A REMOTE SENSING GIS BASED EVALUATION OF URBAN EXPANSION AND LAND USE LAND/COVER CHANGE: A REVIEW

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ABSTRACT

Land is becoming increasingly scarce as a result of population increase and industrialization. One of the reasons for the decline and depletion of land is the rapid increase of population in urban areas. Natural and socioeconomic factors, as well as man's use of them over time and space, all contribute to a region's land use-land cover pattern. The major goal of this work is to use LANDSAT satellite data on a GIS platform to examine multi-temporal land surface temperature (LST) and Normalized Difference Vegetation Index (NDVI) changes in the Ghaziabad district of Uttar Pradesh, India. Landsat LST data for the months of September 2000, 2011, and 2018 were utilised in this work to compute the variations and relationship between Land Surface Temperature (LST) and Land Use Land Cover (LULC). The LST was calculated using measurements from the Red and Near Infrared bands of the Normalized Difference Vegetation Index (NDVI). The present study focuses on Arc GIS Raster functions and Raster calculation using the LANDSAT in September, thermal Bands (10, 11 & 6). The output of this paper shows that the surface temperature was high in the barren and built up area whereas it is comparatively low in the thick vegetation and agriculture land. It is also recommended that in order to reduce the land surface temperature of urban areas, sustainable urban planning strategies that include increasing the vegetated areas and embracing other green initiatives such as urban forestry should be adopted.

Keywords: Urbanization, Land Use Land Cover (LULC), LST, NDVI, Remote Sensing, GIS

INTRODUCTION

Natural and socio-economic factors, as well as human activity in time and space, influence land use and land cover change in a given location. Changes in land use and land cover (LULC) are primarily driven by population expansion (Lambin et al., 2003; Meraj et al., 2021 a, b), economic growth, and physical factors such as terrain, slope condition, soil type, and climate (Setegn et al., 2009; Yalew et al., 2016; Pandey et al., 2010; Pandey et al., 2013; Singh and Pandey, 2014; Bhatt et al., 2017; Sharma and Kanga 2020). When it comes to how people use the land, land-use change is a historical process. It alters the availability of many resources such as plants, soil, and water (Ahmad, 2014; Singh et al., 2017b; Kanga et al. 2020a, b). Changes in land use have a direct impact on evapotranspiration, groundwater infiltration, and overland runoff. When it comes to global dynamics and their responses to environmental and socio-economic causes, land use and land cover change is a major concern (Akpoti et al., 2016; Bewket, 2002; Hurni et al., 2005). On a global and local scale, changes in land use and land cover have a negative impact on climatic patterns, natural hazards, and socio-economic dynamics (Chakilu & Moges, 2017; Hegazy & Kaloop, 2015; Sewnet, 2015). To satisfy the increasing demands for basic human requirements and welfare, information on land use/cover and potentials for their optimal use is critical for selection, planning, sustainable land resource management, and understanding changes in hydrological processes. Remote sensing produces spatially consistent data sets with great spatial detail and temporal frequency that cover enormous areas. Remote sensing can also give consistent historical time series data dating back to 1960. The value of remote sensing as a "unique picture" of the spatial and temporal dynamics of urban expansion and land use change processes was underlined (Herold et al., 2003; Bera et al., 2021; Tomar et al., 2021; Joy et al., 2021; Chandel et al., 2021; Kanga et al., 2021). As a result, satellite remote sensing techniques have been widely utilised to identify and monitor land cover change at various scales, with positive results (e.g., Stefanov et al., 2001; Wilson et al., 2003). Remote sensing has recently been combined with Geographical Information Systems (GIS) and Global Positioning Systems (GPS) to estimate land cover change more efficiently than remote sensing data alone (Muller and Zeller, 2002; Weng, 2002). It has already proven beneficial in mapping urban areas and as a data source for urban growth and land use/land cover change analysis and modelling (Grey et al 2003; Kanga et al., 2017a, b; Rather et al., 2018; Hassanin et al., 2020; Kanga et al., 2021).

In human history, urbanisation has been a key type of land use and land cover change (Weng 2001; Gujree et al., 2017; Pall et al., 2019; Romshoo et al., 2020). Due to population and economic expansion, additional types of land are being converted into urban areas. Land use and land cover changes connected with urbanisation can have a significant impact on the climate and local environment if they are not properly planned and managed. Many studies have focused on urbanisation and its effects on local regions during the last few decades. Urban locations have a higher thermal conductivity and radiation heat budget than rural locations. As a result of modifying the vegetation, the ground becomes more impermeable to road, buildings, concrete, and other forms of construction. When compared to rural locations, metropolitan areas tend to have greater surface temperatures due to changes in the terrestrial environment. In metropolitan locations, these changes affect solar heat radiation, surface temperature, and heat storage (Farooq and Muslim, 2014; Nathawat et al., 2010; Kumar et al., 2018; Joy et al 2019). Finally, the temperature differential between urban and rural areas plays a role in the formation of the urban heat island (UHI). Human and natural processes interact on land, which is a dynamic canvas. The various elements that influence LUCC have been the subject of scientific research spanning numerous disciplines, locales, and scales. Direct measurements, on the other hand, are insufficient to comprehend the forces that drive change. The use of empirical models to link observations at various geographical and temporal dimensions gives a holistic approach to understanding land-cover change (Turner et al. 1995; Ranga et al., 2020 a, b; Meraj et al., 2020 a, b; Kanga et al., 2020a, b). Multi-agent system models of land-use/cover change (MAS/LUCC models) are one potential family of models for simulating and analysing LUCC.

Abutaleb et al. (2015) studied UHI over Greater Cairo throughout the summer and winter seasons on two separate days. They employed Landsat 7 ETM+ data and the mono-window technique in their research. The findings show that both surface and atmospheric heat islands exist in the studied area. Temperature changes ranged from 0.5°C to 3.5°C, with the latter being strongly linked to the present land use/covers. The findings in this research reveal that the expansion of urban areas in Greater Cairo has resulted in increased land surface thermal radiation in densely inhabited areas. Al Kuwari et al., 2016 used the best spatial and spectral resolutions from Landsat and ASTER images to extract thermal infrared data in Doha, Qatar from 1990 to 2015. The computed Urban Heat Island (UHI) using Landsat sensor data was more compatible with ground trothed temperatures, according to the findings. Landsat TM thermal infrared data with a low spatial resolution (60-120 m) was better suited for large-scale thermal investigations, but not for assessing complicated urban thermal settings or determining Land Surface Temperatures (LSTs) for individual structures. The ASTER sensor, which has a 90 m spatial resolution Thermal Infrared (TIR) subsystem, was shown to be more precise in determining thermal patterns and LSTs. The data from Landsat revealed relatively high temperatures, which were more consistent with ground trothed measurements. Ahmed (2018) used remote sensing and GIS techniques to conduct a study on the assessment of urban heat islands and the impact of climate change on socioeconomics in the Suez Governorate. Using quantitative thermal, temporal remote sensing, and GIS tools, hianalyzed Urban Head Island's article. Landsat TM/ETM, 8 and ASTER images recorded during the winter season were used to evaluate variations in land surface temperature (LST) and land-use/cover change from 1988 to 2014. The classification of the study region was done using NDVI, NDBI, and LST. According to the findings, changes in UTFVI distribution can be attributed mostly to the increase of urban areas over the study period. UTFVI hotspots were mostly detected in built-up areas, particularly densely inhabited districts and strongly industrial districts. It is the UHI-vulnerable locations. Choi et al. (2014) used one-year (April 2011–March 2012) land surface temperature (LST) data retrieved from the Communication, Ocean and Meteorological Satellite to examine SUHIs in three East Asian megacities (Seoul, Tokyo, and Beijing) (COMS). Using hourly cloud-free LST data, the spatiotemporal fluctuations of SUHI and the link between SUHI and vegetation activity were investigated. Low latitudes, low altitudes, urban locations, and dry regions had greater LSTs than high latitudes, high altitudes, rural areas, and vegetated areas. The LST over the three megacities, in particular, was always higher than in the surrounding rural areas. The SUHI had its highest intensity (10–13 °C) during noon throughout the summer, regardless of the city's geographic location, but it had weaker intensities (4–7 °C) at other times and seasons. This study suggests that the SUHI intensity is mainly controlled by differences in evapotranspiration (or the Bowen ratio) between urban and rural areas during the daytime. Buyadi et.al. 2013 generated the land surface temperature maps and investigate the impact of land use changes of the surface temperature distribution in area surrounding the National Botanic Garden, Shah Alam. He also used Remote sensing and geographical information system (GIS) techniques to detect the land use changes and its impact on the land surface temperature (LST). Land use maps of two different dates are derived from Landsat images of 1991 and 2001. The findings of this study reveal that the LST of various land uses varied greatly. This research shows that growing urbanisation reduces vegetated areas, raising surface temperatures and altering the metropolitan microclimate. Using remote sensing data, Bahi et al., 2016 highlighted and monitored the spatial distribution of Surface UHI (SUHI) in the Casablanca region of Morocco. A time series of Landsat TM/ETM+/OLI-TIRS images was captured and processed from 1984 to 2016 to achieve this goal. Additionally, nocturnal MODIS photos from 2005 to 2015 were used to assess the SUHI at night. They also looked at the intense heat created by urban cores, calculating the SUHI intensity (SUHII) by calculating the difference in land surface temperature (LST) between urban and rural areas. The industrial regions of the Casablanca region were also affected by a large spike in SUHII exceeding 15 °C in some industrial zones, according to this study. During the summer, however, daytime SUHII has a reciprocal impact, with the establishment of a heat island in rural areas and the growth of cool islands in urban and peri-urban areas. In metropolitan regions, the SUHII remains positive at night all year, with greater values in winter than in summer. Chen, et al., 2012 conducted a case study of Shenzhen, China to evaluate the links between nocturnal UHIs and socioeconomic or topographic characteristics using a combination of remote sensing (RS), geographic information system (GIS), and landscape ecology methodologies. Night- and daytime LSTs were calculated and analysed using pictures from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and the Landsat Thematic Mapper (TM). Then used onscreen digitising to generate land-use data, and they used a normalised spectral mixture analysis (NSMA) approach with TM data to get an abundance of impervious surfaces. The China 2000 census data also provided socioeconomic variables. Traditional regression analysis was used to examine the associations between nocturnal UHIs and socioeconomic and topographic characteristics. Haashemi et al., 2016 looked at the seasonal variation of SUHI in the Tehran metropolitan area, Iran, in relation to a number of surface biophysical variables. The Land Surface Temperature (LST) from the Terra Moderate Resolution Imaging Spectroradiometer (MODIS) was recovered as night-time LST data, while daytime LST was retrieved from the Landsat 8 Thermal Infrared Sensor (TIRS) using the split-window algorithm. Both sets of data covered the months of September 2013 and September 2015. This research reveals that in semi-arid cities like Tehran, with the urban-rural indicator, a surface urban cool island can be noticed during the day while SUHI can be observed at night; with other indicators, SUHI can be observed at any time of day. As a result, SUHI research necessitates the collection of remote sensing picture data at both day and night, as well as the careful selection of SUHI indicators. Hua & Owi, 2018 evaluated the impact of land-use and land-cover (LULC) changes on land surface temperature (LST) in the Kuala Lumpur metropolitan city using multi-spectral and multitemporal satellite data. In this research, they used spectral radiance model to extract the LST from Landsat-8 OLI and Landsat 5 TM. The analysis on LULC changes revealed a phenomenal increase in the urban (high built-up area) areas and a decrease in the forest land area. The distribution of average changes in LST shows that the biggest increase in temperature was observed in urban (high built-up area) areas, followed by urban (low built-up area) areas, grassland, forest land, and waterbodies. In this work, the LST and normalised difference vegetation index (NDVI) were computed based on changes in LULC which indicates that a strong correlation value was observed between LST and NDVI for urban (high and low built-up areas) areas, grass land area and forest land area Hasse and Lathrop (2003) proposed a set of five indicators to measure per capita land consumption in new development in relation to several critical land resource impacts associated with sprawl, including: (1) new urbanisation density; (2) loss of prime farmland; (3) loss of natural wetlands; (4) loss of core forest habitat; and (5) increase in impervious surface. These Land Resource Impact (LRI) indicators were calculated for each of New Jersey's 566 municipalities utilising a digitised database of land use/land cover from 1986 to 1995, as well as population data from the US Census. With Landsat imagery, Fu and Wang (2016) conducted a time series analysis of urbanization-induced land use and land cover change and its impact on land surface temperature. The single channel approach was used to estimate the time series LSTs (TSLSTs) in this work since it only required the parameters of water vapour and land surface emissivity and had a reported inaccuracy of less than 1 K. The Continuous Change Detection and Classification (CCDC) method was used to classify and detect changes in the LULC.

An additive model was used to further breakdown the LSTs into seasonal and trend components. The total LULC classification and change detection accuracies were 89 percent and 92 percent, respectively, according to the findings. To simulate the effects of urbanisation on the local climate of the Las Vegas, Nevada, metropolitan region, Kamal and Huang (2015) employed the Weather Research and Forecasting (WRF) Model and its embedded land surface and urban canopy models. Over the city, high-resolution simulations with a horizontal resolution of 3 km are carried out. Three land use/land cover (LULC) maps for 2006, 1992, and hypothetical 1900 are utilised in numerous simulations with identical lateral boundary conditions. The authors of this paper also used the differences in the simulated climate among those cases to quantify the urban effect. In this study, it is found that the urbanization in Las Vegas produces a classic urban heat island (UHI) at night but a minor cooling trend during the day. Land surface temperature variation owing to changes in elevation in the area surrounding Jaipur, India was studied by Khandelwal et al., 2018. They looked on the impact of elevation change over LST. They employed LST data from the Moderate Resolution Imaging Spectra diameter (MODIS) and an ASTER digital elevation model in their research. For all of the research seasons, there is a consistent inverse linear trend between LST and elevation. Elevation and mean LST have a strong connection ($R2 = 0.73–0.87$). The change in LST due to elevation difference between two points separated in space in a horizontal direction ranges from 3.5 to 4.6 °C per 1000 m, which is lower than the condition when two points are separated in a vertical direction (5.0–10.0 °C per 1000 m) i.e. along a vertical column of air. They found that in any study related with spatial distribution of LST over a large area, effect of change in elevation at different locations shall also be considered and LSTs at different location shall be rationalized on the basis of their comparative elevations. Lee et.al., 2012 said that the heating of the urban surfaces during the daytime sets the initial temperature, and this overheating is dissipated during the night-time through mean convection motion over the urban surface and also discussed the energy balance which shows that this cooling effect can be quantified in an exponential decay in time. Authors told that the minimum temperature reached at the end of this cooling period corresponds to the UHI, which increases with increasing urban length scale and decreasing windspeed. This study was carried out in the Zhujiang Delta by Le-Xiang et al., 2006, who used

SGVU J CLIM CHANGE WATER
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remote sensing and geographic information systems (GIS) technology to detect land use/cover changes (LUCC) and quantify their impacts on land surface temperature (LST). Landsat TM and ETM+ data from multiple time periods were used to identify LUCC patterns as well as quantify urban growth and the resulting loss of vegetative cover. LST was retrieved using the data's thermal infrared bands. The findings in this work demonstrated a robust and uneven urbanisation, resulting in a 4.56 OC increase in LST in the newly urbanised part of the study area. Overall, remote sensing and GIS technologies proved to be useful tools for tracking and analysing urban expansion patterns, as well as assessing their effects on LST. Li, et. al., 2014 conducted this study using Shanghai's inner city as a case study and looked into the disparate impacts of land use and land cover on LST. In their study, Land use and land cover data are derived respectively from aerial photography and high-resolution satellite imagery (ALOS), and the LST is estimated from Landsat TM images. For most land use types, the land cover composition and configuration are varied. By contrast, no statistical difference is observed among old residential, industrial and institutional land uses for LST. The mean LST of new residential and industrial land use is significantly different, although their land cover compositions and configurations are quite similar. These results indicate in this paper shows that the key factors affecting urban LST are not only land cover patterns, but also other anthropogenic forces. As a result, land cover alone is insufficient to explain urban LST. Land use data is more useful than land cover data for predicting the effects of urbanisation on ecosystems, especially at tiny spatial scales. Mohan et al. (2011) assessed land use/land cover (LULC) changes and urban development in Megacity Delhi, highlighting the significant impact of rapid urbanisation and population growth on land cover changes, which requires prompt attention. The findings show that the city is expanding towards its periphery, with rural areas being converted to urban expansions. During the study period 1997 to 2008, the built-up area of Delhi increased from 540.7 km2 to 791.96 km2, accounting for 16.86 percent of the total city area (1,490 km2), with the majority of the growth coming from agriculture land, waste land, scrub-land, sandy areas, and water bodies. They looked at how LULC changed as urban expansion characteristics including population, cars, and gross domestic product changed. The findings emphasise the importance of using urban planning concepts so that more attention is paid to the protection and management of natural land use classes, which will improve the quality of life in urban areas. Patra et.al. 2018 analysed impact of urbanization on land use-land cover changes and also highlighted its impact on local climate and ground water. In this paper, spatio-temporal satellite images and conventional data are used to characterize the urban growth process, whereas K-Means based unsupervised classification technique is used for LULC changes. For the spatial distribution of rainfall, temperature, and groundwater level analysis, the inverse distance weighting (IDW) interpolation approach is also used. For the spatial distribution of rainfall, temperature, and groundwater level analyses, the inverse distance weighting (IDW) interpolation approach is used. While the methodology utilised in the work has the potential to help researchers better understand the urbanisation process, the findings have significant consequences for policy and regulatory design. Peng and Weng (2016) used Landsat images to conduct a time series analysis of urbanization-induced land use and land cover change and its impact on land surface temperature. The single channel approach was used to produce the time series LSTs (TSLSTs) because it only required the parameters of water vapour and land surface emissivity and had a reported inaccuracy of less than 1 K. The Continuous Change Detection and Classification (CCDC) algorithm was used to classify and detect changes in the LULC. An additive model was used to further deconstruct the TSLSTs into seasonal and trend components. The overall LULC classification and change detection accuracies in this paper were 89 percent and 92 percent, respectively. The conversion of evergreen forest to medium-intensity urban land produced the biggest difference in annual LST variation (5.7 K) and the largest trend difference (0.0004K/day) in this study's decomposition analysis. Using multi spectral and multi temporal satellite data, Pau & Ziaul, 2017 attempt to capture the impact of land use land cover (LULC) on land surface temperature (LST) in English Bazar Municipality of Malda District. Seasonal and temporal LST is extracted in three phases in their paper, for example, in 1991, 2010 and 2014. The findings demonstrate that LST grows at a rate of 0.070 °C per year during the winter and 0.114 °C per year during the summer, with considerable LST differences amongst LULC units. In all phases, the built-up area retains the most LST. According to the correlation coefficient between several deriving elements of LST and LST, impervious land controls LST the most ($r = 0.62$), followed by water bodies and vegetation cover. Patra et.al., 2018 done the study on impacts of urbanization on land use /cover changes and its probable implications on local climate and groundwater level. This paper is based on land use/land cover (LULC) changes and normalized difference built-up index (NDBI) computed using remote sensing and GIS techniques. Spatiotemporal satellite pictures and traditional data are employed to characterise the urban expansion process, whereas LULC changes are classified using a K-Means based unsupervised classification technique. For the spatial distribution of rainfall, temperature, and groundwater level analyses, the inverse distance weighting (IDW) interpolation approach is used. The Kendalls Tau test was used to see if hydro-meteorological (e.g., rainfall, temperature) characteristics have any association with hydrological components (e.g., groundwater level). Stathopoulou et al., 2009 used high-resolution multispectral satellite images collected over the Athens metropolitan area in Greece to create (a) a shortwave albedo map depicting albedo spatial variations across the metropolitan area, (b) a fractional vegetation cover map depicting the spatial distribution of urban vegetation, and (c) a daytime and night-time land surface temperature map. Cooling and heating zones were identified and examined using LST maps in order to uncover correlations between surface heat islands and urban surface characteristics. The most frequent building and paving materials used in the urban fabric of Athens were investigated based on data gathered using satellite photos and in order to better characterise the heat island problem and the mitigation actions that need to be done. Their optical qualities, as well as their thermal performance, were measured using a UV/VIS/NIR spectro photometer with an integrating sphere and an emisso metre. Sun et al. (2010) used the Model Maker tool in ERDAS to create a spatial-temporal model. Consider retrieving Land Surface Temperature (LST) and describing variations in urban heat islands and urban growth. Spectral Radiance, Brightness Temperature, NDVI, and Emissivity are computed first from TM and ETM+, then LST is computed using Qin et almono-window.'s approach. The classified the LST based on normalized statistical method, and the normalized heat images are computed between different times. Therefore, the urban heat changes can be shown in the map clearly and directly through an urban heat conversion matrix. The findings show that the LST increasing regions are primarily located near important roadways on the Pearl River's eastern bank, which is a result of rapid urban expansion and should be noted in the future. Schwarz, et.al., 2012 combined data on land surface and air temperatures, enriched the debate by suggesting the application of indicators for the two distinct data sets and systematically quantified indicators of all approaches for the city of Leipzig, Germany. They established relationship between the land surface and air temperatures. Sharma, R. & Joshi, P.K., 2016 investigated the features and process of a decade and a half long urbanization in National Capital Region (NCR) of India, focusing upon the relationship of urbanizing land use land cover (LULC) and the consequent changes in environment. As markers of environmental dynamism, satellite-derived metrics of greenness (NDVI), imperviousness (NDBI), bareness (NDBI), wetness (NDWI), and land surface temperature (LST) were utilised. This study discovered that when the area and density of built-up increased, LST and NDBI increased in the same proportion, whereas NDVI and NDWI decreased. This exemplifies the influence of urbanisation on the environment in India's National Capital Region (NCR). Tayanc and Toros, 1997 have done their work on the impact of urbanization in regional climate in cities of Turkey. Time series climatic data i.e precipitation, temperature of 1951- 1991 are used in this study. Air temperature and precipitation series from 12 locations, four of which are urban, are submitted to numerous analysis in this study. All of the stations' precipitation data passed the homogeneity tests. The method of using time series of temperature differences and logarithmic values of precipitation ratios between urban and rural stations is necessary to separate micro-scale urbanisation effects from large-scale climate changes and thus to obtain the magnitude of urban warming in Turkey's metropolises. The impacts of urbanisation on temperature were found to be marginally stronger for temperatures at 21.00 hr than for those at the minimum. This finding shows that the effects that cause urban warming in Europe are more similar than those in North America. In contrast to temperature, there has been little evidence of a large impact on precipitation. Urban warming is likely to impact micro-scale circulation patterns in the boundary layer, creating more convective activity above the city and a higher probability of having unstable weather showers, especially in the summer when cyclonic activity is at its lowest. Tomlinson et al. (2011) revised an article on Remote sensing land surface temperature for meteorology and climatology, highlighting satellites, sensors, and studies related to land surface temperature measurements in meteorology and climatology. Their main focus is on using the thermal infrared part of the electromagnetic spectrum for useful measurements of land surface t Their main focus is on exploiting the thermal infrared section of the electromagnetic spectrum to obtain useful measurements of land surface temperature, which can be useful for a variety of applications, such as determining urban heat islands. emperature, which can be beneficial for a number of uses, for example urban heat island measurements. Van & Bao, 2010 carried a case study in the northern part of Ho Chi Minh City, which has experienced accelerated urban development since the late 1980s. From 1989 to 2006, Landsat and Aster pictures were used to calculate variations in urban impervious surfaces. The urban heat island effect linked with growing impervious surfaces was investigated both geographically and temporally using thermal bands to derive radiant surface temperatures. The intensity of the surface urban heat island effect was used to demonstrate the effects of urban development on surface temperature. The results show that the built-up area in the northern part of Ho Chi Minh City expanded by 6.5 times between 1989 and 2006. Using remote sensing data in their, the impervious surface was extracted with overall accuracy and a Kappa coefficient for all three years greater than 96%, and the retrieved land surface temperatures with variations from *in-situ* measurements of less than2^{o}C. Weng et.al., 2004 looked at the usefulness of a spectral mixture model-derived vegetation fraction as an alternative measure of vegetation quantity. This is based on a Landsat Enhanced Thematic Mapper Plus (ETM+) image of Indianapolis, Indiana, in the United States. For all land cover types and spatial resolutions, the results showed that LST had a somewhat larger negative connection with the unmixed vegetation fraction than NDVI (30 to 960 m). The strongest correlations were seen at a resolution of 120 metres, which is thought to be the operating size for LST, NDVI, and vegetation fraction pictures. In this paper,the authors suggested that the area measure of vegetation abundance by unmixed vegetation fraction has a more direct correspondence with the radiative, thermal, and moisture properties of the Earth's surface that determine LST. Yao et. al. 2017 completed their study on Urbanization Effects on Vegetation and Surface Urban Heat Islands in China’s Yangtze River Basin. In this study, MODIS (Moderate Resolution Imaging Spectrora diometer) land surface temperature (LST) data and enhanced vegetation index (EVI) data were used to analyze the temporal trends of UEs on vegetation and surface urban heat islands (SUHIs) at 10 big cities in Yangtze River Basin (YRB), China during 2001–2016. The urban and rural areas in each city were derived from MODIS land cover data and nighttime light data. In this it is found the UEs on vegetation and SUHIs were increasingly significant in YRB, China. It was also found that the UEs on vegetation and SUHIs were increasingly significant in YRB, China. The ΔEVI (the UEs on vegetation, urban EVI minus rural EVI) decreased significantly ($p < 0.05$) in 9, 7 and 5 out of 10 cities for annual, summer and winter, respectively. The annual daytime and night time SUHI intensity (SUHII; urban LST minus rural LST) increased significantly ($p < 0.05$) in 10 and 4 out of 10 cities, respectively. Different Patterns in Daytime and Night time Thermal Effects of Urbanization in the Beijing-Tianjin-Hebei Urban Agglomeration were discussed by Zhao et al., 2017. SUHI intensity (SUHII) is computed using remotely sensed land surface temperature (LST) data in this study. To eliminate non-congruency between land cover data and LST data, and to evaluate daytime and night time thermal effects of urbanisation, pure and unchanging urban and rural pixels from 2000 to 2010 were chosen. Daytime and night time SUHIIs showed different patterns of seasonal fluctuations. In particular, the midday SUHII in summer (4 °C) was higher than in other seasons, whereas a cold island phenomenon was observed in winter; in all seasons except summer, the nocturnal SUHII was always positive and higher than the daytime one. Furthermore, the maximum daytime SUHII was identified in August, which is the growing peak stage of summer maize, while the lowest night time SUHII was found in August. Zhang and colleagues. 2013 have attempted to quantitatively analyse the complex interrelationships between urban LST and LULC landscape patterns with the purpose of elucidating their relation to landscape processes. They employed an integrated approach involving remote-sensing, geographic information system (GIS), and landscape ecology techniques on bi- temporal Landsat Thematic Mapper images of Southwestern Sydney metropolitan region and the surrounding fringe, taken at approximately the same time of the year in July 1993 and July 2006. In this paper, the LULC categories and LST were extracted from the bi-temporal images. The LST distribution and changes and LST of the LULC categories were then quantitatively analyzed using landscape metrics and LST zones. The results show that large differences in temperature existed in even a single LULC category, except for variations between different LULC categories. This study also illustrates that a method integrating retrieval of LST and fractional vegetation cover (FVC) from remote-sensing images combined with landscape metrics provides a novel and feasible way to describe the spatial distribution and temporal variation.

RESULTS AND DISCUSSION

The classification of photographs of the research area at various epochs was required in order to detect changes in the various land uses within the study region across the study period. Land use changes arising from built up-area, agriculture, fallow land, barren land, and vegetation and water bodies are some of the contributing factors to land cover changes in Ghaziabad district. Ghaziabad's urban expansion is characterised by uncontrolled growth of urban development, as well as a lack of suitable land use planning and sustainable development strategies. For each classification category, the changes in the LULC are expressed in terms of the number of pixels. Fig. 4, 5 & 6 represent LULC maps of Ghaziabad district in 2000, 2011 & 2018 prepared through supervised classification method. Statistics show that as at 2000, agriculture and fallow land constitutes the largest LULC categories in Ghaziabad followed by barren land and built-up area. They collectively occupy an area of 1098.58 km^2, representing 55.52% of the total land cover of the study area. The water bodies are the least land cover type. It occupied an area of 142.86 km^2 which represents 7.22% of the total land cover of the study area. Observations from year 2011 show a significant increase in the built-up environment/ settlement from 225.93 km^2 in 2000 to 319.53 km^2 in 2018 which implies an increase from 11.42% to 16.15%. Whereas, vegetation land decreases from 7.61% to 6.93% while barren land increased from 18.37% to 21.44%. Table 3 shows that the classification of different types of land uses land cover and its area distribution. This study mainly focus on the application of using Remote Sensing data and Geographic information systems in the drive towards sustainable environmental development with particular interest in uneven urban development, green area loss and significant thermal changes. This study has shown the LULC dynamics of Ghaziabad at different time periods with the corresponding deviation in the thermal environment as influenced by the LULC change. In this study, LST resulting from the Landsat ETM+ and OLI spectral data proved to be a good substitute for UHI. Image-induced LST can assess urban surface temperature not only in quantity but also in spatial patterns in any highly developing city. The results shown in this study reflects that the built-up areas in Ghaziabad district has expanded significantly on the expense of the vegetative areas. The total geographical area of Ghaziabad identified in the image is equivalent to 1977.33 sq.km. In 2000, the built-up areas were 225.93 sq.km while it has increased to 319.53 sq.km. in 2018. Surface temperature variations controls the surface heat and water exchange with the atmosphere resulting climatic change in the region. However some climatic indicators play a significant role in temperature variation, the major role such as land conversion due to rapid growth of urbanization and also from deforestation etc. resulting in temperature variations. Although this study is not the end, initial outputs of this works have shown that there are noteworthy increases in the built-up areas in the Ghaziabad district which resulted in higher LST in built-up areas as compared to the vegetated areas and agricultural land. During this study, a strong negative correlation between LST and NDVI, which specifies vegetation helps to reduce the LST of an area. We were able to determine the optimal answer for urban planning methods that address urban heat island reduction in the research area by looking at the relationship between urban surface temperature and land cover types. Green space has a critical role in reducing the heat island effect by transpiration and heat absorption, as well as reducing the emissivity of hard surface reflectivity by shading the built-up region. It is recommended to surround the highly dense built-up area and industrial areas of Ghaziabad by green belt buffers to more than 400 m for improving temperature condition and to decrease pollution effects to the acceptable limits.

This study will be useful for analysis urban expansion and population growth in the fastest growing city of Ghaziabad district. The urban growth dynamics and its future prediction will be useful for sustainable development.

The study of urbanization effects on environment will be useful for managing urban green spaces. This study will also be helpful in managing the natural resources of the district

CONCLUSIONS

This study depicted Ghaziabad's LULC dynamics over time, as well as the corresponding deviation in the thermal environment as a result of the LULC transition. LST derived from Landsat ETM+ and OLI spectral data was found to be a reasonable substitute for UHI in this analysis. In any rapidly developing area, image-induced LST can assess urban surface temperature not only in terms of quantity but also in terms of spatial patterns. The findings of this study show that the built-up areas in the Ghaziabad district have grown significantly at the expense of vegetative areas. Ghaziabad's total geographical area, as depicted in the picture, is 1977.33 square kilometres. In 2000, the built-up area was 225.93 square kilometres, but by 2018, it had risen to 319.53 square kilometres. Variations in surface temperature regulate the exchange of surface heat and water with the atmosphere, resulting in climatic change in the area. However, certain climatic indicators play a significant role in temperature variation, the most significant of which is land conversion due to rapid urbanisation and also deforestation, among other factors. This analysis is not complete; preliminary findings indicate that there have been significant increases in built-up areas in the Ghaziabad district, resulting in higher LST in built-up areas as compared to vegetated areas and agricultural land. During this research, there was a clear negative association between LST and NDVI, which indicates how vegetation helps to minimise an area's LST. We were able to determine the best approach for urban planning strategies that address urban heat island reduction in the study area by looking at the relationship between urban surface temperature and land cover forms. Green space plays a critical role in reducing the heat island effect by transpiration and heat absorption, as well as reducing the emissivity of hard surface reflectivity by shading the built-up region. Green belt buffers of more than 400 metres should be installed around Ghaziabad's densely built-up areas and industrial areas to improve temperature conditions and reduce pollution effects to acceptable levels.

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