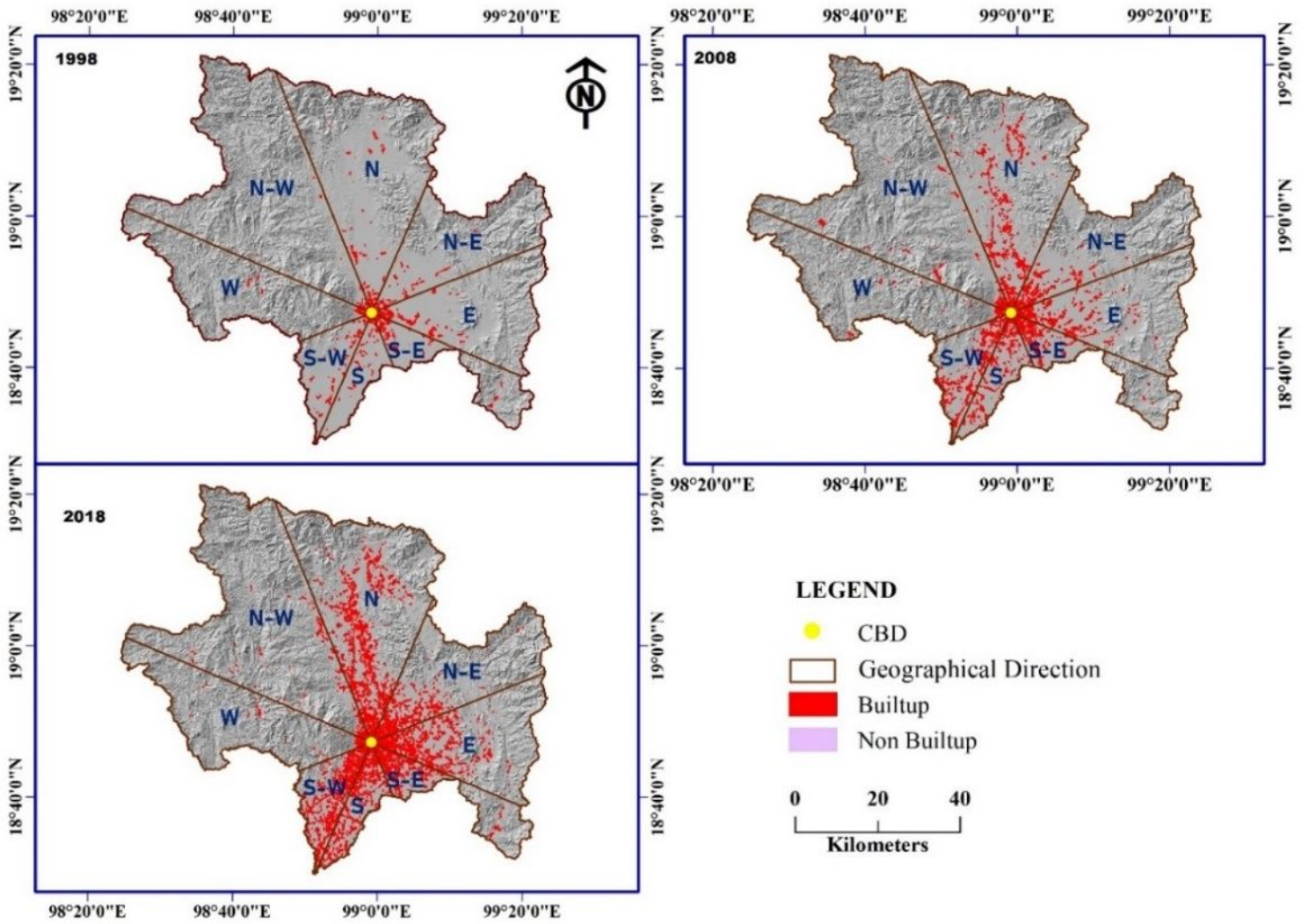


Figure 6

Represent Spatial Built-up in respective geographical direction for the year (a) 1998, (b) 2008, (c) 2018, respectively.