Trend analysis of remotely sensed Greeneries and Green-house Gases data for Enugu metropolis

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Key words: Global warming, resilient settlements, high-resolution imageries, urban heat islands

SUMMARY

In pursuit of the Sustainable Development Goals (SDG) No. 11 and Target 7, the development, maintenance, and accessibility of greeneries for city residents is a priority for building an environmentally friendly, inclusive, and climatically resilient society. As a result of the increased need for urban shelter in Enugu metropolitan city, green space within that environment has been substantially reduced over time. In a bid to restore an environmentally safe and friendly society, there is a need to obtain data as regards the trend of greeneries within the study area in relation to greenhouse gas (GHG) emission, and population using remotely sensed data. This study presents the spatio-temporal analysis of the trend of these variables (population influx, GHG and greeneries degradation) within Enugu metropolis from 2019 – 2022. In this study, population data was obtained from Landscan satellites, greeneries data were obtained by maximum likelihood classification of Landsat imageries while GHGs emission data were extracted from Sentinel 5P using Java script in the Google Earth Engine. GHGs examined in the study were carbon monoxide (CO), nitro dioxide (NO_2), Methane (CH_4). Spatio-temporal variation (trend) and spatial auto-correlation of the various indices were performed using Quantum GIS (QGIS) and the results obtained indicate a strong spatial autocorrelation between reduction in greeneries, population influx and CO emission. However, the study identified that due to the light nature of CH_4 and NO_2 leading to their high atmospheric-mixing rate, it is difficult to establish their trend and spatial auto correlation from annual estimates.

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1.0 INTRODUCTION

Urban areas are witnessing rapid changes in land use and land cover due to population growth and urbanization. These changes have profound effects on the urban environment, including the amount of greenery and greenhouse gas emissions. Like many other urban areas around the world, Enugu's urban metropolis has seen a significant decrease in its greenery due to population growth and associated socio-economic characteristics (Qiang, et al, 2015). This could lead to environmental degradation in the long run due to increased levels of Greenhouse Gas (GHG) emissions in the atmosphere. However, Sustainable Development Goals (SDG) No. 11 and Target 7 aim to develop, maintain, and provide greenery for city residents to create an environmentally friendly, inclusive, and climatically resilient society (United Nations, 2015, Okeke, 2021). Unfortunately, most urban metropolis have failed to achieve this due to the high demand for housing in the ever-increasing urban population. Past literature has established the reality of urban sprawl resulting from rural-urban migration, which shifts the fringes further hinterland (Nwalusi, et al., 2022). This type of spontaneous urbanization could increase GHG emissions due to the decrease in greenery and increased socio-economic activities (Echendu, Okeke & Nnaemeka-Okeke, 2020; Okeke et al., 2021). To restore an environmentally safe and friendly society, it is necessary to gather data on the trend (past and current status) of open spaces/greenery in the study area in relation to greenhouse gas emissions and the population.

Dickson et al. (2022) carried out qualitative research on the significance of rural-to-urban migration in relation to housing delivery in Enugu. The findings of the study highlight the negative effects of urbanization in Enugu, including a severe housing shortage, rising rental prices, heavy traffic, and rising land values, which encourage the growth of slums and informal settlements as well as haphazard development and planning standards violations. Obviously, population increase is negatively impacting the attainment of SDG 11 within the Enugu urban metropolis. This corroborates the earlier findings of Okeke et al. (2020) that identified fragility in most Nigerian urban cities, hence, hampering the attainment of target 7 of SDG, No. 11. Amongst other things, it is obvious that GHG emissions and greeneries degradation is part of the causes of residents' dissatisfaction to the urban environment (Okeke et al., 2020).

Dogan et al. (2017) examined the relationship between population growth and carbon emissions using panel data analysis to examine how population expansion affects carbon emissions globally. According to the research, there is a significant association between population growth and carbon emissions, thus emphasizing the significance of taking population dynamics into account while trying to reduce greenhouse gas emissions and accomplish sustainability goals. Furthermore, studies by Abel et al. (2019) and Fugazza, et al. (2018) highlight the necessity for coordinated strategies to tackle the dual problem of population expansion and GHG emission considering the inter-relationship between them, if the SDG No. 11 must be achieved. Similarly, Kim & Kim (2018) examined the relationship between deforestation and greenhouse gas emissions in the Brazilian Amazon using a panel data analysis methodology. The study highlights the necessity of sustainable forest management and conservation efforts in mitigating climate change.

Empirical studies to validate the trend, relationship, and rate of GHG emissions and greenery degradation in Enugu metropolis are uncommon despite them being a menace to liveable and climatically resilient cities. Therefore, this study examines the dynamic relationship between population growth, greenery, and GHG emissions, by evaluating potential links between the temporal patterns in green cover and GHG emissions and their effects on urban sustainability. The objectives of this study are to identify; (i) the spatio-temporal trend analysis of population, greeneries and selected GHG's within the study area and (ii) spatial auto-correlation and interrelationships between the parameters (population, greeneries and GHG's). Consequently, the research questions which the study intends to answer as follows;

(i) What is the direction and pattern changes population, greeneries and GHG's within Enugu metropolis

(ii) How do these identified parameters interact with each other and what effect does the interplay of their interactions have on the environment.

2.0 STUDY AREA

This study was carried out within the urban areas of Enugu metropolis. Enugu metropolis comprises four Local government areas (see Figure 1). The Local government areas are Enugu North, Enugu South, part of Nkanu West and Enugu East.

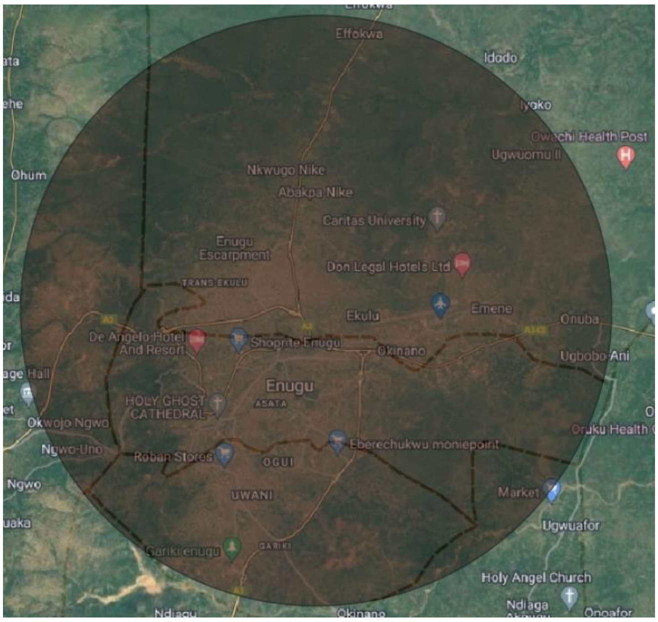

Figure 1: Study area (Enugu metropolis)

3.0 MATERIALS AND METHODS

The data used for this study were all remotely sensed data. Three main kinds of data were used for the study in line with the aim of the study. The data used and their sources are presented in Table 1.

Table 1: Materials used for the study

S/No	Derived data	Source	Resolution(s)	Reference
1	Population	Landscan satellite images	Spatial: 1km Temporal: Annual (2018 – 2022)	Dobson et al. (2000)
2	Greeneries (Vegetation, open space, and wetland)	Landsat satellite images	Spatial: 30m Temporal: 16days (Till date)	Rwanga, S. S. & Ndambuki, J. M (2017)
3	Greenhouse gases (GHG: CO_2, CH_4 & NO)	Sentinel 5P images	Spatial: 5.5km Temporal: daily (2019 - Till date)	Yaacob, et al. (2023)

The Landscan image was downloaded from the Landscan website (https://landscan.ornl.gov/). The Landscan imageries provide estimates of the average population density of an area at 1km grid interval across the globe. Description of the procedure and algorithms used for the population estimation is well documented in Dobson et al., (2000). LandScan uses a combination of data sources, including satellite imagery, land use data, and demographic information, to estimate population distribution. The fundamental principle behind LandScan's population estimation is spatial modeling. It breaks down the Earth's surface into grid cells of 1 km x 1 km spatial resolution and analyzes various spatial factors within each cell using criteria such as road, slope, land cover, and night-time light. By integrating this data with the most recent publicly available census and demographic information, LandScan's modeling techniques assign population counts to each grid cell, providing a detailed estimate of population distribution at a fine spatial resolution. Annual averages of such periodic estimates allow for a comprehensive view of the yearly average population density of any part of the globe.

In order to ensure consistency in the temporal resolution of the images used in the study, the Landsat imagery collected for this study also spanned from 2018 – 2022. However, there were data gaps in the Landsat images covering the study area path and row (188/056) between 2018 and 2021. The few images that covered the study area during that period were either not properly radiometrically corrected or had intolerable cloud cover. Eventually, the selected images used for the study are as shown in Table 2:

Table 2: Landsat images used for the study

S/No	**Image acquisition date**	**Percentage cloud cover**
1	27th December, 2018	4.15
2	19th December, 2021	3.78
3	30th December, 2022	3.96

Extraction of greeneries from the study was done using the image classification technique. The standard procedure for image classification using the maximum likelihood supervised classification method was adopted (Santos, et al., 2011). However, in order to aid in the easy discrimination of greeneries during the sample training, the raw Landsat images were first combined using a false-color composite (FCC) that would enhance the greeneries. Thereafter, the image was trained with the intention of extracting only the greeneries and built-up areas. This choice is because the study is limited to just urban areas in the Enugu metropolis.

The Sentinel 5P-derived data were extracted directly via cloud computation using the codes written in Java-script language. The cloud computation was performed online to aggregate the derived GHGs over the study area from January 2019 - December 2022. The annual averages were obtained and used for the analysis. A diagrammatic presentation of the workflow is shown in Figure 2.

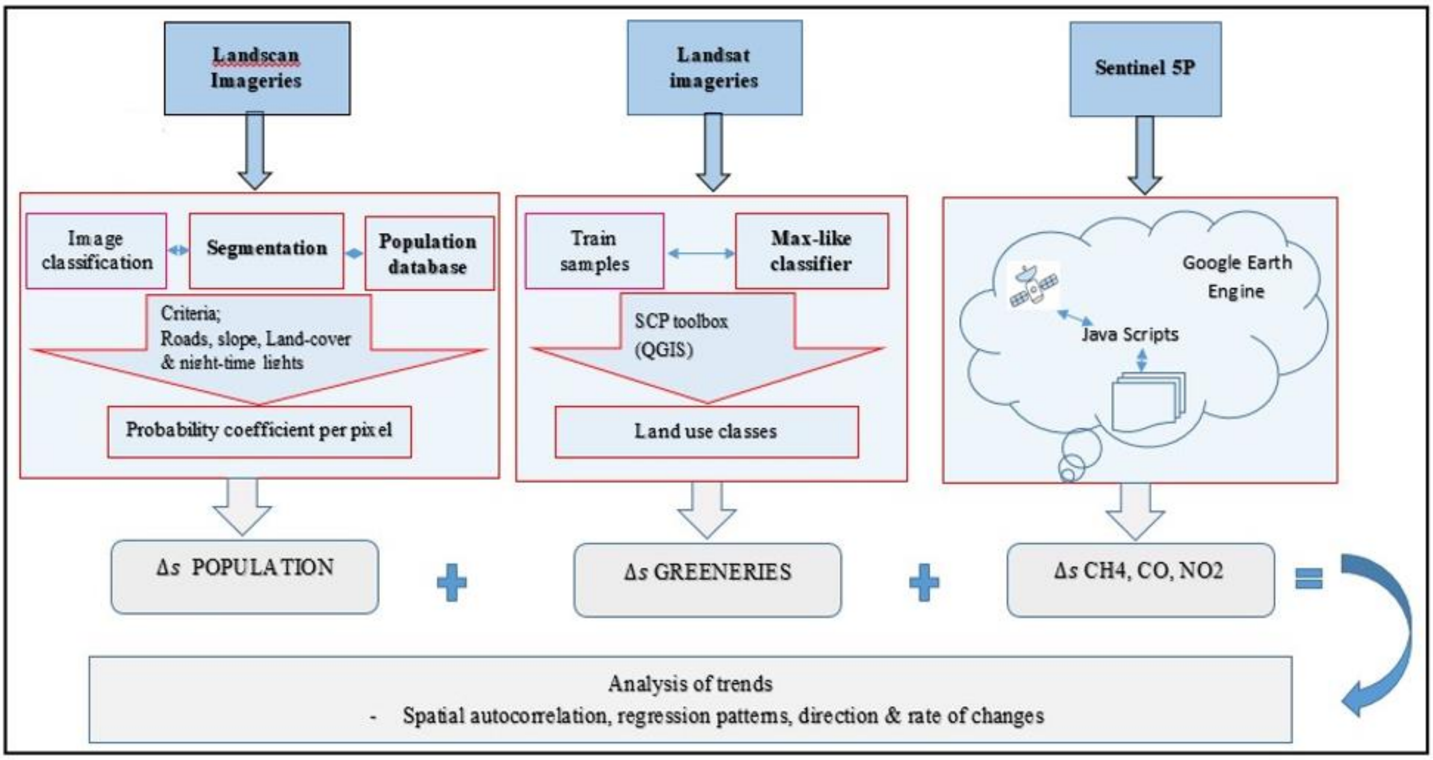

Figure 2: workflow diagram

4.0 RESULTS AND DISCUSSIONS

To ensure a thorough comprehension of the study's findings, the results will be divided into two subsections for presentation and discussion. The initial section will concentrate on the spatial pattern, specifically the trend analysis of the individual parameters being examined. The second section will analyze the parameters' spatial autocorrelation to identify interrelationships and the general discussion of the study's findings.

4.1 Trend analysis

Analysis of the trend of each of the investigated parameters is presented in this sub-section. Where applicable, the spatial-temporal trend as observed is further supported by graphs and tabular values. As seen in Figures 3(a) – (d), the average population Enugu metropolis (when a scaling factor of 0.07 was applied to the sum of pixels values) spans from 830,436 persons in 2019 to 843,737 persons in 2022.

Although the values seem remarkably stable, the pattern of migration is an important metric that could help local authorities plan for efficient regional housing, transportation and public infrastructure program. It can be observed that the pattern of migration is more tilted towards the South eastern part of the central area (Nkanu West and Enugu South). Possible reasons for this could be as a result of the hilly nature of the terrain in the Western side (Udi local government area). Overall, there is about 1.62% gain in population in the study area during the 4-year period.

Using pixel analysis techniques, the descriptive statistics as seen in Table 3, was observed for the study area between the year 2019 and 2022. Take note of the values are negatively skewed which means that most of the pixels have values greater than the mean. This suggests that the reality of the population might be slightly above the Landscan derived estimates within a reasonable range.

Table 3: descriptive statistics of population extracts for the study area

	Population density			
Summary statistics	*2022*	*2021*	*2020*	*2019*
units	per/km^2	per/km^2	per/km^2	per/km^2
mean	188.725	186.175	186.175	185.750
median	255.000	255.000	255.000	255.000
mode	255.000	255.000	255.000	255.000
minimum value	0.000	0.000	0.000	0.000
maximum value	255.000	255.000	255.000	255.000
range	255.000	255.000	255.000	255.000
Total population	843737	832336	832336	830436
skewness	-1.134	-1.081	-1.081	-1.077
kurtosis	-0.376	-0.505	-0.505	-0.507

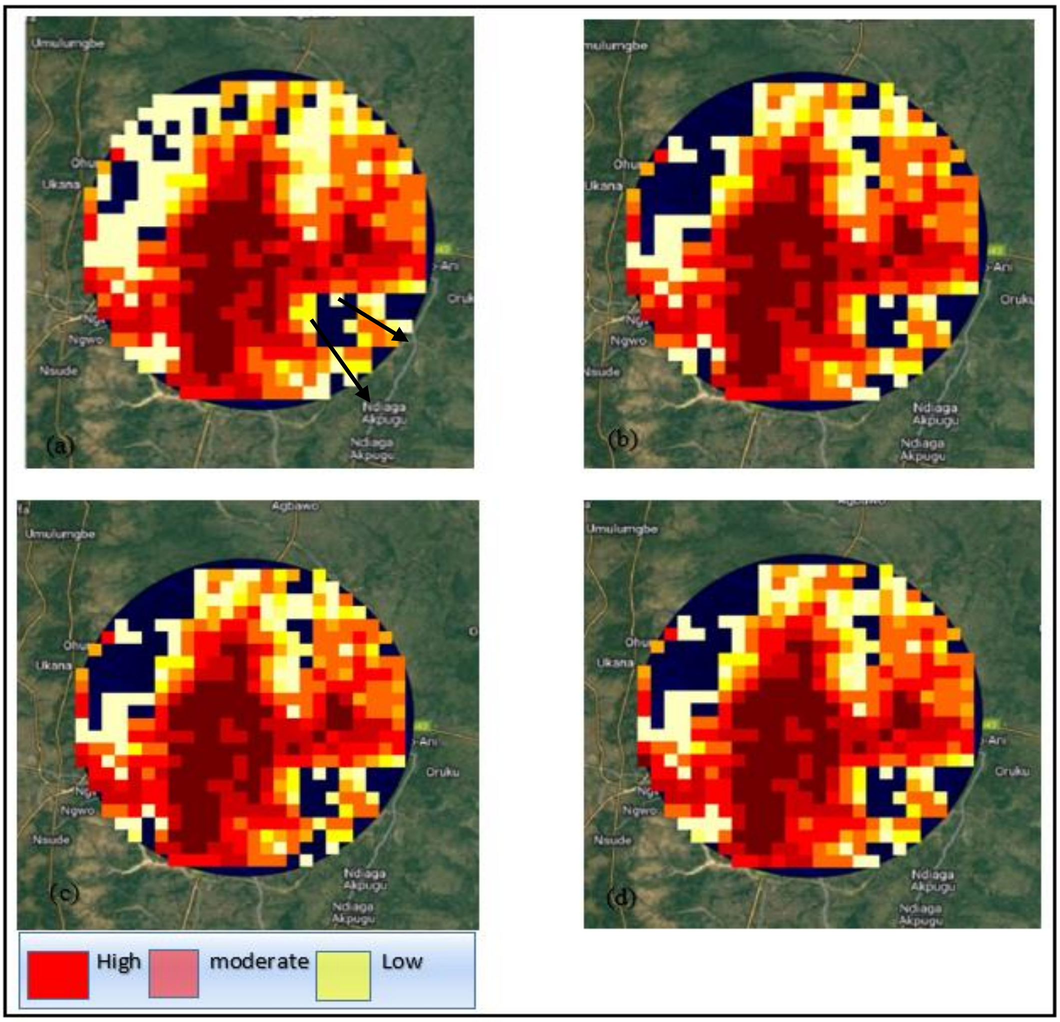

Figure 3: spatial variation of population across Enugu in (a) 2019, (b) 2020 (c) 2021 (d) 2022

4.1.1 Trend analysis of greeneries

The spatio-temporal variation in greeneries within the study area was examined using both the false color composite (FCC) and the final image classification maps. As seen in Figures 4(a) – (c) and 5(a) to (c), the pattern of variation corresponds significantly with the population. It is seen that the area covered by built-up spread in the same direction as the direction of spread of the population. Consequently (shown in Tables 4 (a) – (c), the greeneries also reduce in the same direction. This shows that literarily, as the population spreads hinterland, the greeneries are replaced by built-up areas.

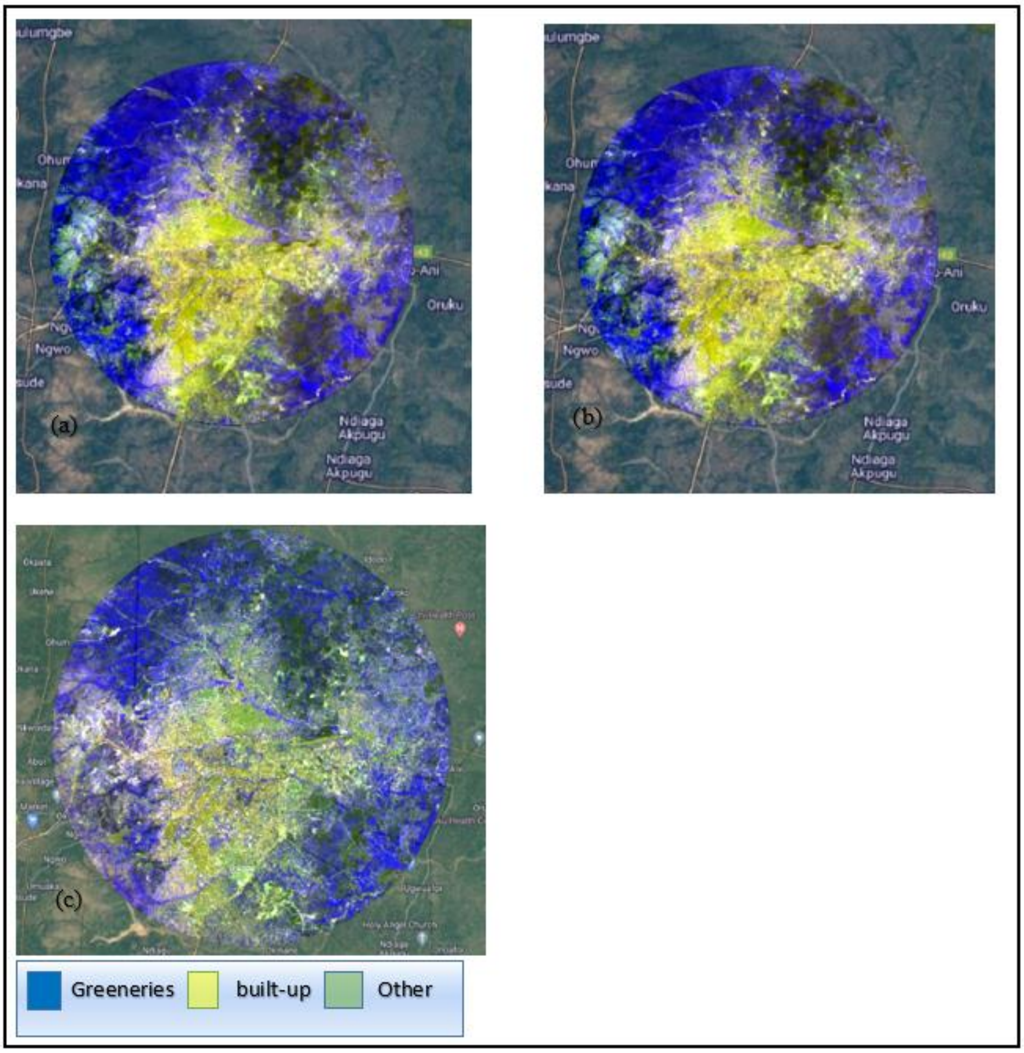

Figure 4: False color composite of the study area; (a) 2018, (b) 2021, (c) 2022

Tables 4 (a) – (c) presents the classification report for the study area. Expectedly, since the area under consideration is the Enugu metropolitan area, much of the land use is devoted strictly to built-up and greeneries. The other areas classified as others are a bit of the wetland and flowing surface hydrology within the city center.

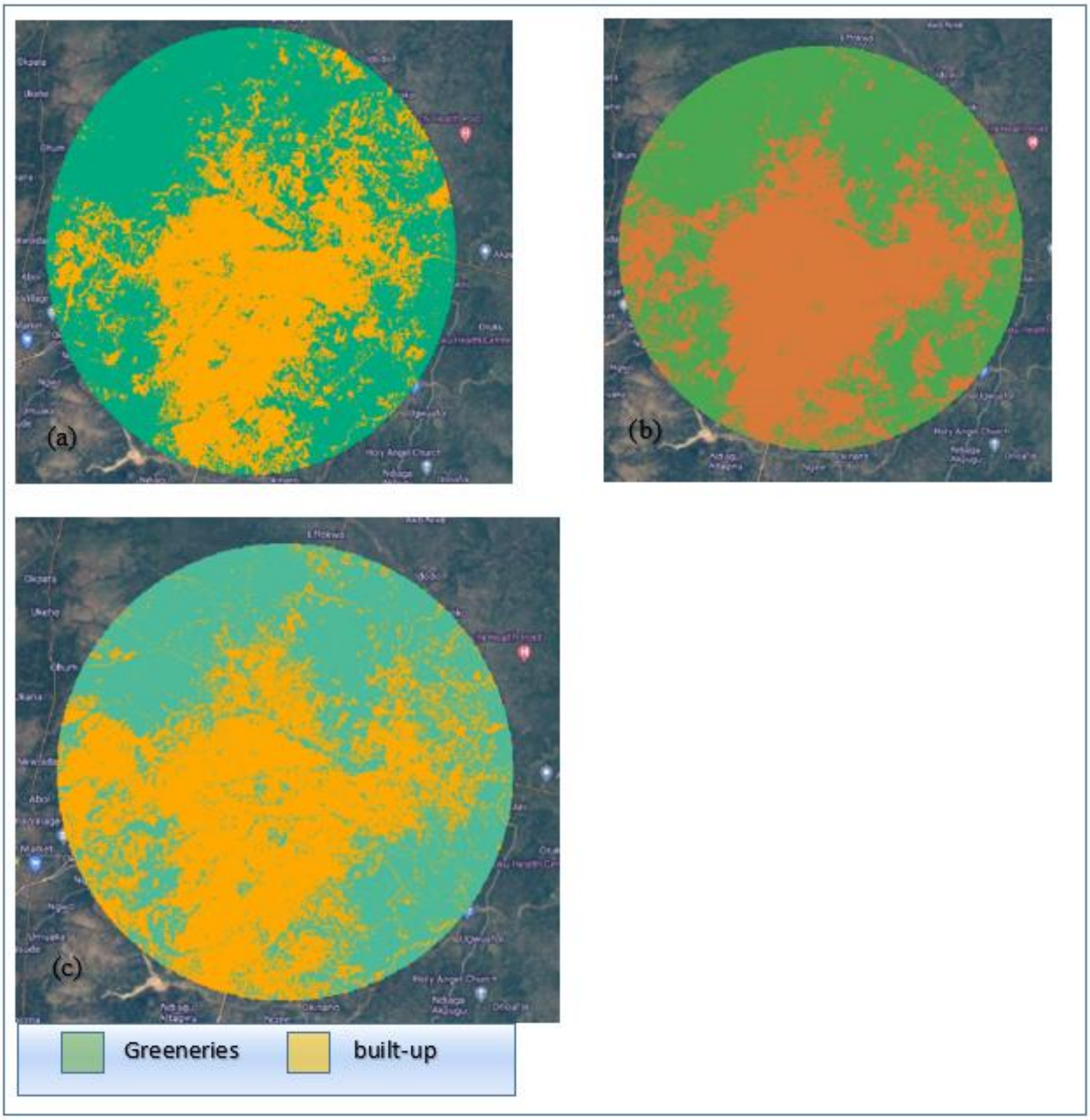

Figure 5: Image classification result for the study area; (a) 2018, (b) 2021, (c) 2022

Confirming the degradation trend observed in Figures 4 and 5, the area covered by vegetation reduced by 6.01% between 2018 and 2021, while it reduced by only 0.36% between 2021 and 2022. Incidentally, the percentages lost by vegetation were gained by the built-up area.

Table 4(a): summary of image classification report for 2018 (overall accuracy = 74.29%)

Land use Class	**No of Pixels**	**Percentage (%)**	**Area (Ha)**	% difference
Others	133192	21.45	11987.28	Not applicable
Built up	212745	34.26	19147.05	
Greeneries	275007	44.29	24750.63	
Total		100.00	55884.96	

Table 4(b): summary of image classification report for 2021 (overall accuracy = 70.33%)

Land use Class	**No of Pixels**	**Percentage (%)**	**Area (Ha)**	% difference (2018 – 2021)
Others	133192	21.45	11987.28	0.00
Built up	250396	40.33	22535.64	6.06
Greeneries	237356	38.23	21362.04	-6.06
Total		100.00	55884.96	

Table 4(c): summary of image classification report for 2022 (overall accuracy = 70.21%)

Land use Class	**No of Pixels**	**Percentage (%)**	**Area (Ha)**	% difference (2021-2022)
Others	133192	21.45	11987.28	0.00
Built up	252655	40.69	22738.95	0.36
Greeneries	235097	37.86	21158.73	-0.36
Total		100.00	55884.96	

Confirming the spatial pattern of the changes in greeneries, Figure 6 shows the direction of flow of the changes in the land use.

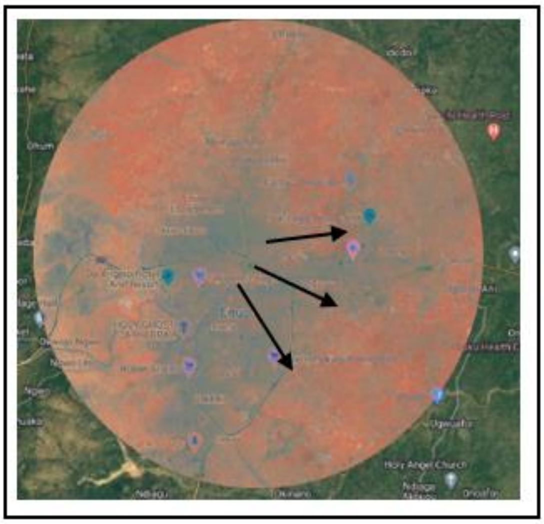

Figure 6: direction of sprawl indicated by arrows

4.1.2 Trend analysis of GHGs

The trend of variation of the greenhouses is presented in Figures 7 – 9 (a) – (d). Figure 7 presents the annual trend of variation in carbon-monoxide (CO), Figure 8 shows annual pattern of variation in Methane (CH4) and Figure 8 gives insight to the annual pattern of variation of nitrogen-dioxide (NO_2) within the study area.

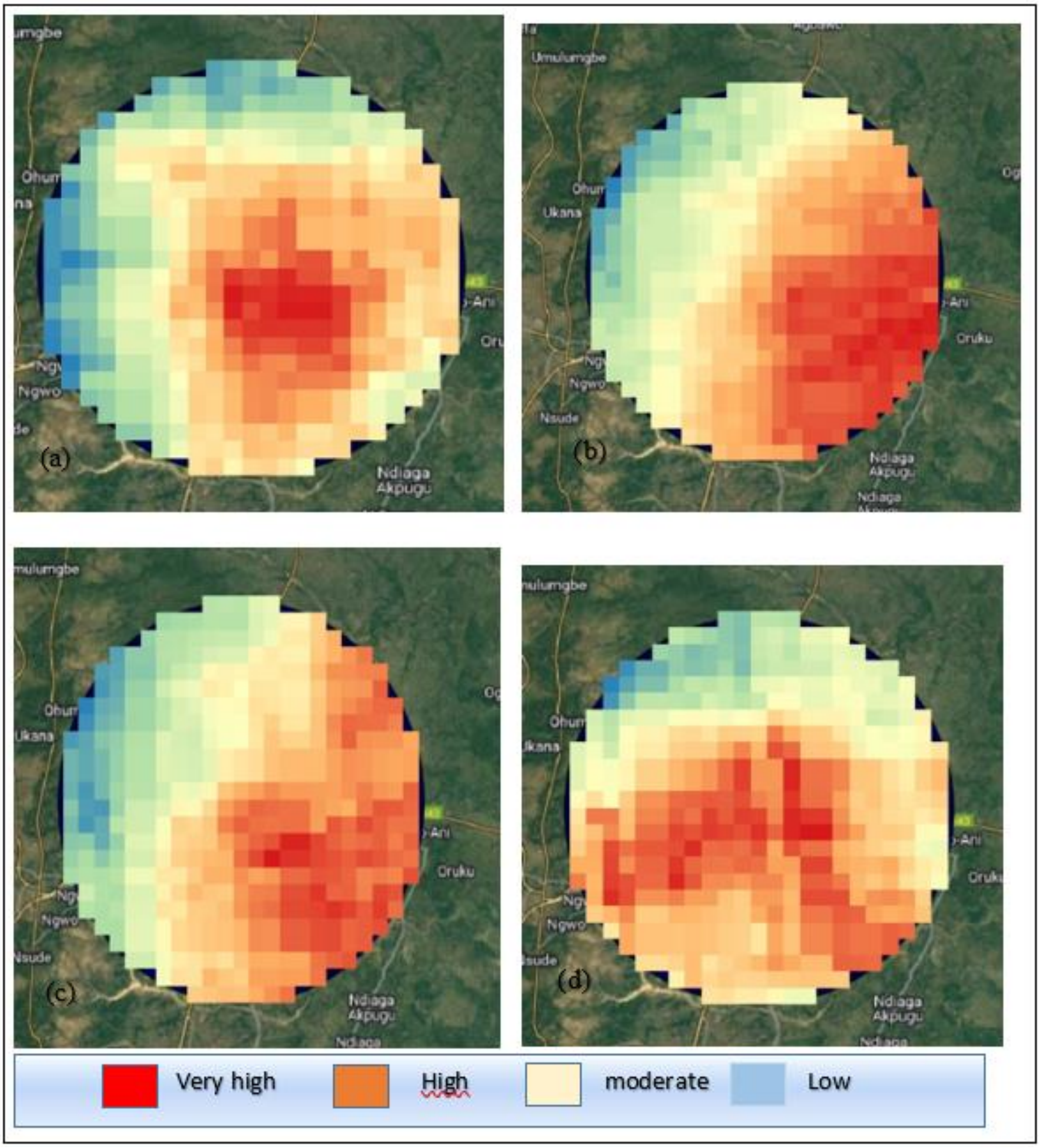

Figure 7: spatial variation of CO across Enugu in (a) 2019, (b) 2020 (c) 2021 (d) 2022

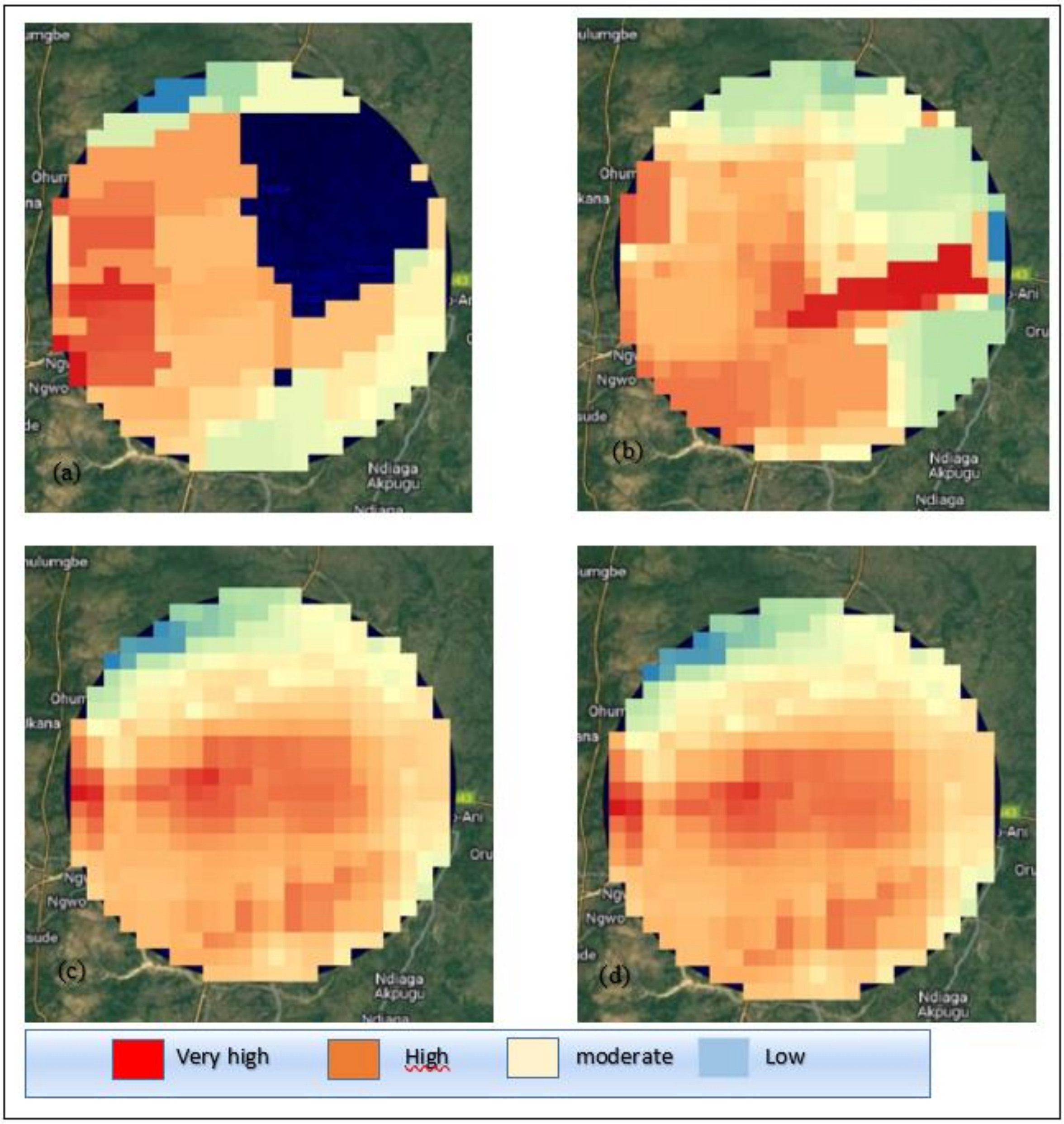

Figure 8: spatial variation of CH4 across Enugu in (a) 2019, (b) 2020 (c) 2021 (d) 2022

From Figure 7, it can be observed that spatio-temporal pattern of spread the CO is similar to that of the population. This could be a direct result of the perceived increase in the volume of traffic that flows in these directions as a consequence of urban sprawl. But in 2022, the pattern of flow appears different from the previous trend. This is because the largest volume of carbononoxide was observed around the Western parts of the study area. Reasons for this could be due to other factors aside from population increase and deforestation.

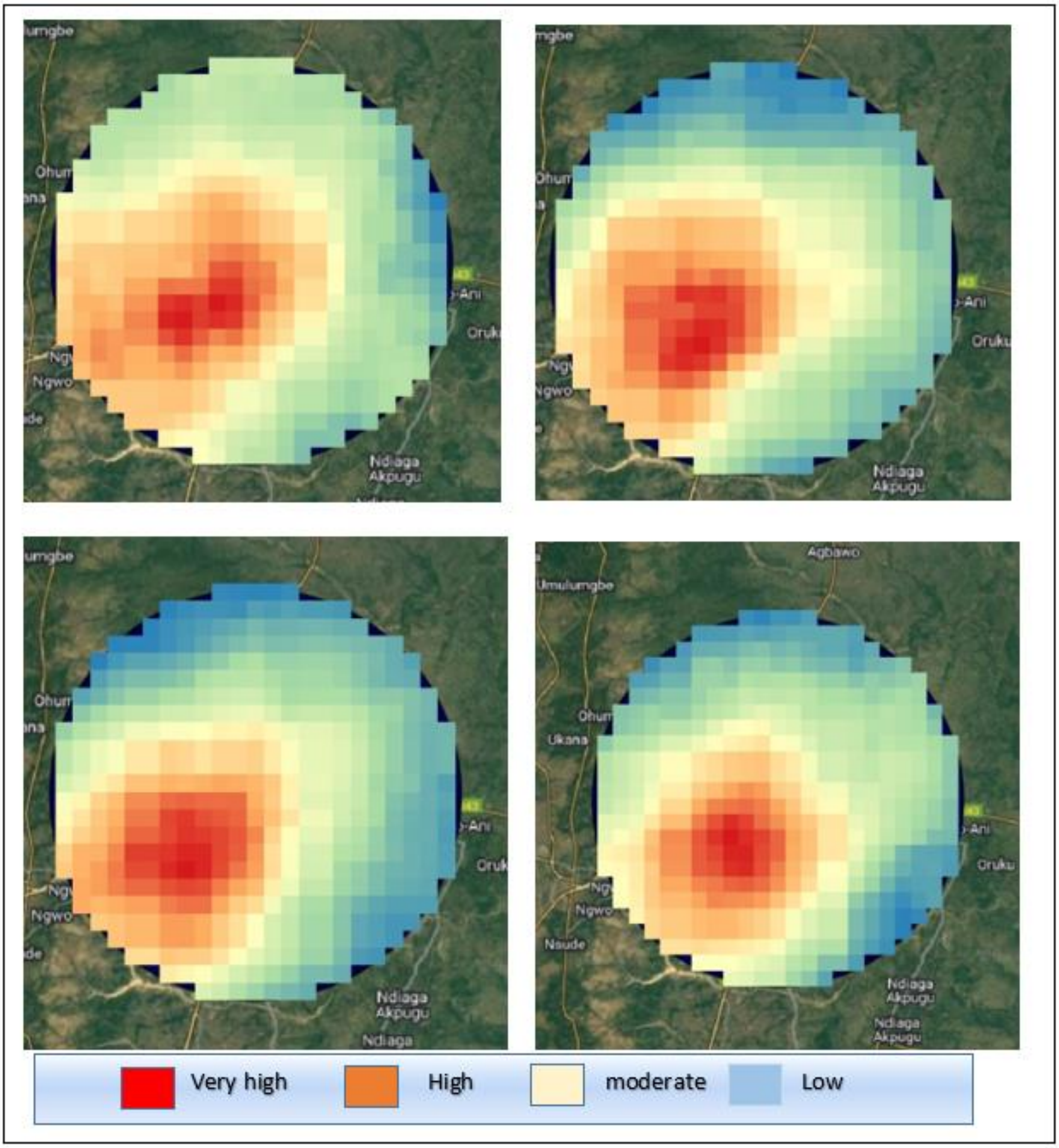

Figure 9: spatial variation of NO_2 across Enugu in (a) 2019, (b) 2020 (c) 2021 (d) 2022

As seen in Figure 8, an haphazard (leap-frog) pattern was observed with the spread of Methane across the study area. Invariably, it can be said that there is clear pattern or trend seen in Methane distribution. Likely reason for this is because Methane is a light gas and is easily carried about by wind in the atmosphere. In comparison to heavier atmospheric gases like nitrogen (N_2) and oxygen (O_2), whose molecular weights are roughly 28 and 32 amu, respectively, methane (CH_4), with a molecular weight of about 16 atomic mass units (amu), is in fact regarded as a light gas (Encyclopaedia Britannica, 2021). Methane is an important fuel source and a powerful greenhouse gas because of its reduced molecular weight, which also gives it buoyancy in the atmosphere and contributes to climate change (IPCC, 2013). Hence, it might be difficult to capture a trend of its behavior over any locality by an annual estimate. In comparison to heavier atmospheric gases like nitrogen (N_2) and oxygen (O_2), whose molecular weights are roughly 28 and 32 amu, respectively, methane (CH_4), with a molecular weight of about 16 atomic mass units (amu), is in fact regarded as a light gas (Encyclopaedia Britannica, 2021). Methane is an important fuel source and a powerful greenhouse gas because of its reduced molecular weight, which also gives it buoyancy in the atmosphere and contributes to climate change (IPCC, 2013).

The nitrogen dioxide concentrate across the study area is maximum within the central urban area and tends to spread towards the Western area. This trend is clearly not in the direction of urbanization. Numerous factors affect the amount of nitrogen dioxide (NO_2) in the atmosphere. The main sources of NO_2 emissions are human activities, such as combustion processes in cars, factories, and power plants while its distribution and concentration depend on wind patterns, weather, and chemical processes. NO_2 levels are also impacted by seasonal fluctuations, geographic location, altitude, and emission control strategies. Wildfires and microbiological activity are additional natural factors that contribute. The management and mitigation of NO_2 pollution, which can have detrimental impacts on air quality and human health, depends on an understanding of these aspects.

4.2 Spatial auto-correlation

Based on the spatial patterns presented in Figures 4 – 9 there exists a very strong spatial auto correlation between greeneries degradation and population increase within the study area. The study confirms that rural – urban migration within the area is causing significant reduction in the space available for greeneries within the study area.

It is similarly observed that CO emissions within the study area increases significantly with increase in population (and consequently decrease in greeneries). This is obvious result is as expected knowing fully well that photosynthesis is symbiotically useful to both plants (for food) and mankind (for reduction of CO). On the other hand, population increase raises the carbon emission from transportation and other anthropogenic factors. This therefore explains the observed trends. The anomaly observed in 2022 however could be as a result of wind pattern and other climatic factors.

However, the case of Methane (CH_4) and nitrogen dioxide (NO_2) is a clear indicator that wind pattern and atmospheric/climatic conditions play significant roles in the pattern of the GHGs (especially the light Gases) as seen from the satellite. Invariably, given the speed at which these particular concentrates diffuse into the atmosphere in the face of atmospheric mixing, it is clear that it would be difficult to establish their spatial auto-correlation by annual estimates. Hence, additional studies would be required wherein the weekly spatial variations of these concentrates can be examined over a period of time in relation to established relationship between greeneries and population increase.

5.0 CONCLUSION

This study provides insights into the trends and interactions between greeneries, population influx, and GHGs emission in Enugu urban metropolis using remotely sensed (RS) data. Based on the available data, annual estimates and spatio-temporal pattern of population influx, change in greeneries, and GHGs emission over the study area has been identified. The study confirms that there exists a very strong positive correlation between population increase and greeneries reduction. Consequently, it was also confirmed that there exists strong spatial auto-correlation between population influx and CO emission. However, due to the light nature of CH_4 and NO_2, the study identified that it is difficult to establish the trend and spatial auto-correlation (interactions) between these GHGs and the other examined variables.

The use of Sentinel 5P imagery data to extract the actual numeric quantities of the GHG's over the study area as well as the automatic extraction of same using the Google Earth Engine (GGE) provides a scientific low-cost solution wherein developing countries can obtain near-realtime information (statistics) about the extent of GHG emission over their country. This would foster frequent mnitoring of the atmosphere and also aid in decision making towards ensuring an eco-friendly and atmospherically-clean environment.

The outcomes of this study will help in further scientific studies that are targeted towards understanding the nature, behavior and altimately charactization of the contributions from the Nigerian space to the overall GHG's emission as well as greeneries depletion across the world. Furthermore, the study provides empirical data as regards GHG's emision within the study area which will serve as model inputs for further scientific analysis about the urban atmosphere within the study area.

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BIOGRAPHICAL NOTES

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