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Study of Urban Sprawl and Its Impact on Vegetation, Land Surface Temperature and Air Pollution Using Remote Sensing and GIS in Kathmandu Valley from 2015 to 2020

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Abstract

The Kathmandu Valley has seen substantial urbanization over the past decades while being the nation's economic centre. Built-up areas have expanded quickly along with the population, having a significantly negative influence on the environment. Recently, Kathmandu was named as the most polluted city in Asia. Urban sprawl has had a negative influence on Kathmandu's residents in several ways. The state of urban sprawl and the effects it has had on the Kathmandu Valley have been examined using land sat imagery. In this study, IDW was used in GIS to analyze the pollution status using data of PM 2.5 and PM 10 obtained from various monitoring sites. A supervised classification was used to create a LULC map of Kathmandu for the years 2015, 2018, and 2020. To assess the state of the vegetation and determine whether the Kathmandu Valley is being affected by urban heat, NDVI and Land sat temperature calculations were also made. The study's results were obtained using remote sensing and GIS technology. The built-up area in Kathmandu Valley has grown by 20% over the past five years, impacting land use patterns and deteriorating vegetation cover. Due to the rise of built-up area, which is a good heat absorber, the temperature in the Kathmandu Valley is rising along with the degradation of the vegetation cover. The pollution in the Kathmandu Valley is at its worst, and residents are compelled to breathe air that is significantly more polluted than the prescribed limit.

Keywords

Urban Sprawl, Pollution, Land Use, Landsat Image, Builtup Area

1. Introduction

Urban growth is a dynamic process that results from the physical conversion of a rural area into an urban one due to socio-economic factors like topography, economy, culture, and population. Urban growth can be characterized by the transition that occurs in natural environment where it turns into an artificial one which is often brought about by built-up areas created by humans (Magar, Magar, & Chidi, 2021).

Kathmandu Valley currently is home to more than two million people. With the development of different infrastructure and various resources made available, the people from all over the country have started to internally migrate towards Kathmandu which causes exponential growth in population (Chitrakar, Baker & Guaralda, 2014). Due to rising migration, the Kathmandu Valley has quickly become the country largest metropolitan area.

As a result of unchecked growth, the Kathmandu Valley has recently seen a lot of pollution, making it one of Asia's most polluted cities (Thapa & Murayama, 2011). The residents of the Kathmandu Valley have endured great suffering as a result of rising pollution. It seriously affects people's health, including asthma and lung cancer (Aryal et al., 2009).

Such rapid growth of the population often times results in unmanaged urbanization. This type of quick transformation in the land area and population results in a loss of vegetation. As population grows, industrial activity will increase which results in production of more greenhouse gases that significantly influence air pollution and urban heat causing it to increase. Unmanaged urbanization occurs mostly in developing nations like Nepal because built-up growth is not properly synced with population increase. Urban heat is mostly caused by densely populated areas and greenhouse gases produced by various human activities. Compared to the surrounding area, the temperature in the city can be observed to be higher because of a phenomenon called urban heat island effect (Magar, Magar, & Chidi, 2021). Comprehending LULC is crucial since it aids in understanding various aspects of urbanization, including geography, morphology, and ecology (Sarif, Rimal, & Stork, 2020). Assessing urban expansion to determine its sustainability also benefits from understanding LULC. The analysis of LULC is complicated because it requires information on the area's natural features and how they are changing over time to make sense of the LULC data. Using remote sensing and GIS technology, numerous studies have been carried out on urban sprawl on a global scale. Due to its low cost and ability to detect change with time, a growing number of people are using remote sensing technology (Jat, Garg, & Khare, 2008). Various government agencies are now using GIS to develop plans and policies for bettering and managing urban sprawl because of the development of GIS technology. The scientific discipline of remote sensing enables one to ascertain an object's characteristics without physically touching it (Lillesand, Kiefer, & Chipman, 2015). Remotely sensed images can be easily understood using computer-based geographic information science by creating various types of maps with features. The emergence of remote sensing has made LULC analysis simple because it offers temporal information about a region (Treitz & Rogan, 2004). In this research, the rate of urban sprawl, NDVI, and land Page 4 of 76 surface temperature have been studied using Land Sat imagery from remote sensing. In contrast, air pollution data from various monitoring stations across the Kathmandu Valley have been used to analyze air pollution. Landsat images are a common type of remote sensing data worldwide. High-resolution, multispectral, panchromatic images with thermal data are available from Landsat data (Aboelnour & Engel, 2018).

2. Materials and Methods

Study Area

The Study area (**Figure 1**) Kathmandu valley is located at the co-ordinates of latitudes of 27˚42'14"N and longitude of 85˚18'31"E. The research area's elevation ranges from 800 to 2700 meters above sea level. There are 20 metropolitan and sub-metropolitan regions in the Kathmandu valley which will be the study region for this research. The total study area is 695 square kilometers. One of the

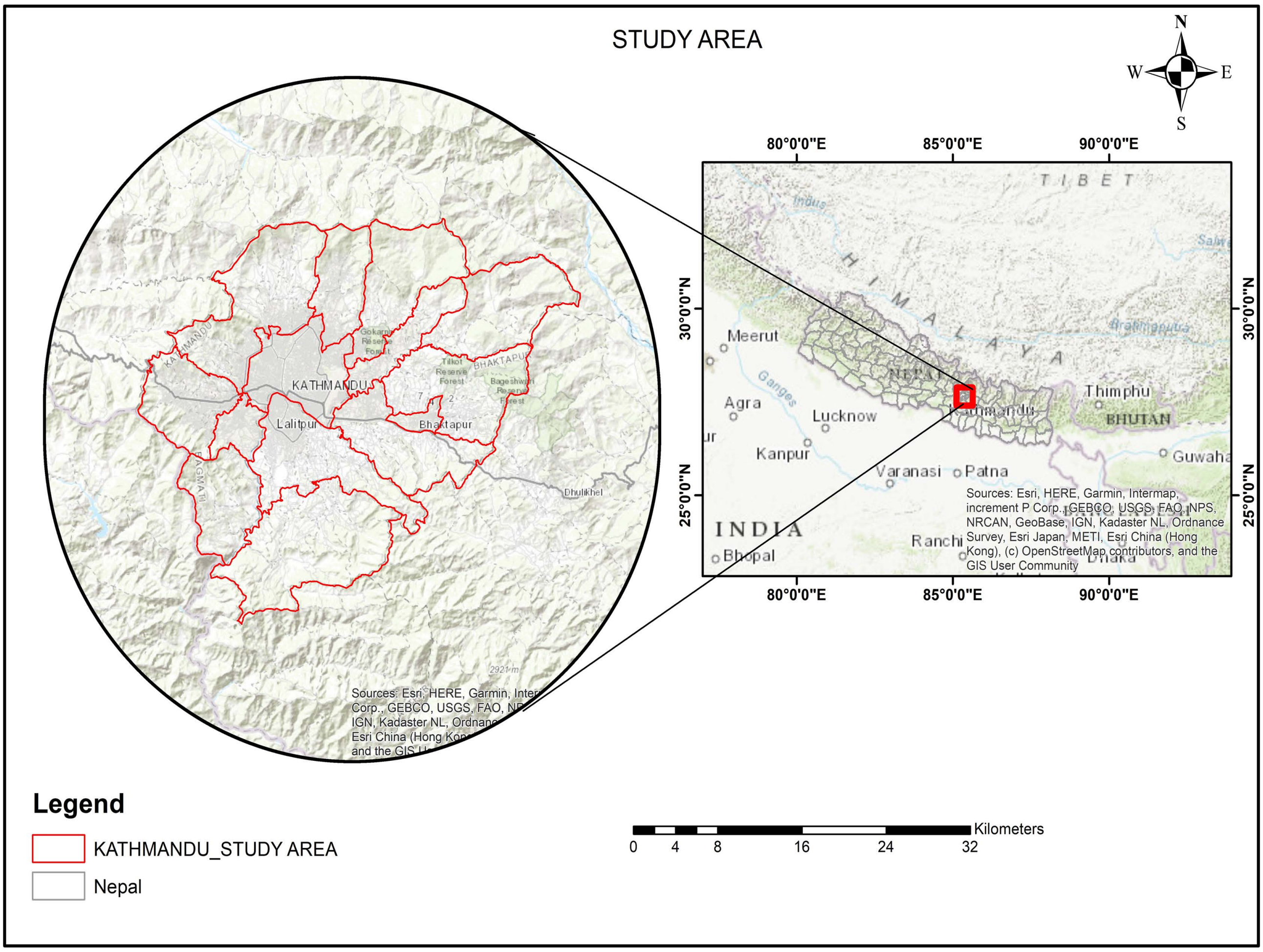

Figure 1. Location map of study area.

main sources of water in the valley is Bagmati River, which is also known to drain the other six tributaries. Within the valley the water from Bagmati River is used for irrigation in agriculture. Kathmandu, which is the nation's capital and economic centre is one of the most populated cities, with a population known to be over 2.5 million. Shivpuri Hills, fulchowki region, Nagarjun as well as Chandragiri Hills make up the four mountain ranges that encircle the bowl-shaped Kathmandu valley.

3. Methods

3.1. Data Acquisitions

3.1.1. Satellite Imageries

Landsat 8 images which have less cloud cover were downloaded from USGS Earth Explorer for the year 2015, 2018 and 2020. One of the best and most trustworthy sources of data known is a Landsat image from the United States Geography Survey (USGS) in order to monitor changes in land cover. The ability to generate high spatial resolution images for up to 30 meters makes Landsat 8 far superior to the earlier versions like Landsat 7 and Landsat six (Acharya & Yang, 2015). The Landsat 8 image has a total of 11 bands and is further classified as 1 to 7 band as multispectral band, where Band 8 is known as panchromatic with 15 m spatial resolution and Band 9 as can be seen in (**Table 1**) is referred to as cirrus, whereas bands 10 and 11 are referred to as thermal bands. A new band called Cirrus has been introduced to the Landsat 8 image to help detect cloud contamination. Thermal bands are used to estimate land surface temperatures. Landsat 8 images for three distinct years images were gathered in the form of Geotiffs for various analysis, including urban sprawl, NDVI, and Land Surface Temperature. Additionally, data from the USGS was obtained to build the digital elevation model.

3.1.2. Air Pollution Data

The World Air Quality Index project, a nonprofit endeavour, helps with production

Table 1. Band name and their features (Data obtained from American Journal of Remote Sensing).

Landsat 8	Band	Wavelength	Spatial-Resolution
Band-1	Coastel-aerosal	0.43 - 0.45	30 m
Band-2	Blue	0.45 - 0.51	30 m
Band-3	Green	0.53 - 0.59	30 m
Band-4	Red	0.64 - 0.67	30 m
Band-5	Near-Infrared (NIR)	0.85 - 0.88	30 m
Band-6	SWIR 1	1.57 - 1.65	30 m
Band-7	SWIR 2	2.11 - 2.29	30 m
Band-8	Panchromatic	0.50 - 0.68	15 m
Band-9	Cirrus	1.36 - 1.38	15 m

of data on air pollution. Since early 2007, the World Air Quality Index has been gathering data on air quality in various parts of the globe. The major goal of this initiative is to offer real-time data on air quality and aid in raising awareness of air pollution. This project has a wide reach and has so far covered 100 nations and established around 12,000 monitoring stations in 700 of the world's largest cities which are known to have higher air pollution. Around Kathmandu valley, total of seven pollution monitoring stations have been installed with the cooperation with the Nepali government and the ministry of population and environment.

To identify all the particle matter, Monitoring station is equipped with a Grimm Electronic Dust Monitor (EDM). For counting particulate matter in the air, EDM uses light scattering technology, and the optical scattering method to determine the concentration of particle matter, at the same time the extrapolation approach is utilized to measure mass concentration of the particle matter in air (Gautam et al., 2020). For the source of light semiconductor is installed in station. This technology has proven to be highly helpful in assessing real-time air pollution data and in delivering information that informs people about the state of cities. For this study, PM 2.5 and PM 10 data were collected from seven monitoring sites in Kathmandu during the years of 2018 and 2020.

3.2. Software Used

To efficiently conduct analysis that are needed for this study, software such as ARC GIS10.8, ERDAS Imagine 2018, R4.1.2 and Excel were used. Using data from remote sensing, GIS has demonstrated its effectiveness helping effectively in the preparation of mapping metropolitan areas. The open-source software called R was utilized in these studies for statistical analysis. RStudio1.4 was used to run R-script which helped in further analysis of the collected data. Collectively using various softwares with each having its own purpose, the study was concluded with a quantifiable report.

3.3. Data Analysis

All the data acquired by various means and methods provided above was further analyzed using the software mentioned within this research paper. The analysis helps create different maps for various analysis and assessment at the same time, the data are also used to conduct various calculation.

Preparation of LULC Map

To construct a Land Use Land Classification Map, various different operations were carried out. After the acquisition of Landsat images processing was carried out in three phases, which includes image pre-processing, image processing and image post-processing.

1) *Image Preprocessing*

From band 1 to band 11, multiple independent bands collectively make up Landsat imagery. For a single multiple band image to be created, all the bands need to be combined. All the spectral bands are stacked using layer stacking within a software called ERDAS imaging. Furthermore, to obtain radiometrically corrected Landsat images from Level one Terrain (LIT), GCPs and DEM are put into use (Ishtiaque, Shrestha, & Chhetri, 2017). The Level 1 AVHRR and Level 2 MODIS bands, are used to create the LIT image. The GCPs are based on topography information for each Landsat. Image preprocessing is a crucial step to remove distortion. To establish a graphical reference to the map's data, all images were projected using WGS84 45N. The data was then processed. The images were rectified, cleaned for further processing. These steps have placed the data in a usable form to be used in the project.

2) ***Classification scheme***

It goes without saying that various types of land have their own different spectre characteristics (Aboelnour & Engel, 2018). Classification strategies for each different types of land are provided to figure out the category of the land. In this research of the proposed study area, Kathmandu valley is divided into five different categories. The different categories are built-up area, Forest, Barren land, Agriculture land and water area. All the five types of classes are acquired from the spectre characteristics of land.

3) ***Supervised classification***

Following the completion of image pre-processing, supervised classification is performed which is usually the next step. It's a type of image processing technology which is used to examine various geographical features (Almazroui et al., 2017). A supervised classification algorithm can identify a land feature with similar type of spectral characteristics. Supervised classification, which is known to be more accurate than unsupervised and other types of classification, is one of the best available techniques for identifying Land Use/Land Classification in remote sensing. The initial stage of supervised classification is digitizing the training samples for each categorization. It is done to identify pixel from each class. Training samples are developed in accordance with the requirements. Training sample is a polygon that contains groups of spectre signatures that are represented as a class. A supervised classification algorithm was employed in ARC GIS 10.8 to classify the land surface after digitizing enough samples from each class. The final step in post-processing involved changing the image from raster to vector. By including a new field in the attribute field, the area of each class is determined.

4) ***Accuracy Assessment***

In the case of creating LULC map, accuracy assessment is required due to the possibility of presence of atmospheric and topographic disturbance in the study area (Ishtiaque, Shrestha, & Chhetri, 2017). In this research accuracy is evaluated by creating an error matrix. The error matrix of the Land Use/Land Cover map is calculated for the detail accuracy for each class (Story & Congalton, 1986). Following the completion of the supervised classification, 100 random points were selected for the accuracy evaluation. Using the editor tool in the arc map, 20 random points from each class were selected to create a total of 100 random points. In the attribute table, two columns were added for Users and Producers.

Using the feature layer to kml in ARC GIS, all of the random points were exported as kml. Using Google Earth's time series tool, the retrieved point was examined for all year. Overall accuracy was calculated using formulae in excel.

Overall Accuracy = Total number of correct sample/total number of samples * 100

3.4. Normalized Difference Vegetation Index (NDVI)

The amount of flora in urban areas is crucial for maintaining oxygen levels because it is capable of absorbing carbon dioxide produced by various urban activities such as transportation. To determine the state of plant biomass in the Kathmandu Valley, the Normalized Difference Vegetation Index (NDVI) is calculated in this study using the data previously collected. To compare the amount of vegetation in the three years 2015, 2018, and 2020, the NDVI was determined for each year. The red band and near-infrared band in the Landsat 8 image are the two bands which are used to calculate NDVI. Plants' chlorophyll reflects light in the form of a red band, whereas mesophyll reflects light in the form of a near infrared band. Due to these characteristics, these two bands are utilised in the NDVI computation. NDVI values vary from 1 to −1. For an area with the most vegetation, the NDVI value will be 1, whereas it falls as the amount of vegetation decreases. Water, rocks covered in snow, and barren land has the lowest NDVI values.

The formula for NDVI is:

$$\text{NDVI} = \text{NIR} - \text{RED}/\text{NIR} + \text{RED}$$

3.5. Land Surface Temperature

Land surface temperatures for the summer months of 2015, 2018, and 2020 in the Kathmandu Valley were computed. The LST of the Kathmandu Valley was detected using ARC GIS 10.8. Level-1 of Landsat 8 collection was downloaded for LST computation. LST was calculated using the thermal band of Landsat image as shown in Figure 2.

The following steps are used in the computation of LST:

STEP 1

- Calculating the Top of the Atmosphere (TOA) is the first step.
- Band 10 input is required for this process.
- The formula for this procedure is:

$$\text{TOA}(\text{L}) = \text{ML} * \text{Qcal} + \text{AL} \tag{1}$$

where,

L = Top of Atmosphere spectral radiance.

ML = Value of multiplicative rescaling.

AL = Additive rescaling factor of Band-Specific.

Qcal = Band 10.

Step 2

- The second stage incorporates converting TOA to Brightness of Temperature.

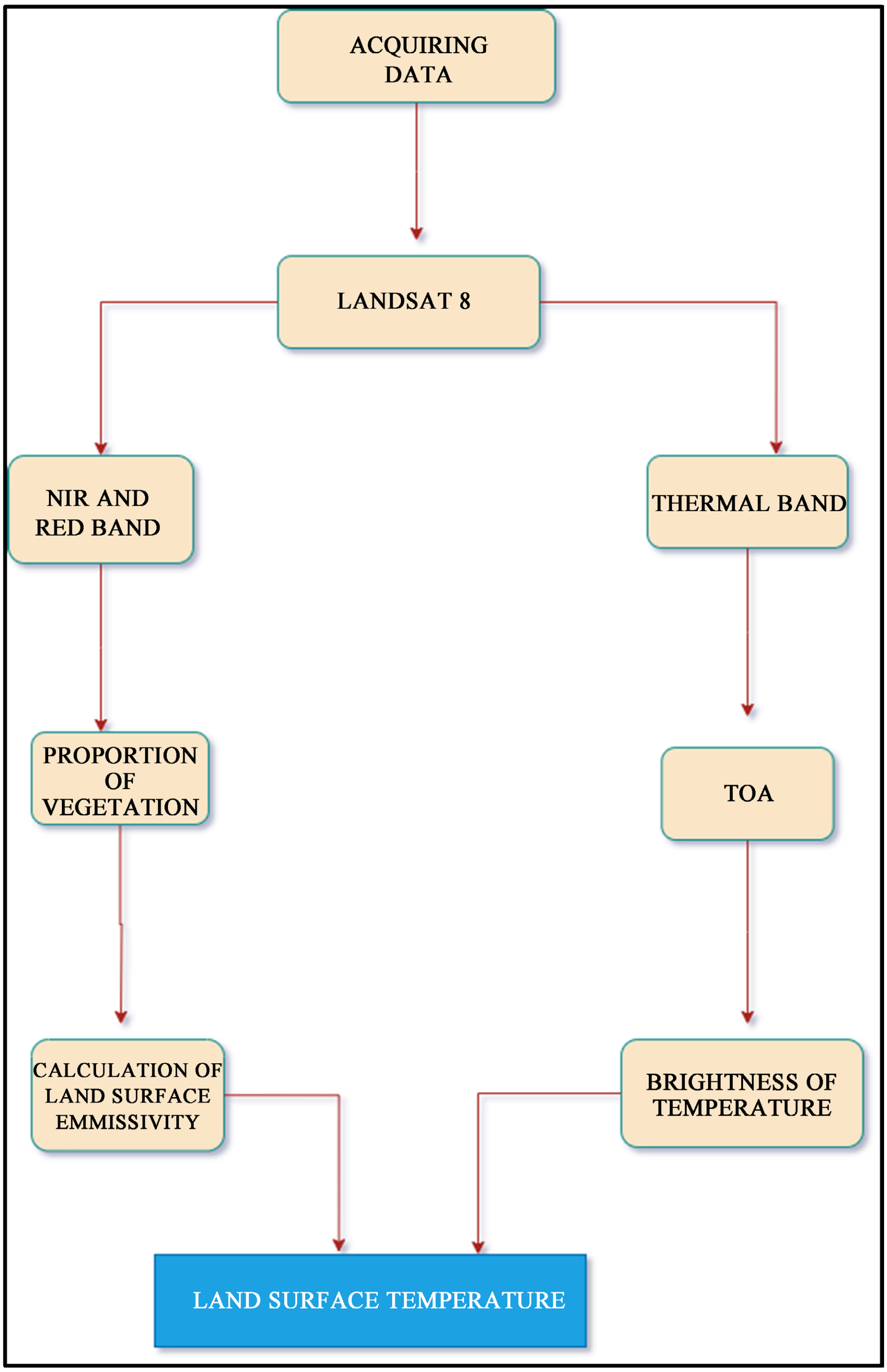

Figure 2. Flow chart for preparation of LST.

- In this method, thermal conversion constants K1 and K2 are used.
- By adding absolute zero, which is equal to −273.15˚C, the obtained temperature is converted to degrees Celsius.

The formula for step 2 is given below:

$$BT = \frac{K2}{\ln\left(K1/L+1\right)} - 273.15$$

where,

K1 and K2 = band specific thermal conversion obtained from metadata.

BT = Brightness Temperature.

L = Top of Atmosphere.

Step 3:

- To determine the Vegetation Proportion (VP), the NDVI should be calculated.

NDVI is determined in the third stage using the formula:

$$\mathrm{NDVI} = \mathrm{NIR} - \mathrm{RED}/\mathrm{NIR} + \mathrm{RED}$$

where,

NIR = Near Infrared Band.

Red = Red band.

Step 4:

Vegetation Proportion is calculated by:

$$\mathrm{PV} = \left(\mathrm{NDVI} - \mathrm{NDVImin}\right)2/\left(\mathrm{NDVImax} - \mathrm{NDVImin}\right)2$$

where,

PV = Vegetation proportion.

NDVI = Normalized Difference Vegetation Index.

Step 5:

- Following the calculation of Vegetation Proportion, Land Surface Emissivity (E) is computed in a further stage.
- Since it is utilised to scale black body brightness, land surface emissivity must be calculated to calculate LST.

It is calculated by:

$$\mathrm{E} = 0.004 * \mathrm{PV} + 0.986$$

where,

E = Land Surface Emissivity.

PV = Vegetation Proportion.

0.004 = Standard Deviation of soil band.

Step 6:

Lastly, LST is calculated using:

$$\mathrm{LST} = \mathrm{BT}/\left(1 + \left(0.0015 * \mathrm{BT}/1.4388\right) * \mathrm{Ln}\left(\mathrm{E}\right)\right)$$

where,

BT = Top Of Atmospheric Brightness.

E = Land Surface Emissivity.

3.6. Inverse Distance Weighting (IDW)

Using ARC GIS 10.8, inverse distance weighting (IDW) was employed to create a pollution map. In this method, within an area of influence, values from the sample area are transferred to the unsampled region. Data on PM 2.5 and PM 10 were collected from all monitoring sites and imported into Arc Map. The provided data was projected using WGS 1984. For this technique, the spatial analyst tool was employed in Arc Map. Inverse Distance Weighting/Mean Distance Sorting (IDW) is a data analysis technique that takes the concept of Euclidean distance between two points and returns an average value in order to reduce variations in real-world distances. By calculating "calculated distance" this method allows for smoother representations of the distribution of distances. This is important because the closer inputs to be mapped, the more likely they are to have similar values and IDW approximates this probability. An inverse weighting field can be created by taking a weighted input vector and calculating its inverse distance. K-means clustering works by finding the number of clusters in a data set, then assigning all points to cluster with the nearest centroid. The inputs are represented as points and the distance between them is used as a weighting field. The point IDW can then be calculated by taking their weighted distance vector's inverse weighting field.

$$Z_j = \sum_i \lambda_i Z_i$$

where,

Z_j is the value (we are trying to predict) at location j.

λ_i Is the weighting for location i.

Z_i is the sampled values at location i.

$$\lambda_i = 1/d_i^p \Big/ \sum_{i=1}^{N} 1/d_i^p$$

The weight (λ_i) is computed as follows:

d_j is the distance between prediction location j and each measured location i.

P is the power function for distance (typically 2).

4. Results and Analysis

4.1. Urban Sprawl in Kathmandu Valley

A detailed LULC map of the Kathmandu valley was produced for the year of 2015, 2018 and 2020 for analysis (**Figure 3**). The LULC map was produced after performing supervised classification using five classification schemes on a Landsat image. The map of the Kathmandu valley presented above shows that in 2015 out of a total area of 695 sq·km about 107 sq·km is used for built up areas. The remaining land within Kathmandu valley is used for agriculture, barren lands, forest, and various water bodies. Among the other type of the land such as agricultural land, barren land, forests and water bodies, they occupy 261 sq·km, 22 sq·km, 270 sq·km and 34 sq·km respectively within the study area. The total study region was mostly covered with a forest which took the most area whereas the barren land occupied the least.

Same as the LULC map for 2015, another LULC map created for the year of 2018. After comparing the two different maps, some changes can be observed in various land area. The built-up area can be seen to have expanded. Previously in 2015 the total built up area within the study area was 107 sq·km whereas in 2018

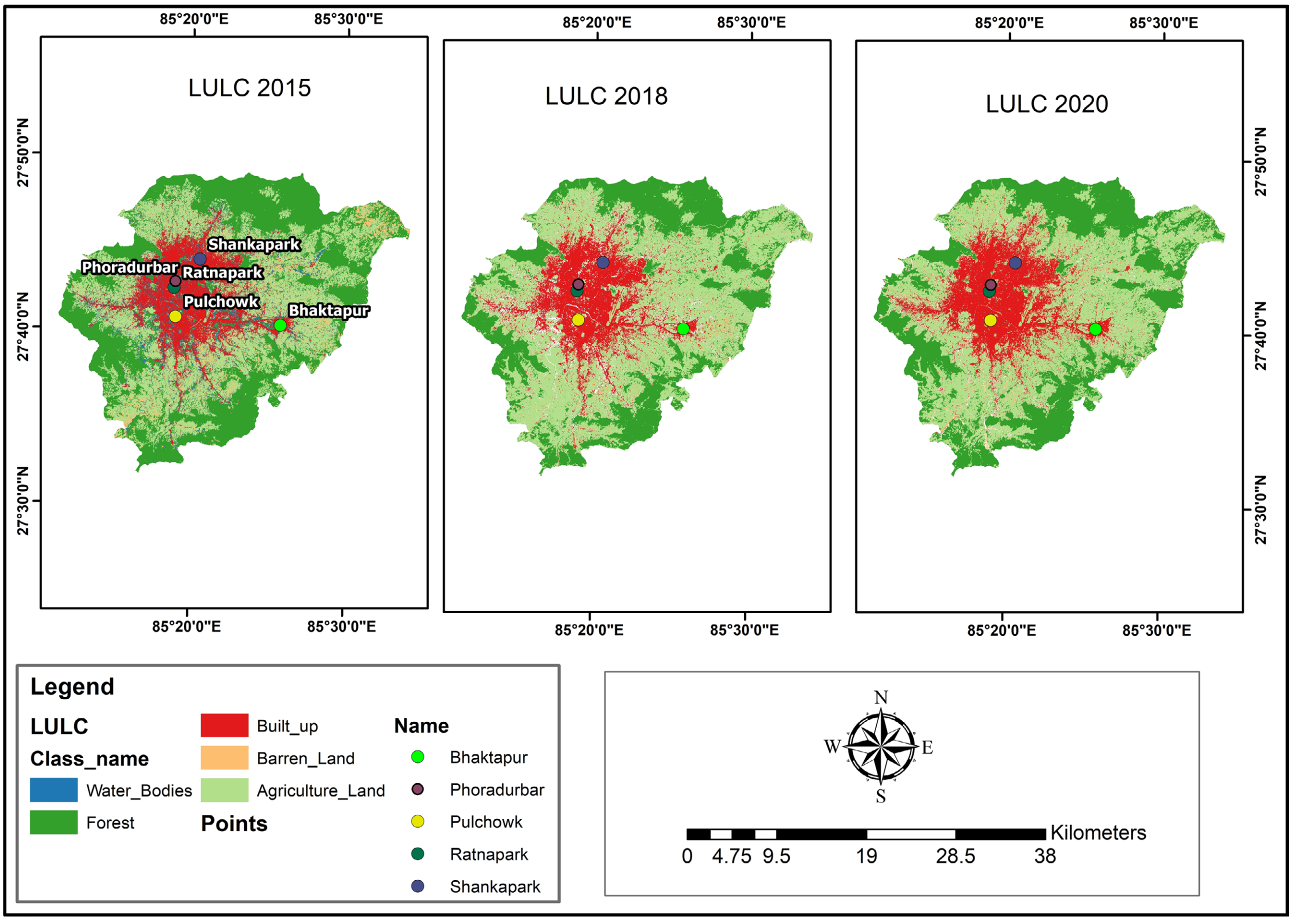

Figure 3. Lulc map of kathmandu for year 2015, 2018 and 2020.

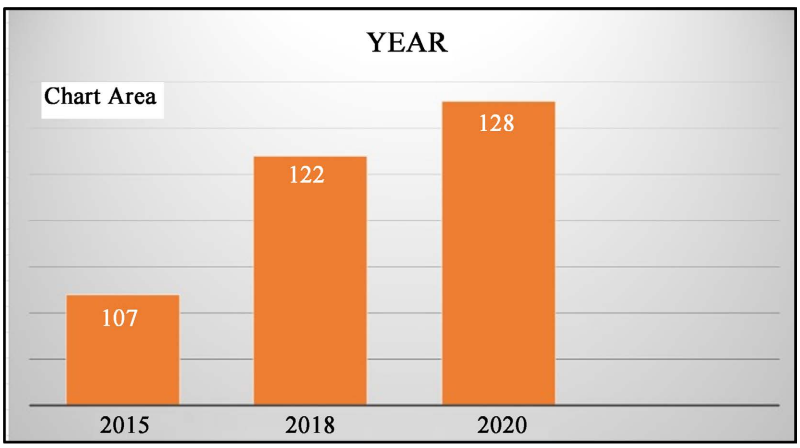

Figure 4. Area of buıltup area of the year 2015, 2018 and 2020.

it was expanded up to 122 sq·km (Figure 4). A total of 15 sq·km of expansion in built up area was observed. From 2015, the built-up area has grown by 14.01%. Furthermore, Agriculture has been introduced to the peri-urban region that was previously inhabited by a forest in 2015 map. The majority of valley residents use open space for agriculture because the terrain in the Kathmandu valley is exceptionally fertile and has favourable temperatures for numerous crops.

Same as in 2018 map where expansion in built-up area was observed compared to 2015 map, same phenomenon exists in 2020 map as well compared to 2018 map. Since 2015, the total increase in built-up area is by 20%. Kathmandu's population has also been growing in Parallel along with the growth of built-up areas. In addition to these to the metro area, the other peripheral regions of Kathmandu have seen significant growth as well. One of the major effects of expanding built-up area is that it reduces the size of the open land. The overall non built area was 588 sq·km in 2015, but over a five-year period, it has shrunk to 566 sq·km. Built-up areas have greeted magnitude changes as compared to any other classification types. Over a five-year period, the built-up areas within Kathmandu valley have increased by 21 sq·km. As much of the space in the inner section of valley has almost been taken and the built-up area has started to develop rapidly while wrapping the outsides of Kathmandu Valley. The majority of the built-up areas on the valley's outskirts are concentrated around roads because the transportation infrastructure enables people to go from different areas of the valley for purposes such as employment, education, etc.

4.2. Accuracy Assessment

Accuracy evaluation was done to determine if there were any errors in the creation of the LULC map. For the accuracy assessment, 20 samples from each categorization scheme were selected from a 100 random sample in this study. Additionally, an error matrix was produced to determine accuracy level. A producer and user accuracy calculation were done using an error matrix as shown in Table 2. The data demonstrate that the accuracy achieved in 2015 was 97% whereas for the year 2018 the accuracy percentage was 98%. Similarly for 2020, the accuracy percentage was 96%. For the years of 2018 and 2020, the user accuracy for water can be seen to be rather low, however for the year 2015, user accuracy for barren land was lower than the other observed years. For the lesser accuracy for water, one of the major causes may be the narrowness of the river. For the years 2015 and 2020, producer accuracy was lower on barren land. For all three years, both built-up area user and producer numbers are high. According

Table 2. Accuracy assessment.

Land Cover Classification	2015		2018		2020	
	User Accuracy	Producer Accuracy	User Accuracy	Producer Accuracy	User Accuracy	Producer Accuracy
Forest	100	95	100	90	100	100
Agriculture Land	90	94	95	100	95	95
Builtup	100	100	100	100	100	95
Barren Land	95	95	100	100	95	90
Water	100	100	95	100	90	100

to (Treitz & Rogan, 2004) the accuracy for measuring changes along the land cover should range from 85% to 90%. Therefore, based on the results, we can say that our analysis had an acceptable accuracy of greater than 95%. Accuracy evaluation also facilitates quantitative analysis of results. It is an essential component of analysis since it allows us to determine whether our finding is accurate.

4.3. Land Surface Temperature of Kathmandu valley:

The given (**Figure 5**) depicts the spatial distribution of land surface temperature within the study area. In 2015 the lowest recorded temperature was 15˚C, while the highest recorded temperature was 33.46˚C as observed in the figure. During that time, Kathmandu valley's mean temperature was 15˚C, with the built-up areas experiencing the greatest temperatures *i.e.* in between 24˚C to 33˚C and while the forest areas experiencing the lowest temperatures *i.e.* from 15˚C to 22˚C. For the agricultural land the average temperature is ranging from 22 to 24 degrees.

In summer 2018, the lowest temperature was 18˚C and the maximum temperature was 37˚C, with an average temperature of that year being 27˚C. Similar to 2015, we can see that the built-up areas in 2018 have the highest temperatures, which ranges from 28˚C to 37˚C. The majority of agricultural area and barren

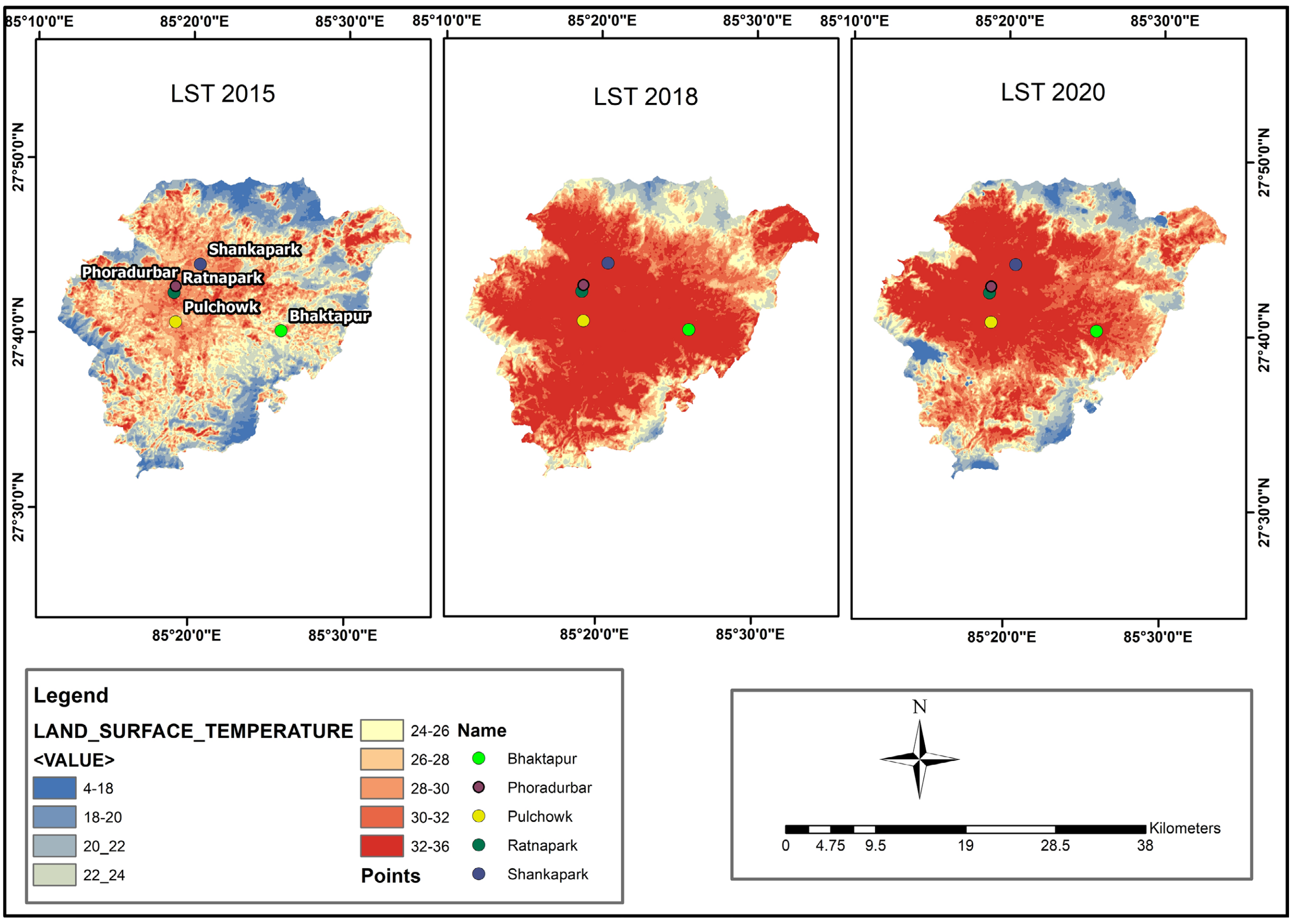

Figure 5. Land surface temperature of kathmandu valley for year 2015, 2018 and 2020.

ground have temperatures between 26˚C and 28˚C degrees, while forests have the lowest temperatures, ranging from 18 to 24 degrees.

In 2020 the temperature of Kathmandu ranges from 4˚C to 36˚C in which built up area possesses higher temperature with 26˚C to 36˚C degrees. In urban areas, the main reasons for the rise in temperature are due to the presence of heat-absorbing materials such as gravel, concrete, and brick. And due to lack of open spaces there is no place to grow green plants which helps to lower temperature. The temperature in forest area is much lower *i.e.* from 4 to 22 degree and the reason is due to presence of abundant amount of green vegetation.

4.4. NDVI

The amount of vegetation present in a certain area or in this case urban area determines the condition of said urban area. Urban areas are often impacted by increased pollution and land surface heating due to a reduction in plant cover, whereas green vegetation is responsible for removing air pollutant concentrations (Shogrkhodaei, Razavi-Termeh, & Fathnia, 2021). For the health of general public to be maintained in urban region with a crowded population, fresh air flow is really essential.

According to **Figure 6** presented above, the NDVI's maximum value for the

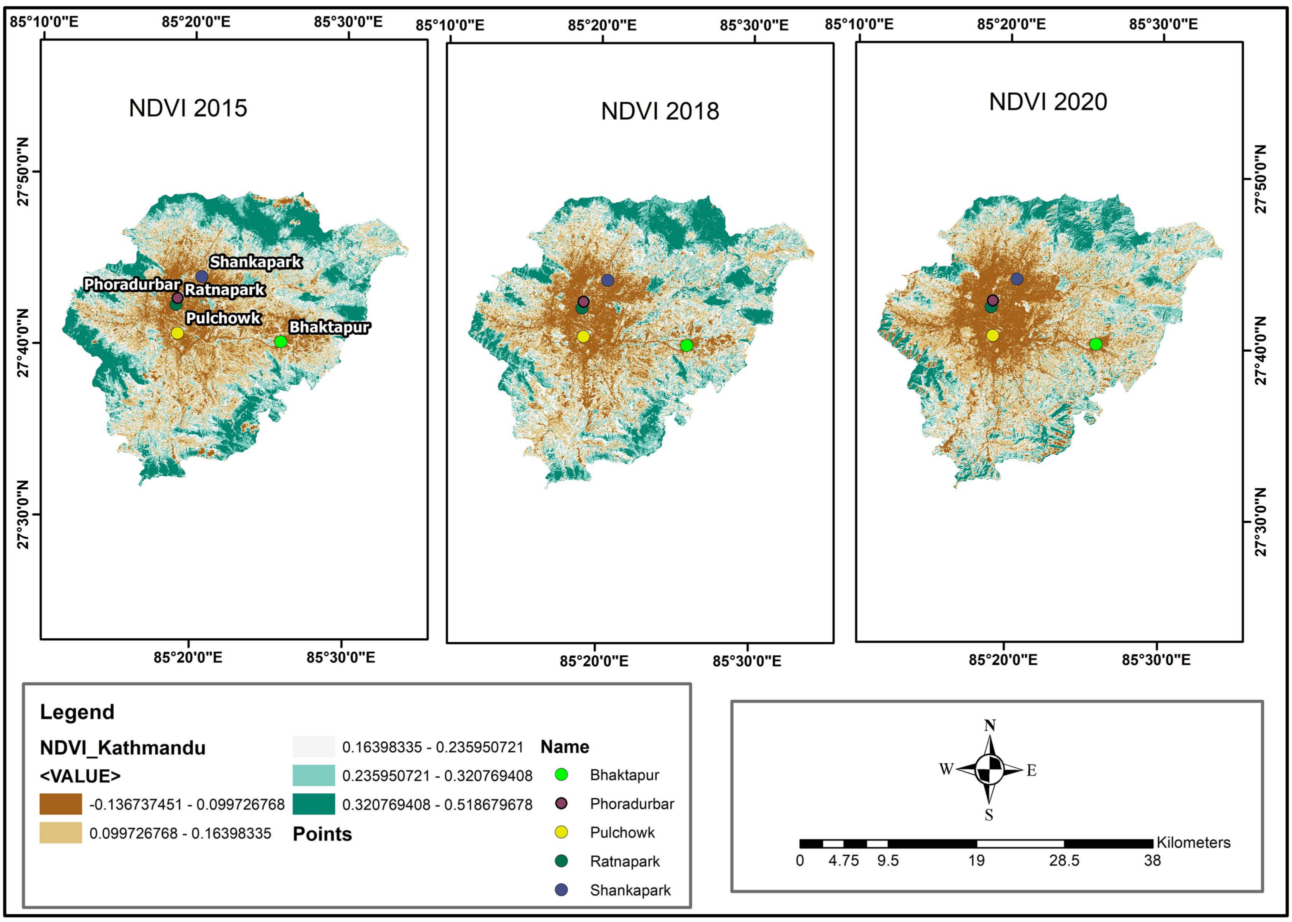

Figure 6. NDVI map of kathmandu for year 2015, 2018 and 2020.

year 2015 was 0.62 and at the same time the lowest value was observed to be −0.09. The average NDVI for 2015 was 0.31. Moving to 2018 figure the NDVI value decreased to 0.53 with a mean value of 0.26. Similarly in the same year, −0.01 was the lowest NDVI value. It can be seen that from 2015 to 2018, the mean value decreased by 0.05. The value of NDVI diminishes as built-up area grows. In 2015 as mentioned previously, 270 sq·km of forest, but by 2020, there was only 220 sq·km of vegetation.

From 2015 to 2020, in the 5-year gap, there was a 50 sq·km loss of forest which is also demonstrated by the decline in NDVI by 10 between 2015 and 2020. According to land cover map, as the built-up area rises, so do economic activities that result in deforestation. The value of the NDVI decreased as a result of the decrease in vegetation. In 2020, the highest value obtained was 0.52, the lowest was −0.14, and the mean value was 0.18. As the built-up area in all three years had the lowest NDVI value, it was determined that an increase in built-up area would be harmful to vegetation. The biodiversity of the study area is impacted by the loss of forest land.

4.5. AIR Pollution

4.5.1. PM 2.5 of Kathmandu Valley

In the year 2018, the highest reported value for PM 2.5 was 117.74 μg/m^3, while the lowest value was 47.67 μg/m^3. In Kathmandu valley, the mean annual PM 2.5 concentration was 82.65 μg/m^3. Among various regions within Kathmandu Valley, Ratnapark area has more pollution in 2018 compared to other region. Ratnapark, Phoradurbar and Shankapark all have PM 2.5 concentration above 100 μg/m^3 as can be seen in **Figure 7**, which falls under health risk and is known to create some health hazard.

The concentration of PM 2.5 increased from 2018 to 2019 and reached a higher number of 124.83 μg/m^3 in 2019. The lowest figure that was noted was 85.08 μg/m^3, while the average mean was 102.07 μg/m^3. Ratnapark recorded the highest PM value in 2019 while the Bhaktapur area recorded the lowest. The minimum value recorded was 70.65 μg/m^3 while the maximum value in 2020 climbed towards 120 μg/m^3.

Compared to the prior year, the mean concentration of PM 2.5 in 2020 was 90.67 μg/m^3. Ratnapark used to have higher levels of pollution, but in 2020, pulchowk was the place which recorded higher levels of pollution. Pulchowk's built-up area was 15 sq·km in 2015; after growing by 4 sq·km in 2019 the total built-up area became 19 sq·km. An increase in the amount of built-up area would contribute to the higher amount of pollution sent to the air, resulting in raise in air pollution. Due to the small area of Pulchowk area and at the same time increase of built-up areas, Punchwok is more congested. Compared to any other types of pollution, PM 2.5 poses a greater risk to human health. The majority of the Kathmandu Valley is within an unhealthy zone. As a result of COVID lockdown, PM level in 2020 is considerably lower than in 2019. In 2020, anthropogenic activities were decreased for a time since the streets were open.

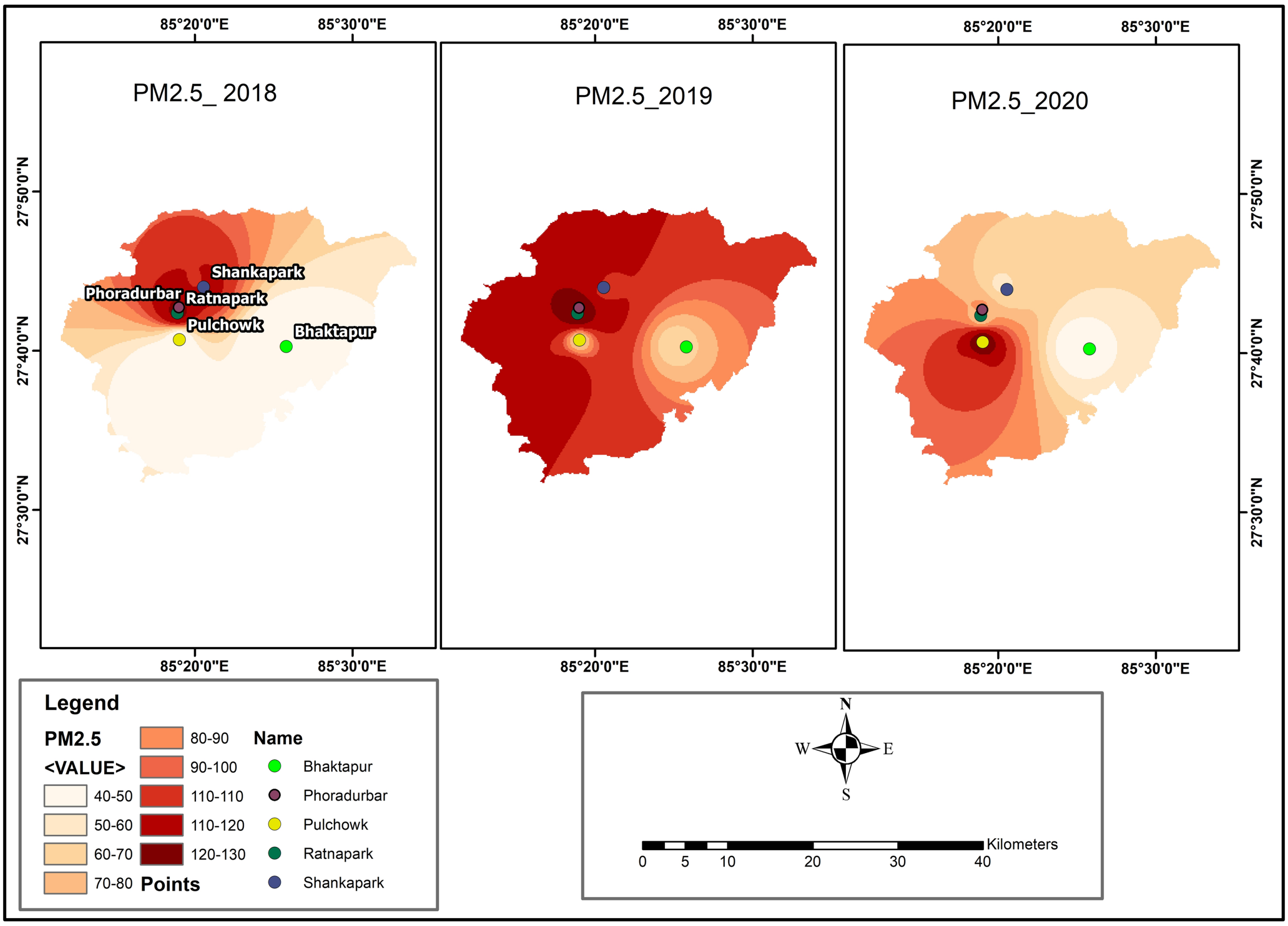

Figure 7. PM 2.5 of kathmandu for year 2018, 2019 and 2020.

According to the EPA, PM 2.5 levels below 15 μg/m³ are deemed healthy and pose no hazard to human health while at the same time 35 is regarded as an average typical figure. The majority of Kathmandu valley is over 70 μg/m³ which is twice the usual value. 2.9 million people in Kathmandu are at risk due to the increased pollution levels.

4.5.2. PM 10 in Kathmandu Valley

Similarly, same study method was utilised to study PM 10 within the Kathmandu Valley. The highest PM 10 number recorded in 2018 according to fig was 65.78 μg/m³, at the same time the lowest was 15.63 μg/m³. Within the Kathmandu Valley, the average PM in 2018 was 40.79 μg/m³. The majority of the urban area, with the exception of Bhaktapur and Pulchowk, had higher pollution levels in 2018.

In the Kathmandu valley, PM 10 values in 2019 range from 29.57 μg/m³ to 67.80 μg/m³. 48.62 μg/m³ was the yearly average value for 2019. In 2019, Ratnapark and Bhaisipati have the highest pollution levels, which as can be seen (in Figure 8) was above 60 μg/m³. In the year of 2020, the value was observed between 34.28 μg/m³ and 58.80 μg/m³. The average value in the same year was 41.96 μg/m³. The value attained in 2020 was lower than in 2019, much like PM

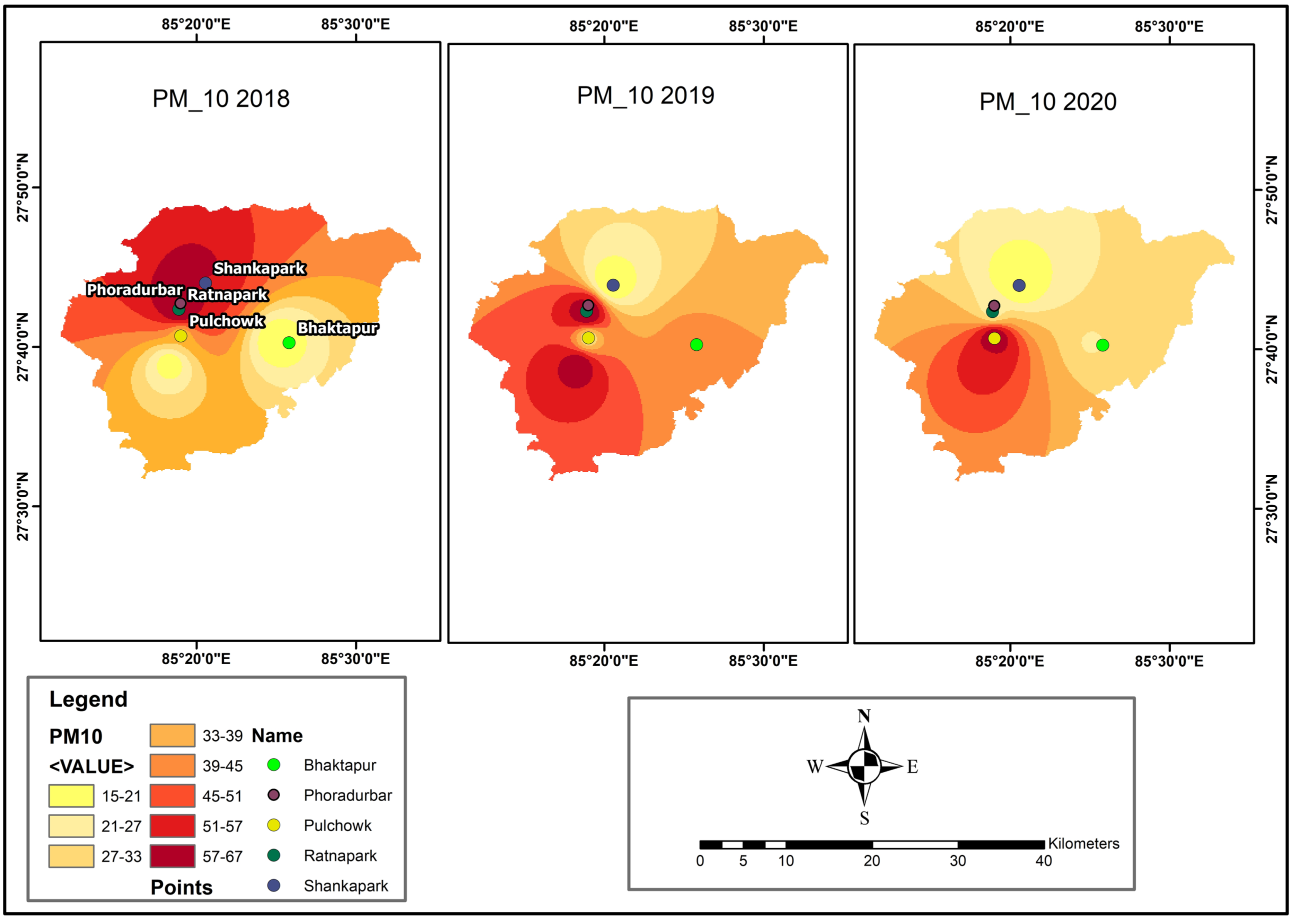

Figure 8. PM 10 of kathmandu for year 2018, 2019 and 2020.

2.5. PM 10 levels should always be kept below 15 μg/m³ in order to ensure that breathing is safe; otherwise, they could enter the circulation can be the cause of various heart and lung illness.

4.5.3. ANOVA Test

In this study, numerous groups were compared using the ANOVA test to see if there was any evidence of a relationship between them. From box plot (Figure 9) we can say that compared to other types of classification, built-up areas have a considerable impact on land surface temperature while forest is less affected by Land Surface Temperature

From the box plot in Figure 10 we can infer that the NDVI values differ for various types of land. Forest has a higher value whereas water possesses lower value. According to the graph, value is significantly lower in built-up areas than in forest areas, indicating that there are fewer plants present there.

Similar analysis was conducted for pollution as well. To determine the extent of pollution's impact on both built-up and non-built-up areas, an analysis was conducted. Based on the comparison, it was discovered that built up areas have greater pollution levels than non-built-up area as can be seen in Figure 11.

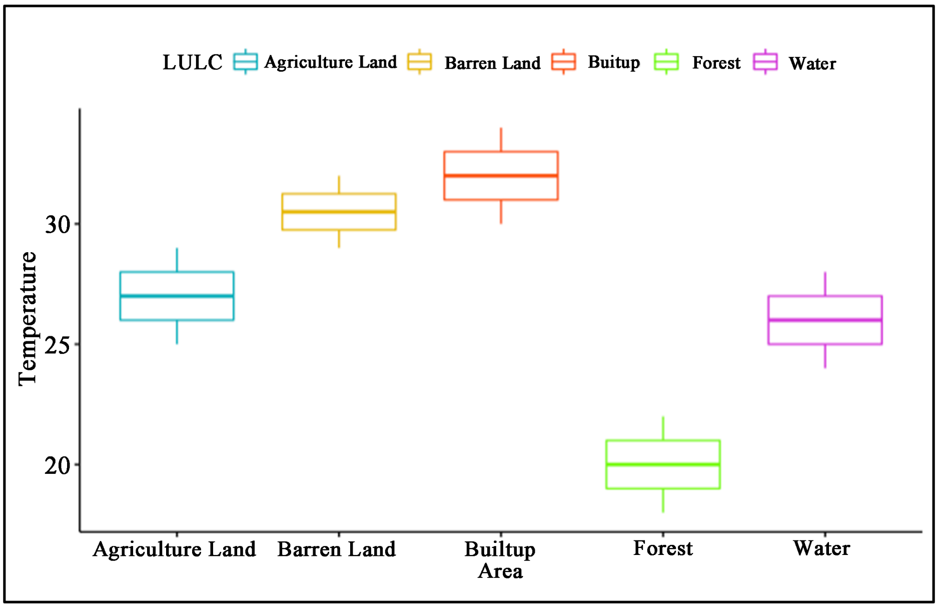

Figure 9. ANOVA test for land surface temperature.

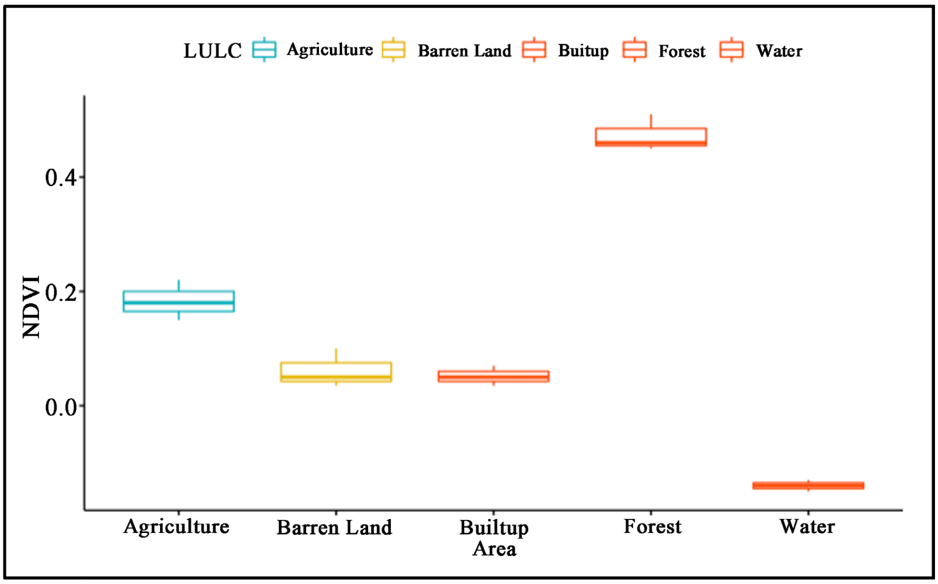

Figure 10. ANOVA test for NDVI.

5. Discussion

Kathmandu Valley has experienced tremendous population expansion as well as an increase in its built-up area, making it one of the cities with the fastest population growth (Saurav et al., 2021). About a third of Nepal's urban population, or 9.32 of the country's overall population, resides in the Kathmandu Valley (Muzzini & Aparicio, 2013). This study effectively employed GIS to successfully analyze urban sprawl, NDVI, Land Surface Temperature and Air Pollution using Landsat imagery technique. As LULC plays a significant role in the planning sector, understanding complex LULC was made simpler by using the enormous potential of remote sensing data and its resolution of up to 30 m. The outlying

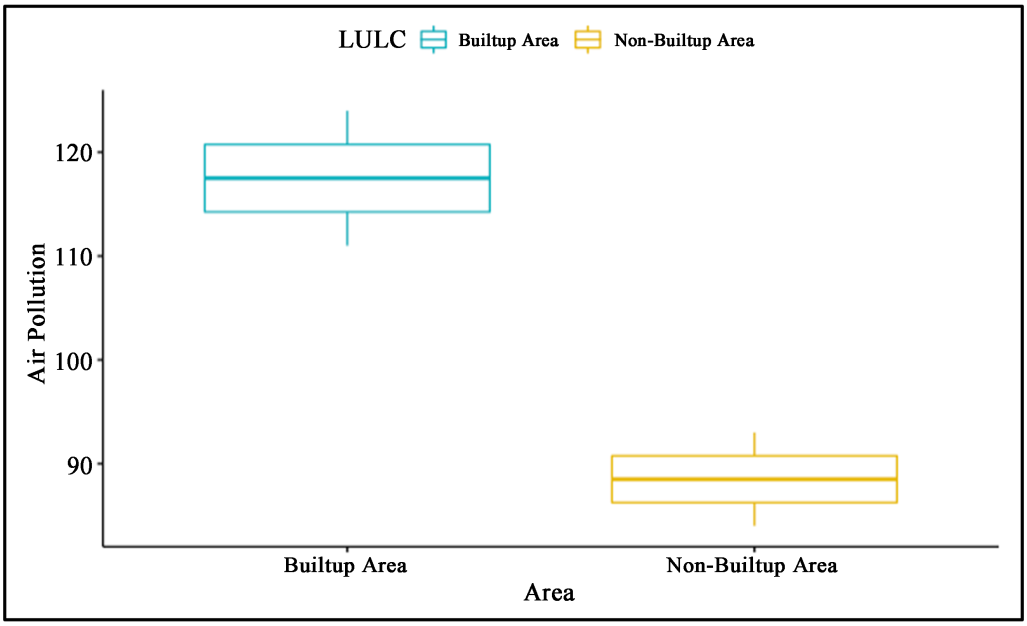

Figure 11. ANOVA test for aır pollutıon.

rural area of the Kathmandu Valley is rapidly turning into an urban area due to the growth in built-up areas. Study indicates that since 2015, the built-up area in the Kathmandu valley has expanded by at least 20%. The main causes of the population growth in Kathmandu Valley is internal migration from other parts of the country and due to migration there have been significant changes in the in the way that land is used within the Kathmandu Valley (Muzzini & Aparicio, 2013). Research reveals that while space in the city's core region shrink, built-up areas are expanding in Kathmandu's outskirts notably towards the west of the city, which can be observed to be getting thicker. There is a less barren land around the valley which suggests that there is hardly any open area available. In 2015 there were a lot more open space but by 2020 those areas had disappeared into huge, crowded buildings.

The population of Kathmandu started to increase in 1990 after the emergence of democracy (Thapa & Murayama, 2011). Kathmandu valley is one of the most vulnerable cites to the earthquake. Due to its geographic fragility, including its surrounding hills and topography, Nepal ranks 11th in the world for earthquake risk (Rimal et al., 2017). In the past, frequent earthquakes have shown to be destructive, destroying the infrastructure and taking many lives in Kathmandu valley. It is essential that there should be open space next to every home because it serves as an escape route in the event of a calamity like an earthquake. The lack of open space can result in individuals dying in such horrible accidents. While other nations have defined minimum open space requirements for all built-up areas, Nepal lacks such a regulation, which has led to an uncontrolled urbanization (Bhattarai & Conway, 2010). The effect of increase in built-up area can also be seen on waterbodies. Due to the encroachment of built-up areas near rivers the rivers are shrinking. If not stopped in a timely manner, such encroachment could result in an urban flood in the valley.

As cities become more urbanized, the quality of their vegetation declines, which weakens the city's ecology. The NDVI value indicates that there has been an increase in the exploitation of vegetation as a result of increased human activity, which has changed the land cover. Only the northern half of the city can be viewed with abundant vegetation which is due to the existence of the conservation area, but the eastern and western potions of the forest areas are shrinking as the population increases and built-up region expands. Particularly small patches of woodland are disappearing in various areas. Human activity, climate change, air pollution, and landcover change are the key contributors to the decline in vegetation in urban areas (Chen, Huang, & Zeng, 2022). Study has shown us that the NDVI value peaked in 2015 and then began to decline as we approached 2020. According to the LULC map, Kathmandu is expanding, and this unplanned urbanization growth is causing the NDVI value to decrease. Population growth and consumption of natural resources are directly correlated. Kathmandu Valley lost 50 sq·km of forest in just 5 years due to rising population and built-up areas. It also shows how heavily Kathmandu valley exploits its natural resources. If this keeps up, then there won't be much forest area in Kathmandu valley. Forest cover is essential for environment preservation because it keeps the water cycle running smoothly, safeguards wild animal habitat, preserves biodiversity, and most critically controls the carbon cycle in the area (Mengistu & Salami, 2007). If deforestation is not stopped in time, it could lead to ecological issues like degraded soil, biodiversity loss, and hydrological cycle disruption. It could also lead to shortage of water in the future if it continues in the same manner as it has in the Kathmandu Valley. Urban greening is something that people in urban areas should use as it enhances the amount of flora in city (Ma, Xiao et al., 2019). The city's land pattern is hampered by the development of built-up areas in kathmandu valley.

The pollution level in the Kathmandu valley has reached a maximum due to the growth of urban areas According to study using data from seven monitoring sites, the Kathmandu Valley is experiencing the highest levels of PM 2.5 and PM 10 pollution. Past research suggests that exposure to particle matter might lead to significant illnesses like cardiovascular and respiratory conditions. Due to the existence of scattered aerosol in the troposphere, visibility is increasingly becoming a major issue in the Kathmandu valleys (Mahapatra et al., 2019). According to the anova test, builts-up areas have higher pollution levels than rural villagers and this is due to the fact that there are more pollution sources than sinks in built-up areas. Pollution in urban areas increases because of presence of more pollution sources, such as factories and vehicles, fewer sinks, such as plants, open spaces, and rivers and lakes. Built-up areas have higher pollution levels than rural villages because there are more sources of pollution.

According the Ministry of Population and Environment, automobile emission are responsible for 67% of increase in PM 10 emissions during the past ten years.

The results suggest that the most area was affected by PM 2.5 in 2019 than in 2020 because of the covid lockdown in 2020. Because of the covid outbreak, there were fewer human activities in 2020 than in prior years, which led to a modest drop in pollution in Kathmandu. Although the few days of lockdown imposed by COVID in 2020 has reduced a certain degree of pollution in several regions, it is still over breathable levels. The concentration of PM 2.5 and PM 10 was higher in the pulchowk area in 2020 as compared to last year as the built-up area increased by 5 sq·km. This demonstrates that as the built-up area in the Kathmandu Valley grows, pollution levels grow proportionately due to an increase in human-caused activities. The concentration of PM 10 was higher in 2019 than last year because of the increasing number of domestic activities and an increase in transportation. The higher concentration of particulate matter in the air results in higher number of air pollution which can lead to various diseases. Additionally, the city's bowl shape also prevents airborne particulates from escaping the valley.

Analysis of Land Surface Temperature shows that the Kathmandu Valley's core region is most negatively impacted by the high temperature. A study shows that between 2015 and 2020 the land's surface temperature increased. The main three key factors that to be blame for the rise in land surface temperature includes, an increase in built-up area, a decline in plan cover, and a rapid increase in pollution. Our study indicates that the built-up area has increased by 20% from 2015, and NDVI has decreased from 0.62 to 0.52. The dense building stock in the central region is to blame for the high hand surface temperature since bricks and concrete, which are used as main component building materials, is known to have a high absorption capacity for solar radiation (Sithole & Odindi, 2015). An increase in Land Surface Temperature can also inhibit the growth of vegetation because it may disrupt the microclimate in urban areas that is beneficial to plant growth (Wang et al., 2021). High temperature also affects urban ecology. Our research shows that the area with more vegetation had Lower Surface Temperature than built-up areas in all three years. Increased temperature increases the risk for infectious diseases. Disease-causing organisms thrive at normal temperature ranges, but infections may develop at different rates upon increase in temperature.

Because forest has a canopy over them, direct sunlight is prevented from shining on the ground, which lowers the temperature in forest area (Karunaratne et al., 2022). In various types of LULC, the spatial distribution of land surface temperature varies. Our analysis's Anova test demonstrates that built-up areas have the greatest values of land surface temperature, whereas forests have the lowest values. This is because built-up areas have a tendency to absorb significant amounts of electromagnetic radiation and then radiate that radiation as heat energy back into the environment. Conversely, forests have a tendency to absorb solar radiation and emit it as thermal energy into the environment. When light waves hit leaves on trees, they are scattered and diffracted, reducing the amount of sunlight that reaches the ground below. It represents the value of greenery in urban areas. Greening rooftops, in accordance with (Athukorala et al., 2021), can be the solution for enhancing vegetation status and lower land surface temperature as it provides a natural cooling impact. Since their surfaces are porous and can absorb heat from the atmosphere, green vegetation can act as heat sinks. Maintaining urban temperatures is crucial because rising temperatures can alter urban environment by varying humidity and evapotranspiration. Changes in the environment can have an adverse effect on people's health. Rising temperature is also capable of affecting flora and fauna as well. A person's capacity to adapt to staying cool may be hampered by the rise in Land Surface Temperature by hampering antibodies.

Situated in a landlocked nation, Kathmandu Valley is a mountainous metropolis with distinctive geophysical characteristics. Such Urban areas need to be continuously monitored because they are dynamic and are always changing. We can use methods such as remote sensing technology to aid us in monitoring urban sprawl and the issues that comes with such an area. By using such aids, the issues can be identified earlier and thus will be much easier to resolve it. With the aid of remote sensing and GIS techniques, this study has found a number of issues, including a growth in built-up area, pollution such as air pollution, land surface temperature, and the condition of vegetation cover in Kathmandu valley. The findings of this study indicate a relationship between LULC, NDVI, and Land Surface Temperature. Modifying LULC may have an impact on the NDVI and Land Surface Temperature values. The value of Land Surface Temperature can change depending on the amount of built-up area and the amount of forest.

6. Conclusion

Research for this paper was carried out by analyzing LULC of the Kathmandu valley using multitemporal Landsat images. From the U.S. Geological Survey, Landsat images for the summers of 2015, 2018 and 2020 were obtained. By using the process of supervised classification, a LULC map of the Kathmandu valley was created. Using a thermal band, the map related to land surface temperature was created, which aids in further analysis of temperature change over time in the summer. Additionally, an NDVI map was also made to aid in the identification of vegetation status. In order to create a pollution map, an inverse distance weighted interpolation approach was used. The pollution maps help visualize the degree of pollution in Kathmandu Valley from the years 2018 to 2020. Based on all the findings of this study, we can conclude that Kathmandu, located at the heat of the country has experienced urban sprawl, which has an impact on vegetation cover, air pollution and land surface temperature. Urban sprawl is known to have more cons than pros. It causes adverse effect within the area. If the sprawl is not stopped in a timely manner, issues including a loss of open space, a decline in biodiversity, and an increase in air pollution may have a significant negative impact on people's health. The Kathmandu Valley's air pollution needs to be reduced by implementing certain precautions that are necessary as it might hamper lots of people in coming days. The pollution concentration level within Kathmandu Valley needs to be reduced to be in compliance with WHO criteria as it is significantly higher. The aesthetic attractiveness of Kathmandu could be diminished as a result of unchecked urban growth.

According to research, the Kathmandu Valley's vegetation state has changed as a result of increased built-up area, and along with it, land surface temperature has increased as well. The results that were obtained from ANOVA test have also demonstrated that land surface temperature is greater in built up areas and lower in non-built up area, particularly in forests. In a densely populated area like Kathmandu valley, vegetation cover is crucial. It helps in reduction of air pollution and also aids in decrease of land surface temperatures. As the built-up area is located within the centre of the city, that part is more crowded and has less vegetation, urban sprawl mostly affects this area. Building encroachment has resulted in the disappearance of several open spaces in the central region in recent years. It can be improved by combining remote sensing technologies and GIS. Urban growth boundaries have been defined with the aid of remote sensing technology. As a result of the high-quality Landsat image, our LULC map's accuracy level was significantly improved where it reached 97% in 2015, 98% in 2018 and 96% in 2020. The LULC map's findings suggest that the amount of built-up land is increasing while the amount of water and vegetation is decreasing.

So, the use of geographic information systems (GIS) in this study of urban sprawl offers important new insights into the patterns, causes, and spatial scope of urban growth. Urban areas have grown significantly over time, transforming rural and natural landscapes into built-up environments, as evidenced by the examination of various GIS data, including land use, vegetation cover, and land surface temperature. The growth of cities causes considerable loss and fragmentation of the greenery. The breadth and spatial patterns of the reduction in vegetation are revealed by GIS analysis, which also highlights the areas most susceptible to urban expansion. The loss of green areas has a negative impact on ecosystem services, biodiversity, and the general standard of the environment. The urban heat island (UHI) effect, which is caused by urban development, is a phenomena whereby built-up areas have higher land surface temperatures than adjacent rural areas. This study, which used GIS-based LST analysis to identify hotspots inside urban regions, shows temperature changes in different region, Additionally, this study makes use of GIS to make it easier to identify urban regions that have hotspots for air pollution, which are places where pollution concentrations, including particle matter (PM), are higher than allowed.

7. Recommendations

To prevent urban expansion from encroaching too far and to safeguard the agricultural land, natural ecosystems, and culturally significant areas on the outskirts of the Kathmandu Valley, it is necessary to establish boundaries for urban growth. Strict zoning laws must be enforced to prevent unapproved buildings in protected regions. To enhance air quality, increase biodiversity, and provide residents with recreational opportunities, green infrastructure features such as parks, greenways, and urban forests should be incorporated into the urban fabric of the Kathmandu Valley. Subdivision ordinances, construction codes, and zoning restrictions must be enforced to promote sustainable development methods and prevent unauthorized land encroachment. Measures should be taken to encourage safe land stewardship and prevent speculative acquisition of land. Community involvement in the planning process should be promoted through public consultations, community workshops, and systems for participatory decision-making. Locals should be given the power to ensure that planning decisions take their needs, values, and goals into account by actively participating in determining how their neighborhoods will grow and develop in the future.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Acronyms and Abbreviation

DEM	Digital Elevation Model
GCP	Ground Control Points
NDVI	Normalized Difference Vegetation Index
LST	Land Surface Temperature
PM	Particulate Matter
SWIR	Short Wave Infra-Red
IDW	Inverse Distance Weighing
TOA	Top of Atmosphere
LULC	Land Use Land Classification