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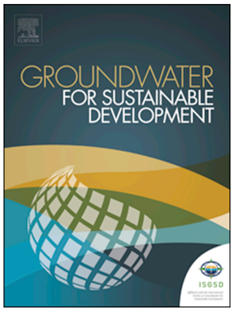

Impact of urbanization on land use and land cover change in Guwahati city, India and its implication on declining groundwater level

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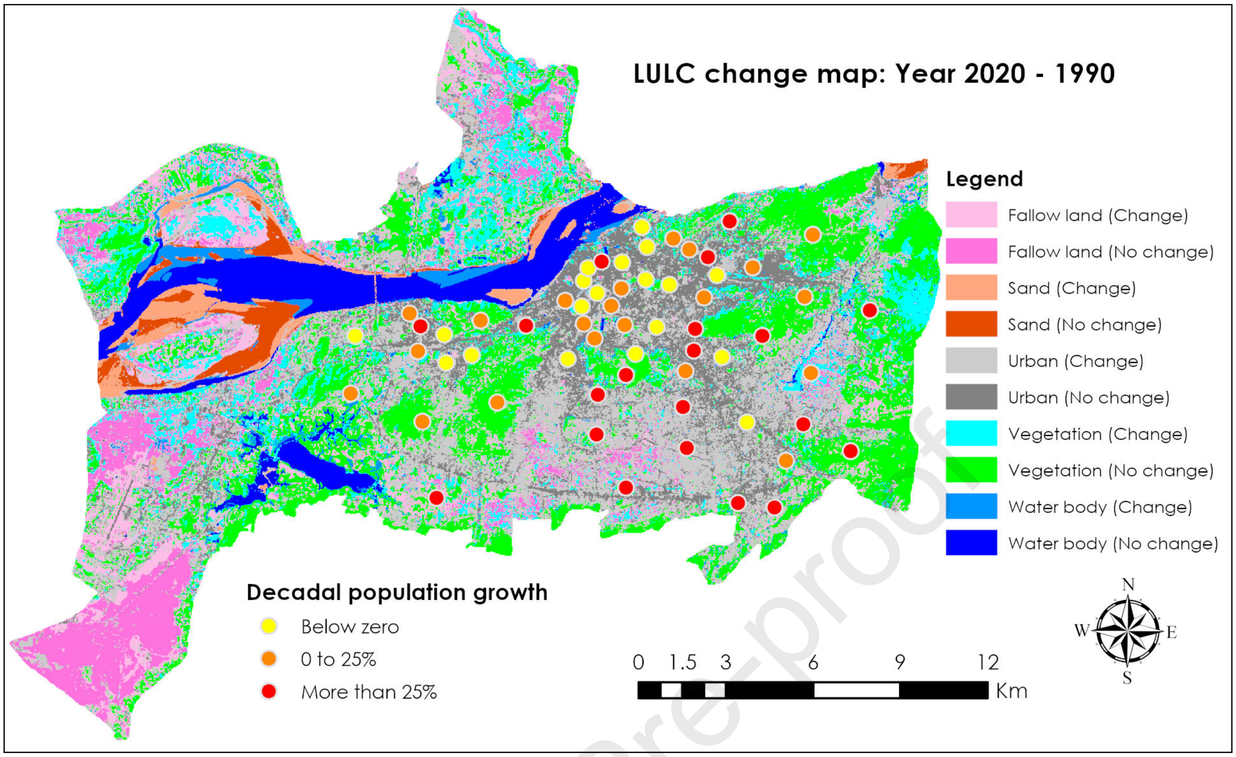

LULC change map: Year 2020 - 1990
Legend
Fallow land (Change)
Fallow land (No change)
Sand (Change)
Sand (No change)
Urban (Change)
Urban (No change)
Vegetation (Change)
Vegetation (No change)
Water body (Change)
Water body (No change)
Decadal population growth
Below zero
0 to 25%
More than 25%
0 1.5 3 6 9 12
Km
N
W
E
S

Impact of urbanization on land use and land cover change in Guwahati city, India and its implication on declining groundwater level

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Abstract

Urban environment continues to expand at an unprecedented rate to meet the demand of increasing population and economic development. The resulting changes to landscapes have increased stress to hydrological cycles, biogeochemical processes, and environmental sustainability of natural resources. This study evaluated spatio-temporal changes of land use and land cover (LULC) between 1990 and 2020 in Guwahati city, India. Time-series Landsat satellite images were analyzed using supervised classification schemes followed by change detection studies to quantify LULC change over time. Five broad LULC classes were identified on the basis of spectral reflectance signature. Confusion matrix determined high classification accuracy with Kappa Coefficient >0.81 in all cases. The results showed that the urban built environment has doubled in area in 30 years (1990 to 2020). The urban environments have increased at the expense of vegetation, fallow land, and open areas and to some extent wetlands. Notably, the expansions of urban areas have taken place from city center to the south, to the south-east, and along the east-west National Highway 37 connecting other NE States of India. There is no clear indication of change in the amount of precipitation in response to urbanization. However, analysis of long-term groundwater level data suggests a steady decline in the depth to groundwater level. The declining trend is attributed to urbanization and population growth. The increase in impervious surface coverage due to urbanization have extensively reduced the areas of high potential groundwater recharge zones and thereby dropping the level of groundwater in the wells.

Keywords: Urbanization, land use and land cover, change detection study, groundwater, Guwahati City.

1. Introduction

Land use and land cover (LULC) change due to urbanization plays an important role in local climate, hydrogeological condition, floodplain biogeochemical processes and environmental sustainability (Lambin et al., 2001; McGrane, 2016). The intensity of these changes worldwide during recent times is at an alarming level. According to a study conducted by the World Bank (2007), developing countries will have the most number of world's megacities by 2020.

Urbanization is mainly associated with cutting of trees and destroying vegetation in forest land and transforming these areas to build houses, industries, developing road networks and modern infrastructures (Dewan and Yamaguchi, 2009). These transformations are the results of migration of population from rural to urban areas (Sahana et al., 2018). The above processes could potentially lead to an increase in the percentage of impervious surface coverage of an area. The modification of earth surfaces during the urbanization often changes existing groundwater recharge pathway, alteration of hydrodynamic framework and floodplain processes (McGrane, 2016). Therefore, a detailed understanding of the spatio-temporal dynamics of urbanization is essential to protect our environment from degradation and facilitate sustainability in the future.

Urbanization can lead to varied stream flow conditions, vegetation dynamics, and surface/subsurface aqueous system contamination (Graniel et al., 1999; McGrane, 2016). In particular, the conversion of land to human-dominated uses may increase stresses to the ecosystem by releasing large contaminant pulses, e.g., metals and nutrients, within relatively a short span of time, and impacting downstream water quality and aquatic habitats (Horowitz et al., 1999; Sorme and Lagerkvist, 2002; Jat et al., 2009). The changes in impervious surface cover increases the contaminant load to receiving water bodies due to high volume of surface runoff and hydraulic efficiency of urban drainage networks (Arnold and Gibbons, 1996; Blanco et al., 2011). Lack of infiltration due to impervious surface cover reduces groundwater recharge and lowering the water level. Previous studies have shown that anthropogenic activities have considerably influenced urban water quality (Alberti et al., 2003; Patra et al., 2018). Graniel et al. (1999) observed changes in groundwater chemistry associated with the degree of urbanization in Mexico. Kaushal et al. (2017) reported increased transport of major ions in streams due to weathering and anthropogenic salts with urbanization. There are several processes responsible for water quality deterioration, e.g., increased wastewater recharge, leakages from sewers and urban drainage soakaways (Jat et al., 2009).

The problem of urbanization in India is at the critical level due to the fact that 16% of the world's population live within 2.5% of the world's geographical area (UNEP, 2001; Patra et al., 2018). In the last fifty years, India's population has doubled. This has resulted in the rapid growth of many cities in an unplanned manner. Among them, Guwahati city has experienced rapid urban population growth in recent decades (www.censusindia.gov.in). The growth of population together with the development and modernization of the city without proper planning has made Guwahati as one of the most unplanned cities in India (Patowary and Sarma, 2018). Previous studies have reported large scale deforestation of the hills and transforming those areas to urban settlements have caused landslides, soil erosion and urban flash floods in Guwahati city (Sarma, 2011; Patowary and Sarma, 2018). In recent decades, the rapid growth of population has led to an increased demand for housing and groundwater causing serious concerns to geo-environmental sustainability (Das and Goswami, 2013). The city is currently facing large-scale freshwater shortages, and declining groundwater levels together with rapid transformation of wetlands, forests and/or open areas into high-rise buildings and shopping malls (Das and

Goswami, 2013; Bhattacharya and Borah, 2014). Such an unplanned development could impact water quality by releasing toxic substances like arsenic, fluoride and mercury in the surface and groundwater of greater Guwahati city (Bhattacharyya and Kapil, 2010; Singh et al., 2017).

Therefore, an attempt has been made to establish a correlation between LULC change and the declining trend of groundwater level. Implying those changes to temporal variation in groundwater quality was depicted and that could form a basis for a future spatio-temporal analysis. Time-series Landsat satellite images from 1990 to 2020, temporal groundwater level and water quality have been analyzed to answer three specific research questions: i) how does urbanization influence spatio-temporal changes in land use and land cover? ii) what are the factors and processes associated with land use and land cover changes? and iii) how does degradation of wetlands, vegetation/forest cover and development of open areas affect the groundwater level?

2. Study area and data used

2.1 Study area

Guwahati is located within 26^{o}10’20’’N latitude and 91^{o}44’45’’E longitude and is the largest urban center in North-East India (Fig. 1). The study area falls within the Guwahati Municipal Corporation (GMC), commonly known as Guwahati city. The city has planned an extension under a Master Plan-2025 for industrial development and to accommodate growing urban population. The total planned area is 328 Km^2 (excluding Brahmaputra River) under Guwahati Metropolitan Development Authority (GMDA).

The population of GMC is approximately 1 million as per the Census 2011 and was estimated to grow 2.8 million by 2025. The anthropogenic activities have been increasing rapidly due to rapid growth of population and changing land use and land cover at an alarming level (Kumar, 2017). The topography is dominated by undulating hills and alluvial plains. The elevation is up to 327 m in the hills, while in the plains the elevation ranges between 49.5 and 55.5 m above mean sea level (Patowary and Sarma, 2018). Climate is subtropical humid with heavy rainfall during May to July and hot summer with high humidity. The average annual rainfall is 1,752 mm, and average temperature is 16.5^{o}C in winter and 26^{o}C in summer.

The study area consists of two broad hydrogeological units: Pre-Cambrian basement areas which are confined to hilly areas and inselbergs, and Quaternary alluvium which are scattered throughout the study area (Das and Goswami, 2013). Groundwater in Pre-Cambrian basement areas occurs in shallow weathered zones and can be developed through open wells. In Quaternary alluvium, groundwater occurs in regionally extensive aquifers down to the depth of 305 m. The aquifer consists of sands of various types with gravel and occurs under unconfined to semi confined conditions (CGWB, 2013). The hydrogeomorphological units are younger alluvial deposits, valley fill deposits, older alluvial deposits and basement rocks in order of high to low groundwater potentiality. The study area can further be grouped into three (high, medium and low) potential groundwater recharge zones (Das and Goswami, 2013).

2.2 Satellite data

A combination of LANDSAT 5 TM (Thematic Mapper) and LANDSAT 8 OLI/TIRS (Operational Land Imager/Thermal Infrared Sensor) satellite data products with a spatial resolution of 30 m and temporal resolution of 16 days were used in this study. Time-series satellite images were collected for the year 1990, 2000, 2010, and 2020, to quantify land use and land cover change. The scenes were collected for the month of January and February to avoid any seasonal changes in vegetation dynamics and land use activities. In addition to that, the date of pass was chosen based on cloud cover (free) conditions above the study areas (Table 1).

2.3 Population, groundwater level, and rainfall data

Population data were collected from the Census report of India (https://censusindia.gov.in/). Depth to water level was collected from Central Ground Water Board (CGWB), India website (http://cgwb.gov.in/GW-data-access.html). The CGWB measures depth to water level during the month of January, April, August and November during each year and these data are freely accessible from their website. Rainfall data were collected from the Regional Meteorological Centre, Borjhar, Guwahati.

3. Methodology

The satellite images used in this study were all have a 30 m spatial resolution (both Landsat 5 TM and Landsat 8 OLI/TIRS) and similar spectral resolution, but with different radiometric resolutions. Therefore, both Landsat 5 TM (8-bit) and Landsat 8 OLI/TIRS (12-bit) data were transformed to surface reflectance products using radiometric correction (radiometric calibration and atmospheric correction) in ENVI 5.5.3 software (L3Harris Geospatial).

Radiometric correction is a pre-processing technique used in remote sensing to reduce or correct errors in the digital numbers of satellite images. This correction is particularly important when comparing data sets over multiple time periods, typically due to radiometric inconsistencies between different satellite sensors and atmospheric conditions during different times of the data collection. Therefore, radiometric errors must be corrected in order to obtain a true ground radiance and reflectance values. The technique produces physically calibrated values by taking into consideration the effects of sensors, sun angle, topography and the atmosphere. For this study, Landsat surface reflectance products have been acquired from USGS. The detailed surface reflectance algorithm characteristics can be found in the USGS website (USGS, 2020).

Prior to image analysis and classification, satellite data were analyzed in detail using spectral profiles, histograms and scatter plots of different band combinations to ascertain the digital numbers (DNs) of different LULC categories. In case of spectral indices calculation and preparation of visual composites, surface reflectance products were used.

3.1 Spectral indices

Three spectral indices were calculated from the multispectral data of four scenes. These are:

1) Normalized Difference Vegetation Index (NDVI) is a well-known and widely used vegetation index that is effective in quantifying green vegetation. NDVI uses spectral reflectance from Near Infrared (NIR) and Red wavelength regions and normalizes green leaf scattering in the NIR wavelength region and chlorophyll absorption in the red wavelength region. NDVI value ranges between -1 and 1. The values close to -1 represent water bodies and the values close to 1 represent dense vegetation (and/or deep tropical rainforests).

2) Normalized Difference Built-up Index (NDBI) was calculated to examine the growth and extent of urban areas in the study area. NDBI values also range between -1 and +1. The low values typically represent non-urban features, while high values indicate built-up areas.

3) Modified Normalized Difference Water Index (MNDWI) was calculated to differentiate the extent of water bodies and built-up areas. MNDWI values also range between -1 and +1.

Built-up areas typically have negative MNDWI values due to higher reflectance in SWIR band than the water, resulting in positive values for water features.

3.2 Supervised classification

Five major land use classes were identified based on visual interpretation and spectral reflectance signatures. These land use classes were then classified using supervised classification schemes. The land use classes are as follows: 1) vegetation (including dense vegetation, open forest, and agricultural land with crops, trees and shrubs), 2) built-up area (including residential, commercial and industrial areas), 3) fallow land (including exposed bare soil and agricultural land currently fallow), 4) River sand (river sands and other exposed sandy areas), and 5) water body including wetlands (Table 2).

In supervised classification, the following steps were taken: 1) selection of training samples from known areas for five classes using high resolution satellite images, e.g., Sentinel 2A image and Google Earth image of the classification date, 2) generation of signature file of training samples using ROI tool in ENVI 5.5.3 software, 3) assessment of spectral profile of training samples for uniqueness of each land use classes by analyzing histograms of different bands, and 3) run classification using training samples to classify unknown pixels based on the Maximum Likelihood algorithm. A minimum of 120 spectral signatures (i.e., 20 times the number of bands) were collected for each land use and land cover classes through random selection of pixels.

3.3 Change detection studies

Post-classification change detection studies were performed to detect land use and land cover change. Post-classification analysis have been effectively used by various researchers to study urban growth because such analysis can efficiently detect the location, nature and rate of change (Hardin et al., 2007; Dewan and Yamaguchi, 2009). Visual composites and cross tabulation methods were used to obtain the changes in land use/land cover during the specified time period.

Visual composites were produced from NDVI, NDBI and MNDWI images of four scenes by assigning RGB color guns to make an interpretation of 'what was there' and 'what is there'. Cross tabulation analysis was performed on classified images. The analysis provides a quantitative estimate of change (e.g., percentage and area of change) from a particular land use/land cover class to another class over the evaluated period on a pixel to pixel basis. A new thematic change map was produced to visualize the changes that have occurred.

3.4 Accuracy assessment

Accuracy assessment is an important step to assess an individual performance of how well a classification was carried out and a tool to interpret the usefulness of a classified image (Mas, 1999). It is a useful measure parameter in the change detection studies. For the accuracy assessment, ground truth data for each classified land use and land cover classes were extracted using visual interpretation of original satellite images, high resolution Google Earth images, Sentinel 2A images and authors field knowledge of the study area. About 100 randomly distributed points in the images were selected to collect ground truth pixels. The classification results were compared with reference data using post-classification confusion matrix using ground truth ROIs in ENVI 5.5.3 software. Overall accuracy, producer accuracy, user accuracy, omission error and commission error were calculated (Table 3). Kappa Coefficient was also calculated to measure the percentage correct values based on the: 1) agreement between classified and reference pixels, and 2) chance agreement, indicated by the marginal. If kappa coefficient is <0.00, there is a poor agreement between the classified image and the reference data. If kappa coefficient is >0.81, then the classified image and the reference data are almost perfect agreement (Landis and Koch, 1977). The overall accuracy and the corresponding Kappa Coefficient of our classified images, agrees well with the reported global accuracy of 85–90% for LULC mapping as recommended by Anderson et al. (1976).

The accuracy of thematic change map (change detection study) was also determined by generating samples of 10 random pixels for each class (changed and not-changed) using ENVI's post-classification tool. Pixels that fell within the area comprising mixed land use and land cover classes were discarded. In total 250 ground truth pixel information were recorded for twenty five classes (20 changed and 5 not-changed classes). The nature of change within each pixel were determined by comparing color composites, high resolution Google Earth images and Sentinel 2A images. The overall accuracy of the change detection study is 67%. However, if we exclude five changed classes that classified inaccurately, the overall accuracy for the remaining 20 classes would improve to 82%.

4. Results

4.1 Satellite images and spectral reflectance signature

The visual analysis of satellite images (false color composites – Bands 742 for Landsat 5 and Bands 753 for Landsat 8) show 5 major land use types – vegetation in green color, water body in blue color, fallow land in light grey color, built-up area in purple color, and river sand in white color (Fig. 2). The image clearly shows the spatial expansion of built-up areas with time, spreading towards south and southeastern direction from the city center. Urban expansion has also occurred along the east-west by-pass road connecting the airport on the west and the inter-state highway on the east. The spatial patterns of urban sprawl is indicated by light purple color.

Surface reflectance profiles (mean values of 5 random pixels for each category) of five major classes are shown in Figure 3. According to the profile, river sand have the highest reflectance values in all the bands and these are the brightest features in the image. Fallow land also showed higher reflectance values and placed between built-up area and river sand. Vegetation showed low reflectance value in the visible region but showed higher values in the near-infrared region of the electromagnetic spectrum. Water body showed slightly higher reflectance values in the visible range but showed most absorption in the higher wavelength region. The spectral profiles are mostly similar for all years, except in 2010 when the range of reflectance values were narrower.

4.2 Spectral indices and visual composites

The results of the spectral indices are shown in Table 4. The NDVI values are ranging between -0.23 and 0.95 for all years, but the range was narrow during the year 2000 (ranges between -0.23 and 0.57). The NDBI values are ranging between -1.00 and 0.78. The range was much wider in 1990 because of a few outlier pixels. The MNDWI values are ranging between -0.85 and 1.00. The MNDWI range was wider in 1990 compared with all other years. Vegetation has the highest NDVI values, while water body has the lowest NDVI values. Built-up areas have NDVI values in the intermediate range. However, the NDVI values of built-up areas are quite similar to fallow land (bare soils and open areas) and river sands. Dense vegetation typically has NDVI values >0.5. The NDBI values are the highest for built-up areas and lowest for water bodies. Vegetation have the NDBI values in the intermediate range. NDBI values of built-up areas, fallow land and river sand are quite similar because the difference between spectral reflectance of SWIR and NIR bands are comparable between three classes. The MNDWI values are greater for water bodies, typically >0.4, while vegetation along with fallow land and river sand have the lowest MNDWI values, typically <-0.3. Built-up areas have MNDWI values in the intermediate range (0.1 to -0.3).

Visual composites were prepared by assigning red color guns to NDVI, green color guns to NDBI and blue color guns to MNDWI to understand land use and land cover characteristics in different years (Fig. 4). Vegetation is seen as a red color but the color intensity increases with density, while clear water is blue. Although, river sand, fallow land and built-up areas all have similar NDBI values, the visual composites of three indices could separate these three classes. Here the green color determines fallow land, white color determines river sand and light blue/cyan color determines built-up areas.

In visual composites, temporal change in spectral indices can be seen clearly. The vegetation becomes much brighter and denser in 2020 in comparison with other years. This has also been indicated by much higher mean NDVI values in 2020 (Table 4). Visual composites also indicated that during 1990 and 2000, the hills in the study area have much lower canopy cover which is indicated by greenish color suggesting barren hill surfaces. While NDBI values did not show much temporal change which could be due to conflicts in reflectance profile of built-up areas, fallow land and river sand. MNDWI values remained nearly stable throughout the study period.

4.3 Land use and land cover classification

The results of the supervised classification using Maximum Likelihood Classification (MLC) are shown in Figure 5. According to the confusion matrix, the overall accuracy is greater than 85% and the corresponding Kappa Coefficient is greater than 0.81 for all years. This suggests an almost perfect agreement of the classification and the reference data.

The MLC schemes identified the spatial extent of five land use classes in 1990. Two major wetlands (Deepor lake in the southwest and Silsako lake in the east), classified as a water body, are identifiable. These wetlands with time were partially replaced by built-up areas and vegetation as marked by green/cyan and red color, respectively in the imagery. The road networks are also clearly visible in 1990 mainly because of low density built-up areas. With time, these built-up areas were not only expanded but also became more densely populated. Some of the fallow land/open spaces were also converted to built-up areas, mainly in the southern part of the study area. The city's expansion in the northern bank of the river and near the airport in the west can be seen, but the growth is much slower compared with other parts of the study area.

The results show that the areas under the water body remained nearly constant during 1990-2020, while vegetation cover has decreased from 42.41% in 1990 to 31.97% in 2020 (Fig. 6). Built-up areas have increased from 18.07% in 1990 to 36.67% to 2020, mostly by replacing vegetation. However, vegetation remained as a major portion of the land cover till 2010, while between 2010 and 2020 built-up areas became the major portion of the land cover. Fallow land had declined rapidly from 1990 to 2000, and then declined slowly till 2020. The area under river sand had changed slightly consistent with river hydrodynamic conditions. There is a slight change in the area of water bodies during initial phases, typically the wetlands, which were mostly converted to built-up areas. Some of the areas within the hills in the center of the study area were misclassified as an urban area during 1990 and 2000 due to lack of vegetation, but the conversion to urban areas were actually seen during 2020.

4.4 Changes in land use and land cover classes

The results of the change detection study (initial state - 1990 and final state - 2020) showed a reduction in vegetation cover by –40 Km^2 and fallow land by –22 Km^2 with a corresponding increase in the urban land cover by +71 Km^2 in the study area (Table 5). Change detection study showed some urban areas classified in 1990 have converted to vegetation. This could be potentially due to mixing of spectral signatures of two classes, because many pixels have overlapping urban and vegetation class in the 1990 image, giving rise to potentially incorrect classification. While some built-area areas have shown to be converted to river sand, fallow land and water body. Conversion of initially classified urban areas to river sand, fallow land and water body is highly unlikely, and there could be an incorrect classification. This has been confirmed later with ground truth pixels which indicate that no urban areas have converted to other land uses. Urban areas also gained from fallow land and water bodies including wetlands. However, the chances of urban areas gained from river sand is highly unlikely and could be associated with incorrect classification. Overall, our change detection study showed approximately 68% urban areas persisted from 1990 to 2020. This could potentially be due to incorrect classification associated with low density urban housing along with the presence of vegetation during 1990. Overall there is a gain of 103% in urban areas over 30 year's period.

The loss of vegetation to urban class suggests that the trees or other vegetative surfaces were cut down for human use, while vegetation to fallow land suggests that there was a destruction of vegetation for either urban use or use for other activities. Conversion of vegetation to water body suggests that some of the vegetative areas within the wetland disappeared during the final state. Additionally, the loss of vegetation to river sand could be possible due to sand deposition over the vegetative surfaces (typically shrubs) near the river (which is about 0.81 km^2 in area). Vegetative areas gained from river sand could be possible due to agricultural activity along the river bank. Vegetative areas gained from fallow land and water body are also possible, for example agricultural activity in the fallow land and vegetation grown in the wetland water body. Overall, approximately 53% vegetation class remained persisted with an overall loss of 25% in area.

Conversion of river sand to water body is possibly due to erosional activities in the river, while river sand to fallow land could be possibly due to gradual deposition of finer sediments over sandy surfaces. The gain of river sand from fallow land is likely due to sand deposition over the surfaces of fallow land near the river. River sand gained from the water body could be due to deposition of sand in the river bed. Overall, approximately 39% river sand class remained persisted with an overall loss of 10.4% in area.

Fallow land to water bodies can happen near the river or flooding during final state. Approximately 39% fallow land class remained persisted with an overall loss of 25% in area. The loss of water body to fallow land is possibly due to flooding during initial state and become fallow land during final state. Approximately 58% water body class remained persisted with an overall loss of 17% in area.

The data suggests that urbanization has happened dramatically over the last 30 years and most of these developments have happened by cutting down forest/vegetation and reclaiming fallow land and open areas. There are some limitations in the change detection study because the classified images have already contained inaccuracies and that could contribute to the overall accuracy of the change detection map. Therefore, it is important to have a high resolution ground truth data to validate the results. For change detection study, the overall accuracy was found to be 67%.

5. Discussion

5.1 How does urbanization influence spatio-temporal changes in land use and land cover?

Urbanization is a process by which a rural, forested and/or agricultural landscape is transformed to an urban landscape to accommodate the need of growing population and upgrading people's way of living. A large part of the inhabited world is continuously being transformed by the rapid population growth and urbanization. Currently, there are little over 55% of the world's population living in urban areas (https://ourworldindata.org/). People are now more attracted to an urban life due to benefits associated with living within the limits of an urban area, such as better job opportunities, education, healthcare, transportation, communication, and business. In developing countries, the intensity of land use and land cover changes due to urbanization are more extensive and rapid than in the developed countries (Dewan and Yamaguchi, 2009). However, the impact of the changes in landscape on the natural environment due to urbanization are highly variable and complex (Carlson and Traci Arthur, 2000; Xiao et al., 2006; Dewan and Yamaguchi, 2009).

Guwahati is a major commercial hub and a business center in the northeast India, and it is connected by road to all other northeastern states of India. The region is also one of the major oil and gas producers in India. The growth of Guwahati is accelerating due to increasing population demand and implementation of various developmental projects. An increase of 103% in urban areas (i.e., doubled in area) over three decades (from 1990 to 2020) is enormous and most of these changes have occurred at the expenses of vegetation which was decreased by 25%, fallow land which was decreased by 25% and water body/wetlands which was decreased by 17% in area. The thematic map showed spatio-temporal patterns of the changes in land use classes during 1990-2020 (Fig. 7). The growth of urban areas is marked by light blue color, while the areas that have not changed (i.e., persisted) are marked by dark blue color.

The most notable changes were observed through time is the development of - i) East-West National Highway 37 in the south during 2000, ii) Modernization of the International Airport that has further caused major change to land use and land cover in 2010, and iii) Since 2010, an increase in the density of urban areas throughout the city was observed based on the high resolution satellite imagery from Google Earth. In addition to that, the growth and development of built-up areas can be seen on the hills based on the close examination of high resolution Google Earth images.

5.2 What are the factors and processes associated with land use and land cover changes?

The land use and land cover change together with urban expansion over space and time is mainly governed by the combination of natural phenomenon and anthropogenic activities, e.g., climate, population growth and economic development (Xiao et al., 2006).

Among the natural factors, the changes in rainfall pattern/intensity and climatic condition of a region can influence the changes in land use and land cover. Because, the intensity and variation in rainfall patterns can control natural vegetation dynamics as there is a direct relationship between rainfall and vegetation growth (Herrman et al., 2005). However, the overall rainfall pattern in the study area has not changed dramatically over the 30 years period, as represented by the moving average of monthly rainfall amount (Fig. 8a). Previous studies showed micro-level changes in rainfall patterns associated with urban heat island effects (Shepherd et al., 2002; Kharol et al., 2013), typically within urban areas and downwind regions (Liu and Niyogi, 2019). Because with urbanization, the cutting of trees reduces the amount of transpiration by the plants together with evaporation from the urban areas in comparison with non-urban areas. The changes in evapotranspiration increases the chances of precipitation in an urbanized setting than in a non-urbanized setting (Pickett et al., 2001). In the present case, the rainfall pattern follows a steady trend with some temporal alterations which seems unlikely to cause any significant reduction in vegetation cover and/or declining agricultural activities. The overall rainfall patterns depicted here are mostly resulted from regional climatic variabilities, e.g., temporal variations in monsoonal rain and are not related to urbanization.

On the contrary, the population of Guwahati has been increasing at a rapid rate (rather exponentially) during the last couple of decades and it is predicted to grow at a very high rate (Fig. 8b). The decadal growth was 40.12% between 1990 and 2000. During this decade, the built-up area has increased from 18.07% in 1990 to 26.9% in 2000 with an urban growth rate of 49%. Although, the decadal population growth rate had declined to 17.53% between 2000 and 2010, the growth of built-up areas remained high, i.e., from 26.9% in 2000 to 32.2% in 2010 (the growth rate of 20%). Figure 7 showed decadal population growth in different GMC wards (symbols are at centroid position) associated with changes in LULC. Most of the population growth has occurred further away from the city center coinciding with increase in urban areas. Overall, the population grew by 65% between 1990 and 2010 which is consistent with 78% increase in built-up areas during the same time period. There is an indication that the decadal population growth rate will peak during 2011-2021, and this has already reflected in the decadal growth rate in urban areas of 14%. This is the reason why Guwahati Municipal Corporation has initiated an urban extension project, called Master Plan-2025, to accommodate more people in a sustainable manner and carry on the developmental work. Although the rate of land development follows population growth, the demand for lands for various commercial and business activities have increased significantly with increasing numbers of people living within smaller urban spaces (e.g., multi-storied residential buildings).

Therefore, it can be concluded that the urban expansion is primarily driven by the concentration of population in the city that has drastically changed the land use of Guwahati Metropolitan areas. There could be contributions from other factors, such as economic development, modernization and other physical factors to the urbanization of Guwahati city.

5.3 How does degradation of wetlands, vegetation/forest cover and development of open areas affect the groundwater level?

Population explosion together with urbanization can be considered as a driving force for increased groundwater use (Hazarika and Nitivattananon, 2016). Urbanization increases imperviousness of a land surface, which in turn reduces infiltration and recharge to groundwater (Jat et al., 2009; McGrane, 2016) and thereby can act as a negative feedback to environmental sustainability (Arnold and Gibbons, 1996). As the imperviousness increases the rainwater runs off faster than it was previously due to less time available for water to infiltrate (O'Driscoll et al., 2010). Therefore, the ability of soil layers which normally act as a filter to pollution is impaired due to creation of an impermeable barrier. Thereby the diffuse pollutants from urban areas can be transported through the storm drains and directly into the waterways.

The groundwater level data from 1996 to 2018 reveals that the depth to water level is increasing rapidly with time in the areas that have experienced most urbanization, which is indicated by the changes in the percentage of built-up areas (Fig. 8). The LULC change map indicated that built-up areas have increased from 17% to 45% in the areas that have a high groundwater recharge potentiality. The open areas (fallow land) have decreased from 30 to 20%, while vegetation have decreased from 42 to 26% (Fig. 9). This suggests a significant loss of surface areas that had good groundwater recharge potentiality. In the study area, the demand for fresh water is rising exponentially due to the combined impact of rapid population growth and subsequent urbanization, industrialization and irrigation (Devi and Nair, 2018). The extraction of groundwater is increasing through time to fulfill the demand for households and industrial activities. Over-pumping is a major issue in the study area which is further complicated by poor regulation and management of groundwater resources (Hazarika and Nitivattananon, 2016). Because urban lifestyles demand more water than non-urban areas (Kataoka, 2010). Thus the growth of population in Guwahati city increases the chance of more water withdrawal because 69% population are directly dependent on groundwater and merely 27% depend on piped water supply (Goswami et al., 2005). According to the estimate the pressure of population explosion and urbanization on groundwater is 79 million liters a day (MLD), which exceeds the safe yield amount (Goswami et al., 2005; Hazarika and Nitivattananon, 2016). There is a general decline in groundwater level in the Kamrup Metropolitan District during the pre-monsoon period with a maximum falling trend of 0.812 m/year (CGWB, 2017). However, the annual rainfall in the area has not changed significantly. Indeed, the amount of rainfall during 2010-2012 has increased slightly, as indicated by the higher moving averages (Fig. 8). These areas usually have moderate to high levels of groundwater recharge potential (Das and Goswami, 2013). Despite the fact that the study area had received higher amounts of rainfall during 2010-2012, the groundwater level continues to decline at an unprecedented rate. Goswami and Rabha (2020) observed a general rise in the values of groundwater levels in post-monsoon and winter, albeit small, represented by the troughs of the upper moving average. Devi and Nair (2018) evaluated the status of groundwater in the region based on GRACE data and observed decrease in dynamic groundwater reserves. Thus the increasing utilization of groundwater and reduced subsurface infiltration due to urbanization (Schueler, 1987) could have already started showing signs of stress of groundwater availability in parts of Guwahati city. The likely future groundwater level scenario would be an important consideration given that the changes in groundwater dynamics have already started to show. The estimate of the change in recharge and new abstraction regime needs to be studied further.

6. Implication to water quality and further studies

Land use and land cover change due to urbanization can have a major impact on natural resources, especially degrading the quality of water, air, and soil (Haas and Ban, 2014; Liu et al., 2019). Deforestation increases soil erosion in the watershed and increases flooding risks due to siltation of major drainage channels. The changes in land use and land cover can modify the hydrodynamic condition of an area by altering the hydrologic cycle, for example reduced evapotranspiration, and groundwater recharge. Imperviousness increases the volume of surface runoff and therefore the diffuse pollutants from urban areas directly enters the surface water bodies in the absence of wetlands or open areas that acts a buffer between land and water for pollutants sink (Buffleben et al., 2002). Therefore, it is important to investigate the impact of urbanization in the natural environment and consider proper planning prior to any major developmental project and modernization of a city.

NIH (1998) had studied detailed water quality of greater Guwahati city in 1994-1995 and found that the groundwater is generally safe for drinking, with the exception of slightly high fluoride and iron concentrations in parts of Guwahati city. Bhattacharyya and Kapil (2010) reported the presence of high levels of toxic elements such as arsenic, fluoride and mercury in surface waters of Deepor Lake that receives urban storm water from Guwahati city. High levels of chloride were also observed in both the surface and groundwater of Guwahati city (Borah et al., 2020). Gogoi (2017) further showed high levels of fluoride, arsenic, selenium and chromium in groundwater of the city and suggested that the groundwater is highly vulnerable to these water quality parameters. A comparison of fluoride concentration based on two-time measurements, in 1994-1995 by NIH (1998) and in 2016-2017 by Gogoi (2017), of different wells was depicted to show if any changes to groundwater quality have occurred (Fig. 10). The spatial pattern shows much larger areas within Guwahati city have fluoride concentrations much above the permission limit in drinking water as stipulated by the Bureau of Indian Standards (BIS, 2012). Therefore, it is important to compare these results with the current surface and groundwater quality and study the geochemical processes in response to urbanization. As the majority of the population living within the city are dependent on groundwater for drinking and other purposes. A detailed time-series analysis of water quality would be essential to safeguard the health of millions living in the city.

7. Conclusion

This study assessed land use and land cover changes and expansion of urban areas in Guwahati city, India using remote sensing data. Guwahati city has experienced rapid changes in land use and land cover, particularly built-up/urban areas with an overall increase of 103% in area over the last 30 years. There has been a substantial reduction in the areas of vegetation, cultivated/fallow land, and wetlands/lowland. The changes in the land use and land cover are primarily driven by the rapid growth in urban population, economic development and modernization of the city during the studied period. Urban expansion has resulted in the transformation of land surfaces with high groundwater recharge potentiality. The percentage of open areas and vegetation have reduced significantly in the zone with the highest groundwater yield. Fluoride concentrations in groundwater have shown in extensive areas of Guwahati city, suggesting an alarming sign of groundwater pollution. A future study is directed to understand the affect urbanization on the geochemical processes and groundwater pollution and therefore could play an important role in the health of millions living within the city.

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Figure captions

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Figure 3. Surface reflectance profile (mean values, n=5) of 5 major land use and land cover classes from 1990, 2000, 2010, and 2020. The valid range for surface reflectance is 0 – 10,000 (scale factor: 0.0001).

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Figure 8. The histogram shows depth to water level (in m) below land surface during different months of 1990 and 2020 in Boragaon, Kahilipara and Khanapara of Guwahati city (water level data is from CGWB, India). The above three locations have experienced high degree of urbanization during 1990 and 2020. Vertical 'orange' bars show percent urban area within a 1 km buffer of the water level wells. The decadal population growth is – 75% for Boragaon, 16% for Kahilipara, and 38% for Khanapara between 2001 and 2011 as per Census of India.

Figure 9. Land use and land cover class change during 1990-2020 in the areas that have a very good groundwater recharge potentiality.

Figure 10. Fluoride concentration in groundwater wells sampled during 1994-1995 (from NIH, 1998) and 2016-2017 (from Gogoi, 2017).

Table 1. Details of satellite data product used in this study.

Satellite	Product Identifier	Date of pass	Path/Row
Landsat_5	LT05_L1TP_137042_19900224_20170131_01_T1	2/24/1990	137/042
Landsat_5	LT05_L1TP_137042_20000220_20161215_01_T1	2/20/2000	137/042
Landsat_5	LT05_L1TP_137042_20100130_20161017_01_T1	1/30/2010	137/042
Landsat_8	LC08_L1TP_137042_20200211_20200225_01_T1	2/11/2020	137/042

Table 2. Land use and land cover classes delineated on the basis of visual interpretation and spectral reflectance signatures.

Class No.	Class Name	Description
1	Vegetation	Forest area (including dense and open forest), agricultural land (cultivated areas/green vegetation), wetland vegetation, trees, and shrubs.
2	Built-up area	Residential (both low and high density), commercial and services, industrial, transportation, roads and other mixed urban areas.
3	Fallow land	Exposed soil, open areas, bare soils, areas of active excavation influenced by human activity, and areas with no agricultural activity.
4	River sand	River sands and other exposed sandy areas (typically sand mining areas).
5	Water body	River, swamp, low-lying areas, permanent and seasonal wetlands, pond and drain.

Table 3. Confusion matrix of Maximum Likelihood Classification of the time-series satellite images.

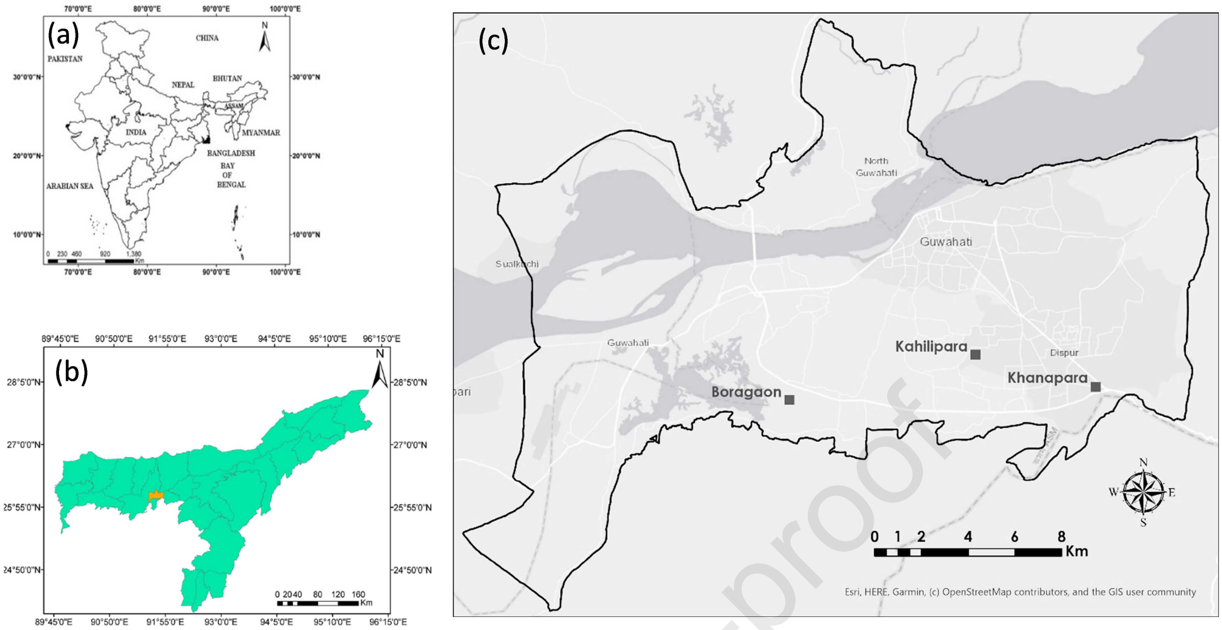
Year	**Class**	**User accuracy (%)**	**Commission error (%)**	**Producer accuracy (%)**	**Omission error (%)**	**Overall accuracy and Kappa Coefficient**
2020	Water body	96	4.0	88	12	88% and 0.85
	Vegetation	79	21	92	8.0	
	Urban	95	5.0	84	16	
	Fallow land	75	25	86	14	
	River sand	96	4.0	88	12	
2010	Water body	96	4.0	92	8.0	85% and 0.81
	Vegetation	91	9.0	80	10	
	Urban	81	19	84	6.0	
	Fallow land	68	32	88	12	
	River sand	95	5.0	80	10	
2000	Water body	100	0	96	4.0	90% and 0.87
	Vegetation	80	10	96	4.0	
	Urban	95	5.0	72	28	
	Fallow land	84	6.0	84	16	
	River sand	93	7.0	100	0	
1990	Water body	100	0	96	4.0	91% and 0.89
	Vegetation	86	14	96	4.0	
	Urban	95	5.0	76	14	
	Fallow land	82	18	92	8.0	
	River sand	96	4	96	4.0	

Table 4. Spectral indices: NDVI, NDBI and MNDWI, in different years.

Spectral indices	**1990**	**2000**	**2010**	**2020**
NDVI	-0.49 to 0.80 (mean: 0.28±0.21)	-0.34 to 0.95 (mean: 0.25±0.16)	-0.23 to 0.57 (mean: 0.18±0.12)	-0.32 to 0.90 (mean: 0.33±0.20)
NDBI	-1.00 to 0.78 (mean: -0.04±0.20)	-0.89 to 0.51 (mean: -0.01±0.16)	-0.84 to 0.53 (mean: -0.04±0.16)	-0.81 to 0.39 (mean: -0.07±0.15)
MNDWI	-0.85 to 1.00 (mean: -0.26±0.34)	-0.61 to 0.95 (mean: -0.25±0.28)	-0.68 to 0.91 (mean: -0.13±0.24)	-0.71 to 0.84 (mean: -0.25±0.28)

Table 5. Change detection statistics of land use and land cover classes (area in Km^2) during 1990-2020.

	Class	**Initial state (1990)**						
		Vegetation	**Urban**	**River sand**	**Fallow land**	**Water body**	**Row Total**	**Class Total**
Final state (2020)	Vegetation	85.36	12.15	2.32	17.69	4.87	122.4	122.4
	Urban	53.61	47.25	2.29	32.44	4.79	140.38	140.38
	River sand	0.81	0.99	7.27	1.26	6.40	16.73	16.73
	Fallow land	18.08	6.78	3.39	33.36	3.19	64.79	64.79
	Water body	4.49	2.02	3.41	1.70	26.94	38.55	38.55
	Class Total	162.35	69.20	18.67	86.45	46.18		
	Class changes	76.99	21.95	11.41	53.09	19.25		
	Image difference	-39.95	71.18	-1.94	-21.66	-7.63		



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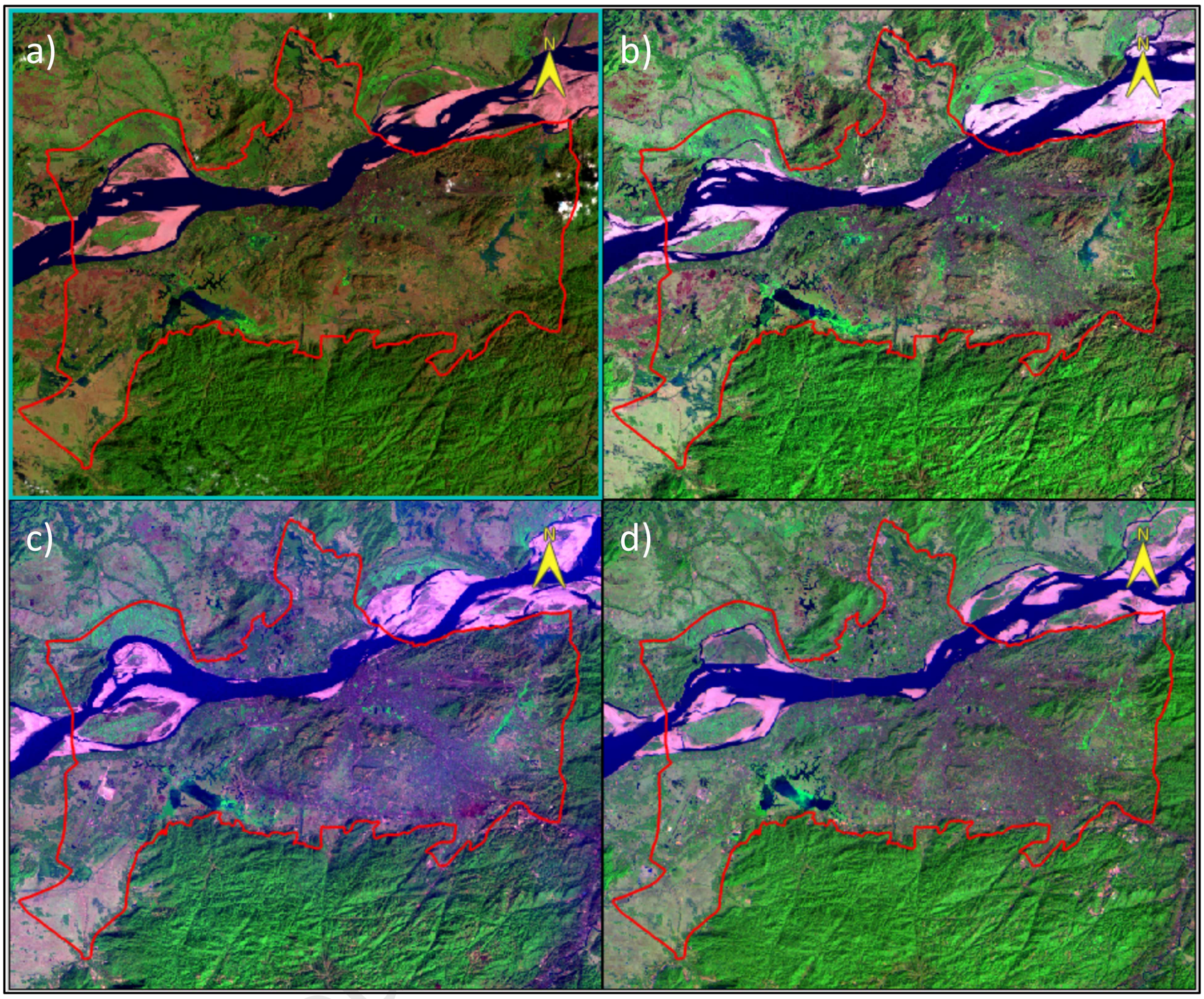

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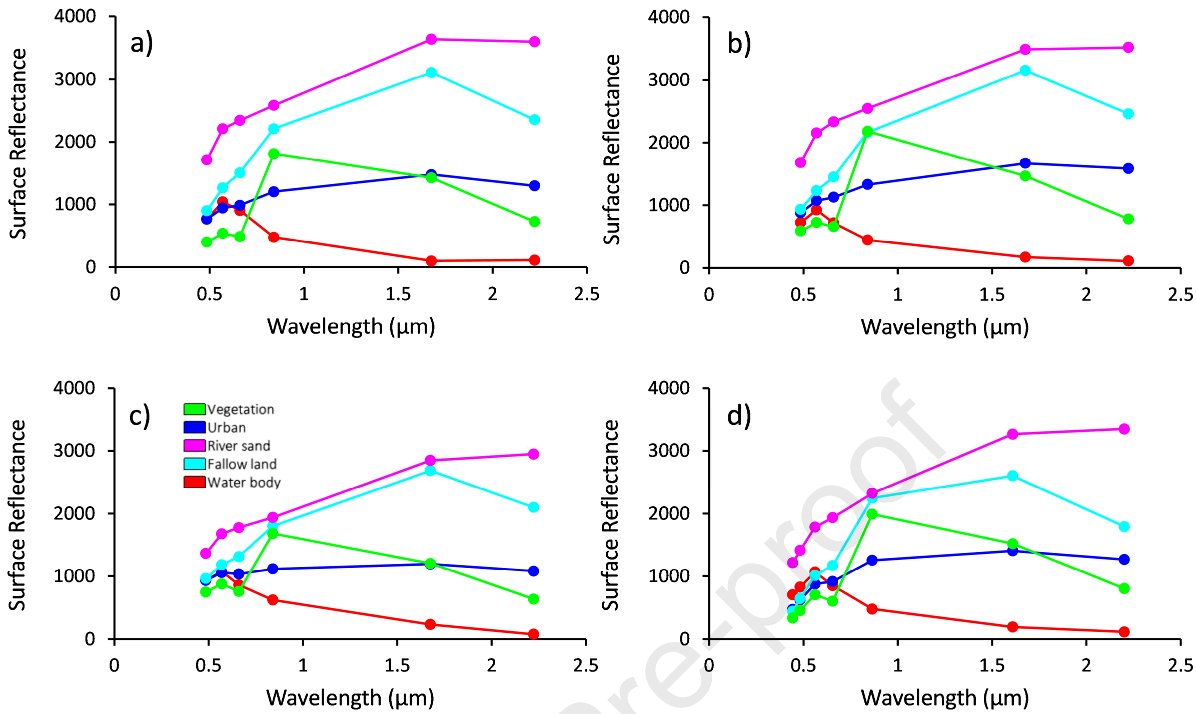

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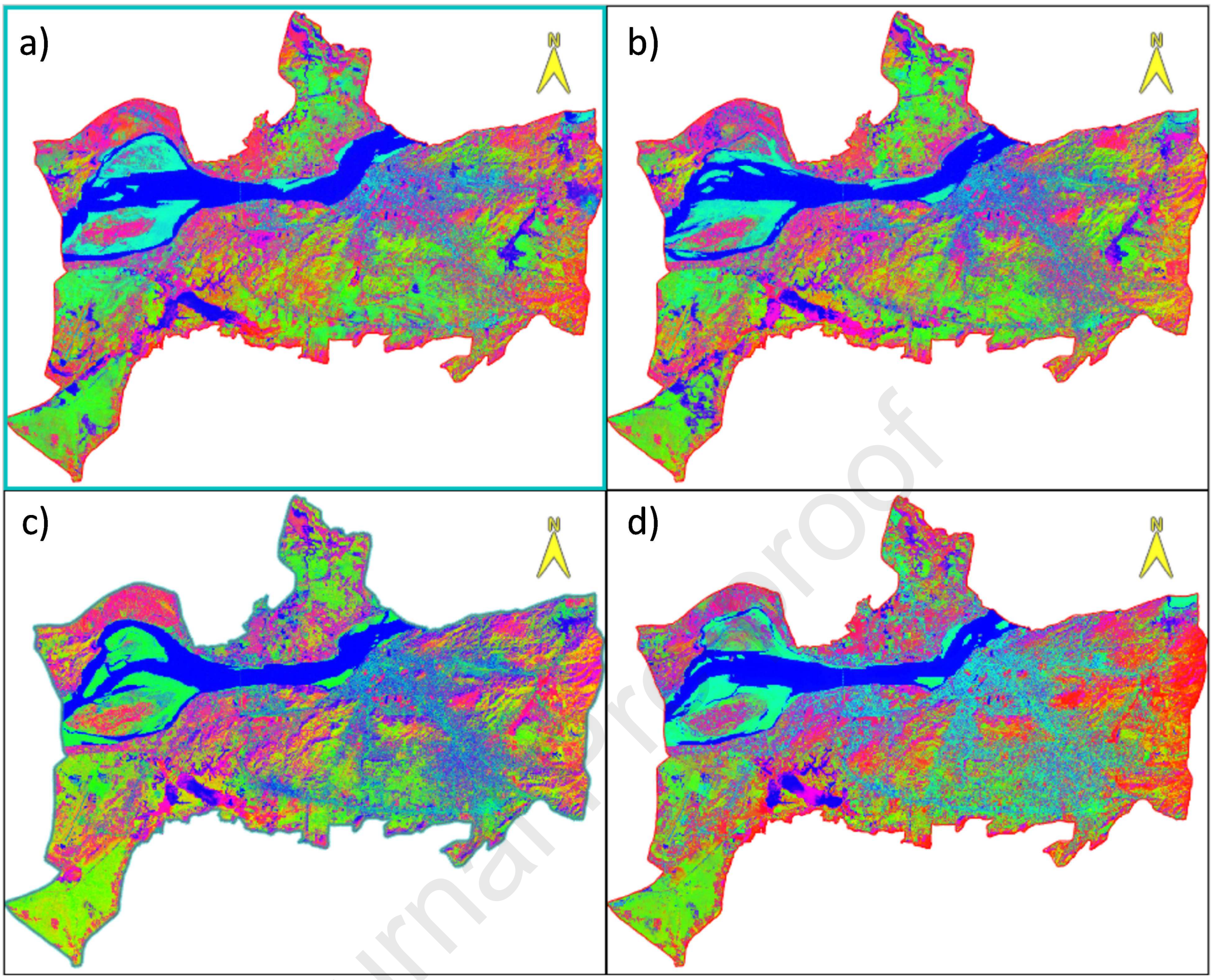

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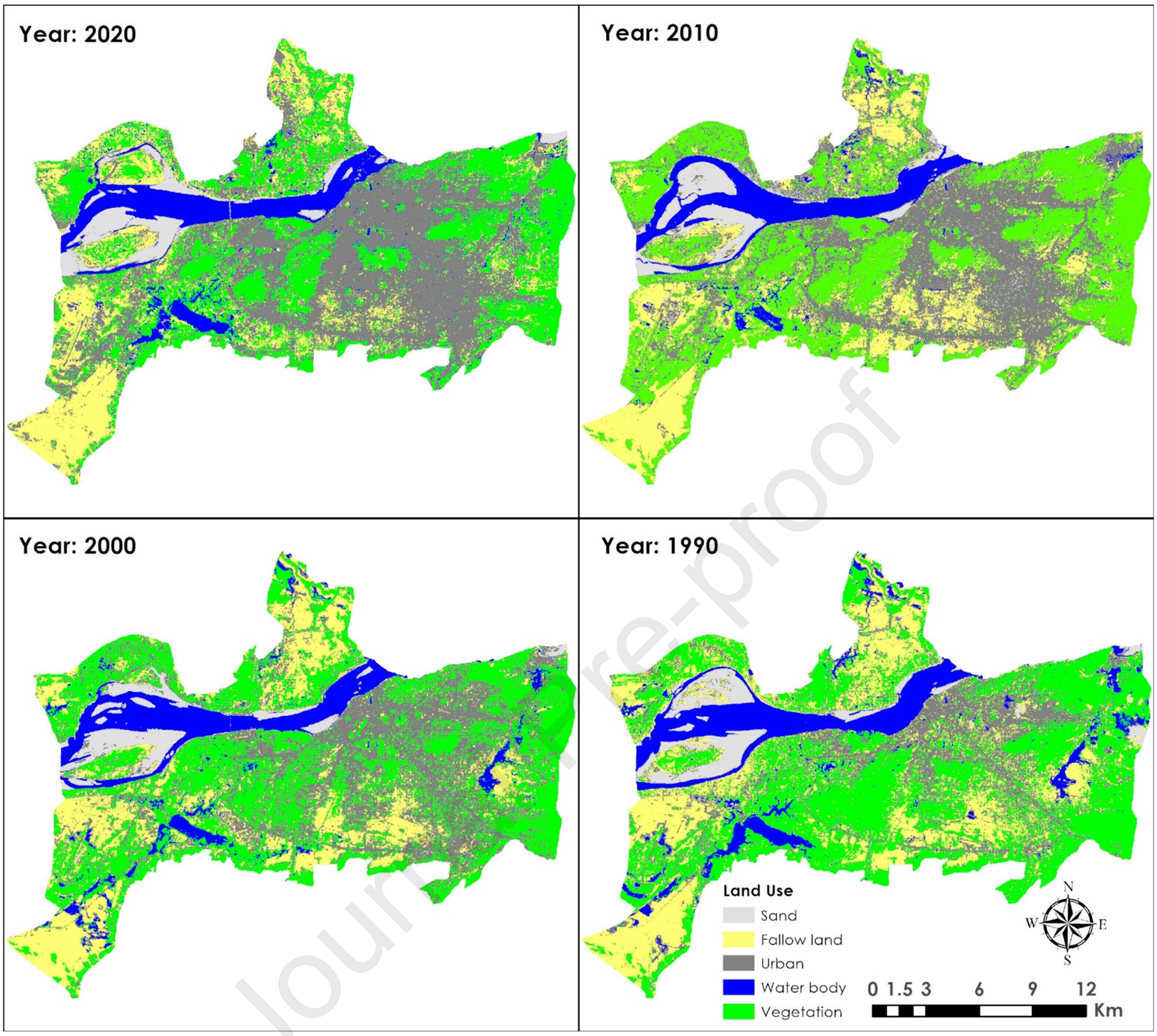

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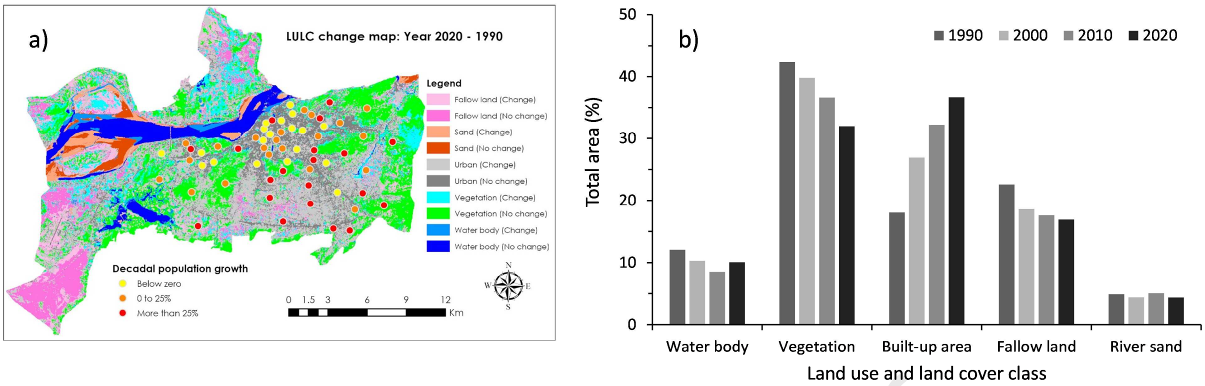

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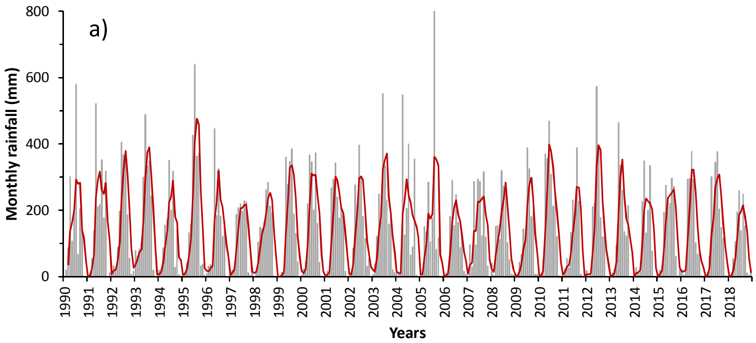

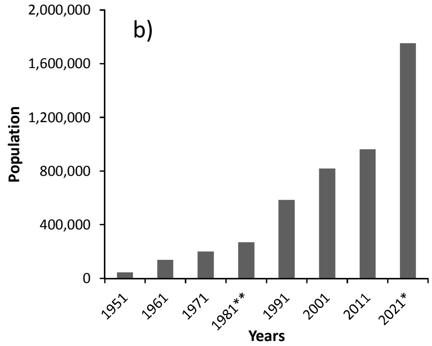

Figure 7. a) Monthly rainfall pattern in Guwahati city from 1990-2018 together with 3-period moving average for each series. Data source: Regional Meteorological Centre, Borjhar, Guwahati. b) The population growth of Guwahati Municipal Corporation Area. Source: Census of India, 2011 (http://www.censusindia.gov.in). * Projected population, and ** No census was conducted in 1981 in Assam, but extrapolated on the basis of 1971 and 1991 data.

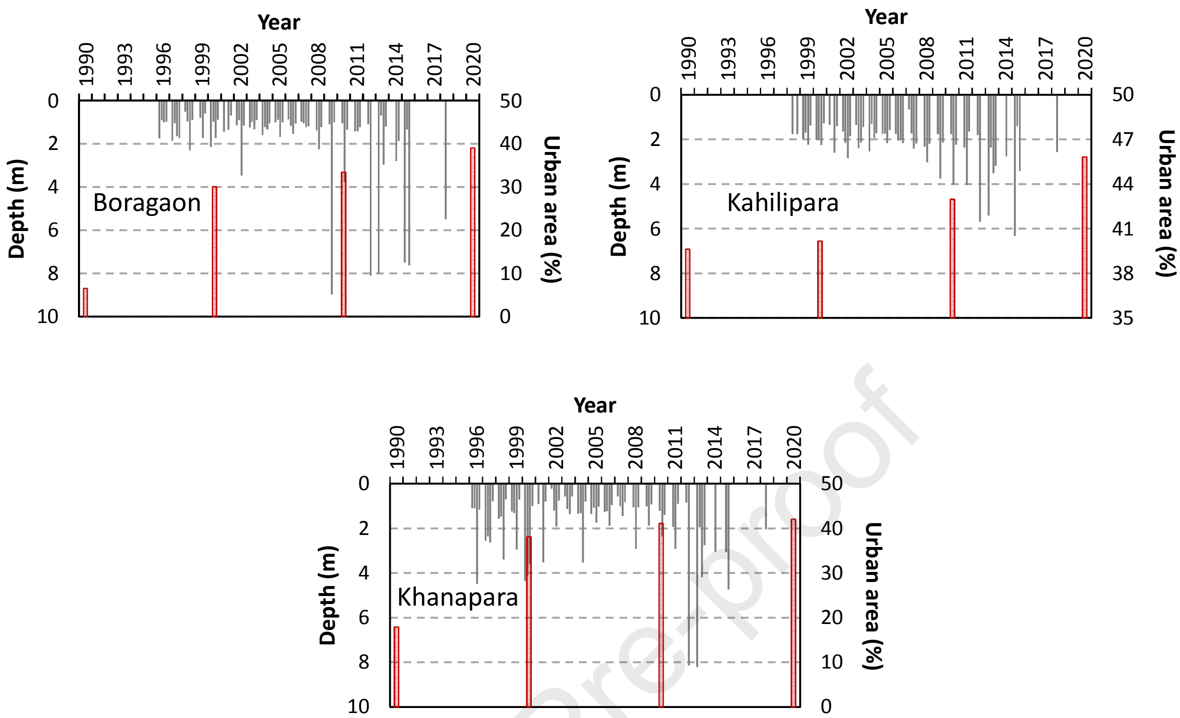

Figure 8. The histogram shows depth to water level (in m) below land surface during different months of 1990 and 2020 in Boragaon, Kahilipara and Khanapara of Guwahati city (water level data is from CGWB, India). The above three locations have experienced high degree of urbanization during 1990 and 2020. Vertical 'orange' bars show percent urban area within a 1 km buffer of the water level wells. The decadal population growth is – 75% for Boragaon, 16% for Kahilipara, and 38% for Khanapara between 2001 and 2011 as per Census of India.

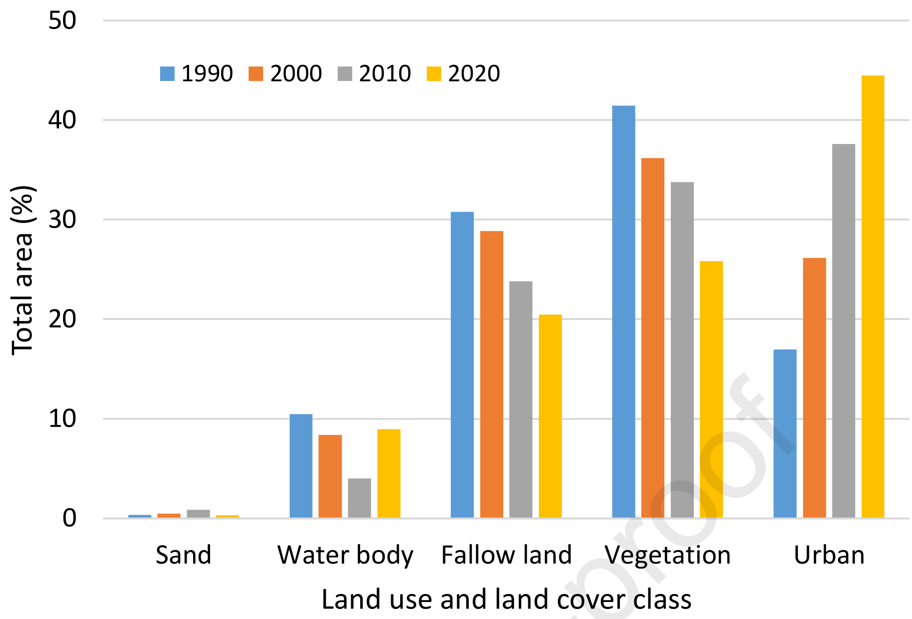

Figure 9. Land use and land cover class change during 1990-2020 in the areas that have a very good groundwater recharge potentiality.

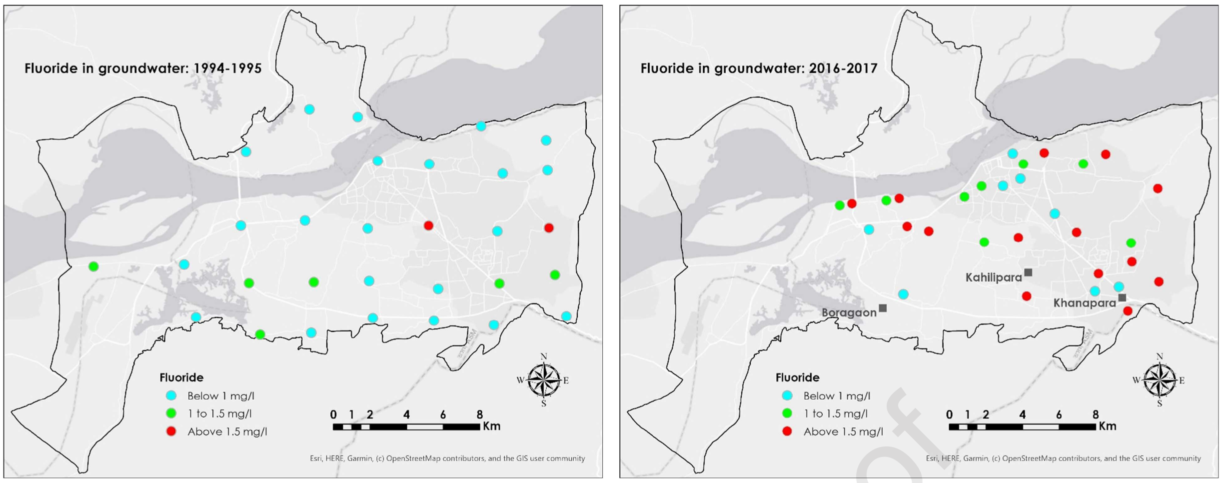

Figure 10. Fluoride concentration in groundwater wells sampled during 1994-1995 (from NIH, 1998) and 2016-2017 (from Gogoi, 2017).

Highlights:

- We evaluated spatio-temporal changes in LULC in Guwahati City, India.
- Increase in built-up areas were resulted at the expense of vegetation and fallow land.
- Water level decline is higher in the areas of intense urbanization and population growth.
- Urbanization has transformed land surfaces with high groundwater recharge potentiality.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: