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Assessing the Air Quality Index based on Vegetation Level: A Case Study of Narayanganj City Corporation

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- Air Quality,
- NO_2,
- SO_2,
- CO,
- AOD,
- NCC

Abstract: A global degradation of air quality has become a prominent issue in the present time since it has a significant impact on climate change and public health due to increased morbidity and mortality. Air Quality Index (AQI) is an index for describing the air quality which is comprised of five major air pollutants – ground-level ozone, particulate matter ($PM_{2.5}$, PM_{10}), Carbon Monoxide (CO), Sulfur dioxide (SO_2), and Nitrogen dioxide (NO_2). In this study, we have observed a comparative condition of air quality with the trend of LULC for 2019 and 2021, in the Narayanganj City Corporation, which is renowned as the Dundee of Bangladesh. Every year our country earns an indicative percentage of revenue from these sectors. Along with population growth, rapid industrialization is a rudimentary reason behind the deterioration of the environmental condition of this city. The primary objective of this study is to examine the impact of Land Use Land Cover (LULC) on the air quality index to identify how industrial and human activities influence air quality. The assessment has been conducted from 2019 to 2021 using Google Earth Engine (GEE) as well as the normalized difference vegetation index (NDVI) and the normalized build-up index (NDBI) are estimated using Landsat 8 images. Spatial Statistics and regression analysis were performed to examine the impact of LULC on the air quality in the Narayanganj City Corporation Area. It has been vindicated that with the reduction of the vegetation area, the build-up area has increased within these two years. During this duration, the concentrations of NO_2, and SO_2 have increased and the concentration of CO, PM, and O_3 have hardly changed. The negative correlation between the vegetation index and air particles and the positive correlation between the build-up index and air particles exhibit the low rate of vegetation coverage and high rate of buildup index debilitated the environment as well as public health. Urban development is also an essential part of global development which cannot be disaccorded. Hence this study bears a significant impact on acknowledging the scenario and pursuing policy recommendations.

1. Introduction

1.1 Background of Study

Air quality forecasting in terms of air pollution characteristics has been a crucial area of study in environmental science in recent years as the impacts of pollutants on public health through ambient air have received significant concern (Kumar and Goyal 2011) (Kurt and Oktay 2010). In recent times, the effect of climate change has had a significant impact on the global environment and natural resources. Urban temperatures are often experienced higher compared to the surrounding rural areas as a result of rapid urbanization, industrialization, and economic development an increased level of emissions in the environment causing disruption including water, soil, and air pollution (Howard 1833) (Oke 1995) (IPCC 2007). The increased amount of air pollutants in the atmosphere has direct and adverse effects on global respiratory health (Prakash, et al. 2021) (Dominici, et al. 2006) (Hansel, McCormack and Kim 2015), especially in the risk of fatality in Severe acute respiratory syndrome (SARS) (Chu, et al. 2016) (Chakraborty, et al. 2020). According to World Air Quality Report 2021, around $8 billion (USD) has been estimated as the daily economic cost of air pollution, which is 3-4% of the gross world product. Bangladesh has positioned 1st in Air Pollution and Potential Change in Life Expectancy in 2020; 6.9 years gain in life expectancy would have happened if WHO guidelines is met (AQLI 2022). The Air Quality of Dhaka is continued as “Unhealthy” and the AQI was recorded at 187 on September 18th, 2022 (The Daily Star 2022) (Ministry of Environment and Forestry 2009). Air Quality Index is an index that reports the daily accumulated effect of ambient air pollutants in different monitoring sites

(CASE 2012). A complex mixture of components including ground-level ozone (O_3), suspended particulate matter ($PM_{2.5}$, PM_{10}), Carbon Monoxide (CO), Sulfur dioxide (SO_2), Nitrogen dioxide (NO_2), and Aerosol Optical Depth (AOD) are considered the measuring units for determining Air Quality Index (Künzli, et al. 2000) (Chen, Yan and Zhao 2015) (Kumar and Goyal 2011). The Land Surface Temperature (LST), Urban Heat Island (UHI), and Land Use Land Cover (LULC) are the key parameters for determining the relation between air temperature, vegetation, and air pollutants to understand the air quality of a specific area (Li, et al. 2013) (Voogt and Oke 2003) (Chen, Yan and Zhao 2015) (Sultana and Satyanarayana 2020) (Sherafati, Saradjian and Rabbani 2018). Urban Micro-Climate Warming is a result of UHI which has close relation with LST and LULC (Ahmed, et al. 2013) (He, et al. 2007). The common land cover indices such as the normalized difference vegetation index (NDVI), the normalized build-up index (NDBI), normalized difference bareness index (NDBaI), soil adjusted vegetation index, urban index (UI), etc. (Ullah, et al. 2019) can be used to extract a relationship with the air pollutants.

Several research conducted in the Dhaka Metropolitan and nearby areas had also a similar result exhibiting AOD and Particulate matter has a negative correlation with NDVI which vindicate that this factor provides a broader scale impact on Air Quality (Faisal, Rahman and Haque 2022) (Hassan, Islam and Bhuiyan 2022). During the period of 1994-2009, a significant amount of vegetation cover loss (6.65%) had been experienced with a corresponding increase in LST (23°C – 31°C) along with a massive amount of carbon emission, one of the major air pollutants in Cumilla, a fastest-growing city of Bangladesh (Kafy, et al. 2022). The aim of this study is to explore the impact on the Air Quality Index (AQI) as an aftereffect of the change in Land Use and Land Cover (LULC) based on the land cover indices (NDBI and NDVI) in Narayangonj, one of the major polluted cities in Bangladesh in the duration of 2019 to 2021. To understand the impact we have tried to build up a relationship between the land cover indices (NDBI, NBVI) for the components of the Air Quality Index ($O_{3,}$ $PM_{2.5}$, $PM_{10,}$ CO, $SO_{2,}$ $NO_{2,}$ AOD).

1.2 Study Area

Narayanganj is the central city of the southeast region of Bangladesh. It is located at the confluence of the Sitalakhya and Dhaleswari rivers. The approximate location of Narayanganj City Corporation has been shown in figure 1, which covers an area of 33.57 km^2 (NCC). The land elevation of NCC is nearly 10 ft above mean sea level. It is situated between 23°37' north latitude and 90°30' east longitude. This city is known as the center of business and industry, known as Dundee of Bngladesh. It is especially famous for trading and processing jute plants and textile sectors. According to ICLEI 2020, it has been found that carbon emissions in Narayanganj are increasing at 5.8% annual rate, primarily due to industry. There are 344 brick kilns in Narayanganj, contributing significantly to the air pollution. In 2018, Narayanganj was identified as the most polluted air with a 565 score in AQI (Siddique 2018).

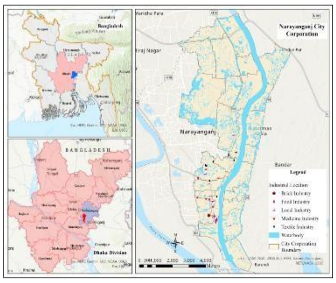

Figure 1: Study Area

2 Methodology

2.1 Data Collection

In this case study, Sentinel 5P and Landsat 8 have been used to collect required data. Sentinel has been used to collect data of air particles by using GEE. On the other hand, Landsat 8 has been used for determining the normalized digital vegetation index (NDVI) and normalized digital build-up index (NDBI) and Land Use land Cover (LULC) detection. Two Landsat 8 satellite images from 2019 and 2021 were obtained from the USGS website. Cloud coverage for both sets of data was less than 10%. Because these Landsat data were obtained in order to work on the Land Use land Cover classification, the date was chosen to fall between March and May to avoid cloudy pixel problems. To perform spatial analysis, all of these datasets were converted to 30m cell size and placed in the same projection. All satellite images were pre-processed, and the LULC classification, NDVI, and NDBI computations were carried out in ArcGIS 10.8.

Table-1: Data Used and the details

Sensor	*Path*	*ROW*	*Image Acquisition Date*
Landsat 8	137	44	16/03/2019
Landsat 8	137	44	16/04/2021

2.2 Retrieval of Air Quality Component

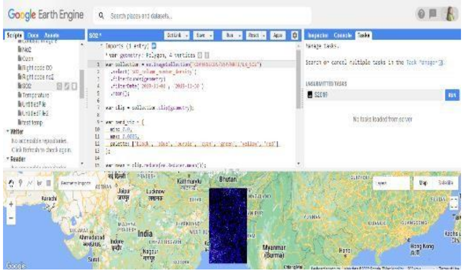

Figure 2: The Earth Engine Interactive Development

The Earth Engine public data catalog is a curated multi-petabyte collection of widely used geospatial datasets. The majority of the catalog consists of Earth observing remote sensing imagery, including the entire Landsat archive as well as complete data archives. Earth Engine employs a straightforward and broadly applicable data model based on 2D gridded raster bands in a lightweight "image" container. Sentinel 5P was launched to monitor the atmosphere on October 13th, 2017. Sentinel 5P is a new remote sensing data source whose measurements are made by the cutting-edge TROPOMI instrument (Potts 2021). This spectrometer detects reflected solar radiation or that which is scattered back to space from the Earth's atmosphere and surface. Because each atmospheric gas's spectral signature is known, its concentration can be estimated by identifying the spectral signature in different parts of the electromagnetic spectrum. Sentinel 5P imagery was used to assess total columns of NO2, SO2, and CO concentrations, as well as MODIS for Aerosol Optical Depth (AOD). (Satya Prakash 2021).

2.3 Image classification

The image classification was done using supervised classification. There are numerous methods for supervised classification, including parallelepiped classification, K-nearest neighbor classification, minimum distance classification, maximum likelihood classification, and Bayes' classification. The Maximum Likelihood Classification (MLC) method was used in this study. When classifying an unknown pixel, the MLC quantitatively evaluates the variance and covariance of the category spectral response patterns. It is one of the most accurate classifiers because it is based on statistical parameters. (NajibaRashid, et al. 2022)

MLC was used to select training sets for image classification such as waterbody, Built Up Area, Vegetation and Barren Land. Aside from that, the literature review reveals that significant work has been done to identify land use dynamics by following built-up areas, vegetation, water bodies, and unused land.

2.4 Estimation of NDBI & NDVI

Both NDVI and NDBI have collected from Landsat 8 satellite image. 2019 and 2021 Landsat images have been downloaded from USGS earth explorer. Then NDVI and NDBI have estimated by the following formula.

$$\boldsymbol{NDVI = \frac{NIR - Red}{NIR + Red}} \qquad \boldsymbol{NDBI = \frac{SWIR - NIR}{SWIR + NIR}}$$

Where**,** NIR = Near Infrared Light which Indicates Band 5; Red = Visible Red Light indicating Band 4; SWIR = Short Wave Infrared Imaging indicating Band 6

3 Result & Discussion

3.1 Relation between NDVI & NDBI

During the study, a relationship between NDVI and NDBI was also discovered.

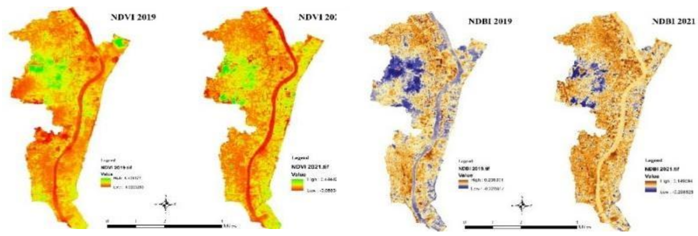

Figure 3: Spatial Map of NDBI & NDVI of 2019 and

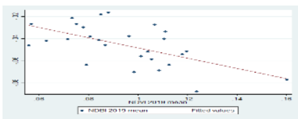

Figure 4: Correlation between NDVI & NDBI 2019

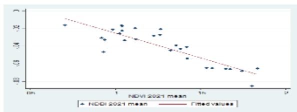

Figure 5: Correlation between NDVI & NDBI, 2021

In 2019, and 2021, the minimum and maximum ranges of NDBI are 0.0223203 to 0.478177 and -0.0883191 to 0.444421, respectively. In the last two years, NDVI has demonstrated a strong negative relationship with NDBI. The scatter plot shows the linear correlation of NDVI vs NDBI.

3.2 Relation between NDVI, NDBI & Air Particles

To understand the air quality index we have intended to explain the scenario of O_3, $PM_{2.5}$, PM_{10}, CO, SO_2, NO_2, and AOD with the vegetation level. Spatial and graphical analysis have been done to visualize the relationship between the air pollutants and the vegetation level with spatial and temporal variations of atmospheric parameters. Based on remote sensing interpretation, in figure 6, NO_2 concentrations will be significantly higher in 2021 than in 2019. Though the mean NO_2 measurement in 2021 and 2019 was very close (0.000236 mol/m^2 in 2021 and 0.0001414 mol/m^2 in 2019), a significant increase has been observed in 2021. A negative relationship between NDVI and NO_2 here indicating the statement that with the decrease in vegetation level the amount of NO_2 in the atmosphere has increased. The density of SO_2 columns in Narayanganj City Corporation has decreased from 0.000180 mol/m^2 in 2019 to 0.000149 mol/m^2 in 2021. In the Low range, however, this column number was raised from 2019 to 2021 expressing that the actual density increased day by day. In this study, it is observed that the distribution of sulphur dioxide is closely related to NDVI & NDBI, which provides an important reference for the comprehensive management of air pollution. The maximum value of CO in 2021 was 0.0443 mol/m^2, and the value in 2019 was 0.0455 mol/m^2, indicating a slight decrease during this period. In Narayanganj City Corporation, for example, the difference between the minimum and maximum levels was 0.0012 mol/m^2 exhibiting a negative correlation between the NDVI values, and positive correlation with NDBI. An analysis of AOD maximum revealed that AOD levels were high (-1.29) in 2021 and low (-0.175) in 2019. The AOD map, as well as the NDBI and NDVI, show that the low quantity of vegetation and the high rate of build-up area has a negative impact on the

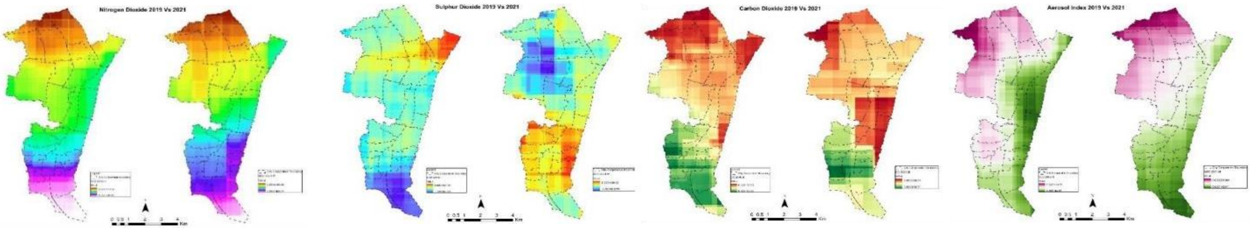

Figure 6: NO_2, SO_2, CO and AOD (from left to right)

environment by increasing the Aerosol Index. The following correlation graphs are indicating the same relation stated above.

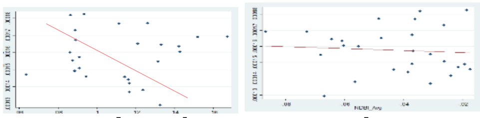

Figure 7: Correlation between NO_2 and NDVI, NDBI

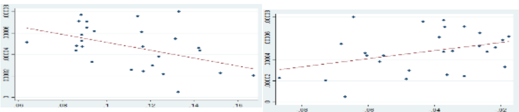

Figure 8: Correlation between SO_2 and NDVI, NDBI

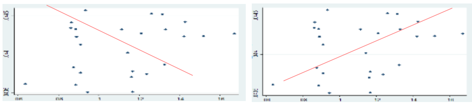

Figure 9: Correlation between CO and NDVI, NDBI

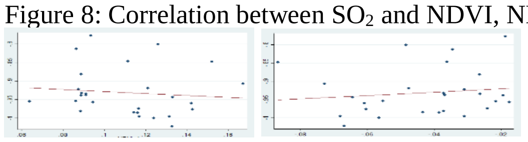

Figure 10: Correlation between AOD and NDVI, NDBI

3.3 Relation between Land Use Land Cover & Air Particles

The vegetation area calculated in 2019 image was 10.65 km^2 i.e. 22.60% but in 2021 image the area was decreased to 8.43% that means the area was lost its vegetation rapidly. The results above show that there is a significant difference between 2019 and 2021, which is clearly visible in Figure 11, as shown in Figure 12, the water body covers 4.43 km^2 (9.41%) in 2019 and 4.05 km^2 (8.59%) in 2021. Settlement

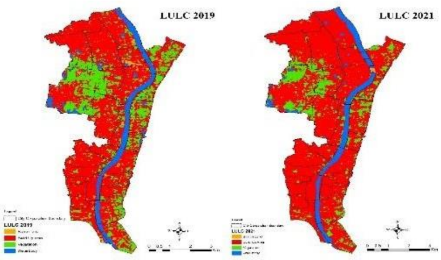

Figure 11: LULC 2019 vs 2021

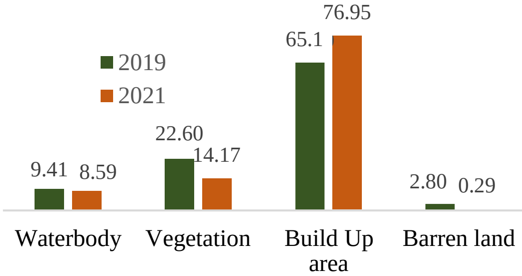

Figure 12: LULC Change Detection in 2019 & 2021

is the land cover/land use class identified by the supervised categorization. A settlement is a place where people live and have access to a network of public transportation, buildings, and other facilities. About 30.74 km^2 and 36.31 km^2, or 65.19% and 76.95%, respectively in 2019 and 2021, of the entire research area are thought to be covered by settlements. As shown in the Figure 12, the second most extensive land cover category is barren land, which had covered about 1.32 sq. km (2.80%) in 2019 and 0.14 sq. km (0.29%) in 2021. There is a negative influence on the environment by diminishing the vegetation. In areas where vegetation is decreasing, more air particles are being produced every day. Figures No 13 and 14 show that in these two years, the build-up area has expanded while vegetation has decreased, upsetting our natural equilibrium by increasing air particles.

3.4 Relationship between $PM_{2.5}$, PM_{10} concentration and ground level Ozone and LULC

The figure is indicating a seasonal pattern along with the impact of the lockdown due to the COVID-19 pandemic in the concentration of particulate matters. During the lockdown in 2020, it can be assumed that the sources of particulate matter were inactive which led to a drop in $PM_{2.5}$ and PM_{10} concentration and the reason for the unavailability of data from June 2019 to July 2020. Moreover, during the winter or dry season (December to March), the higher PM concentration, and during the rainy season or wet season (June to October), the lower PM concentration vindicates the seasonal variation of Particulate Matters. The data were collected from the DoE, MoEF under the CASE Project. The air pollution level was Level 2 indicating a Moderate Level of Health Concern.

Table 2. Air quality index (AQI) values, $PM_{2.5}$, and PM_{10} concentration color codes, the air pollution level of health concern

AQI Value of Index	*Levels of Health Concern*	*$PM_{2.5}$ Con. (µg/m^3)*	*PM_{10} Con. (µg/m^3)*	*Daily AQI Color*	*Air Pollution Level*
0–50	Good	0–12	0–54	Green	Level 1
51–100	Moderate	12.1–35.4	55–154	Yellow	Level 2
101–150	Unhealthy for Sensitive Groups	35.5–55.4	155–254	Orange	Level 3
151–200	Unhealthy	55.5–150.4	255–354	Red	Level 4
201–300	Very Unhealthy	150.5–250.4	355–424	Purple	Level 5
301 and Higher	Hazardous	250.5–Higher	425–Higher	Maroon	Level 6

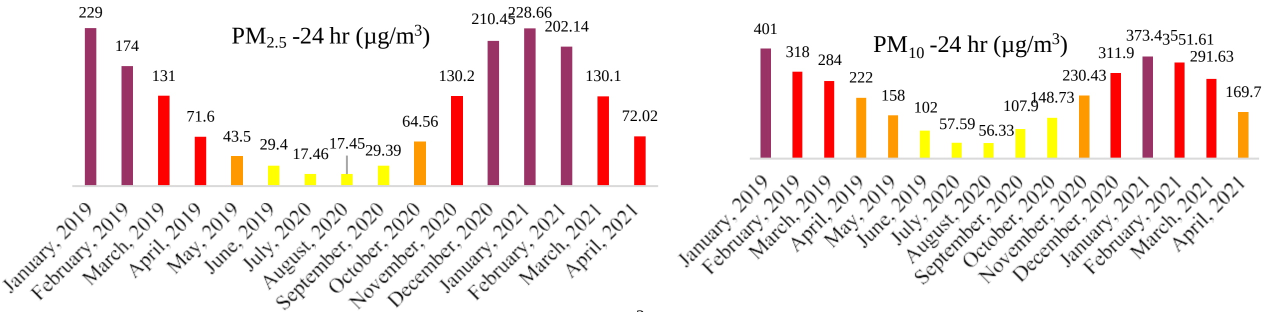

Figure 13: $PM_{2.5}$ & PM_{10} Concentration (µg/m^3) for different times and corresponding AQI color code

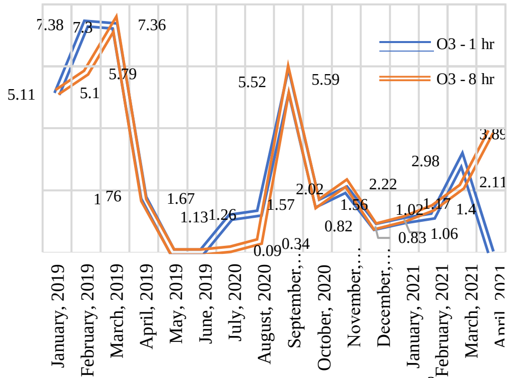

Figure 14: O_3 1-hr & 8-hr Conc. (µg/m^3) for different times

However, the Seasonal trend of Particulate matter in January 2019 and January 2021 seems relatively constant, indicating a "Very Unhealthy" environment for urban health. The reason behind this constant degradation is the decreased rate of vegetation and it is observed that 14.17% loss of vegetation. An effect of COVID-19, as a natural purification mechanism as a consequent result of the lockdown, has been observed in the concentration of ozone in 2021. From figure 15, we can see, in 2019 the concentration of ozone was high where the LULC was 22.60% and a lower ozone concentration in 2021 with the LULC 8.43%. This significant observation, with the decreased amount of vegetation level and the decreased ozone concentration, is indicating the presence of another factor in the concentration of atmospheric air particles. However, this natural purification system should have continued a significant decrease in 2021 in both $PM_{2.5}$ and PM_{10} whereas the concentration of these particles remains close to constant in this study which is a matter of immediate attention for the policymakers.

4 Conclusion

Narayangonj, the city of industry, has a severe air quality indicating the "Unhealthy" environment for the urban health. Overall we can state that there is a negative correlation between NDVI and air pollutants. In other words we can maintain that with the decrease of vegetation level the amount of air pollutants is increasing (except some components). In this Asian region as well as Bangladesh similar seasonal variation has already been seen in different air pollutants including particulate matter and during the months of December to February (winter) the air pollutants, particularly $PM_{2.5}$ and PM_{10} are observed to higher than other duration of the year (Hoque, et al. 2020). The low rate of vegetation coverage and high rate of buildup index have a detrimental effect on the environment and public health. Therefore, this study desires to create an impact on the policy level to improve air quality and pursue sustainable city management, and effective industrial and land use management strategies.

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