Scientific Research Publishing

Open Journal of Air Pollution, 2024, 13, 1-22
https://www.scirp.org/journal/ojap
ISSN Online: 2169-2661
ISSN Print: 2169-2653

Mapping Air Quality Using Remote Sensing Technology: A Case Study of Nairobi County

Quinto Juma Meltus[1,2*], **Faith Njoki Karanja**[1]

[1]Geospatial Engineering Department, The University of Nairobi (UoN), Nairobi, Kenya
[2]Data Management, Modeling and Geoinformation Unit (DMMG), International Centre of Insect Physiology and Ecology (ICIPE), Nairobi, Kenya
Email: *meltusquinto@gmail.com

How to cite this paper: Meltus, Q.J. and Karanja, F.N. (2024) Mapping Air Quality Using Remote Sensing Technology: A Case Study of Nairobi County. *Open Journal of Air Pollution*, **13**, 1-22.
https://doi.org/10.4236/***.2024.*****

Received: December 19, 2023
Accepted: March 10, 2024
Published: March 13, 2024

Abstract

Nairobi County experiences rapid industrialization and urbanization that contributes to the deteriorating state of air quality, posing a potential health risk to its growing population. Currently, in Nairobi County, most air quality monitoring stations use low-cost, inaccurate monitors prone to defects. The study's objective was to map Nairobi County's air quality using freely available remotely sensed imagery. The Air Pollution Index (API) formula was used to characterize the air quality from cloud-free Landsat satellite images *i.e.*, Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI from Google Earth Engine. The API values were computed based on vegetation indices namely NDVI, TVI, DVI, and the SWIR1 and NIR bands on the QGIS platform. Qualitative accuracy assessment was done using sample points drawn from residential, industrial, green spaces, and traffic hotspot categories, based on a passive-random sampling technique. In this study, Landsat 5 API imagery for 2010 provided a reliable representation of local conditions but indicated significant pollution in green spaces, with recorded values ranging from -143 to 334. The study found that Landsat 7 API imagery in 2002 showed expected results with the range of values being −55 to 287, while Landsat 8 indicated high pollution levels in Nairobi. The results emphasized the importance of air quality factors in API calibration and the unmatched spatial coverage of satellite observations over ground-based monitoring techniques. The study recommends the recalibration of the API formula for characteristic regions, exploring newer satellite sensors like those onboard Landsat 9 and Sentinel 2, and involving key stakeholders in a discourse to develop a suitable Kenyan air quality index.

Keywords

Air Quality, Air Pollution Index (API), Satellite Imagery, Vegetation Indices, Nairobi County

1. Introduction

Worldwide, air pollution continues to pose a major threat to public health [1] [2] [3]. The World Health Organization (WHO) estimates that air pollution claims the lives of almost 7 million people annually (WHO, n.d [4]). Numerous countries have conducted studies on the impact of air pollution on human health, with a focus on respiratory issues [5] and, in severe cases, results in mortality [6] [7]. Air pollution exacerbates respiratory ailments such as lung cancer, bronchitis, pneumonia, and asthma among others [8]. Countries around the world must, therefore, implement best practices to reduce and control the negative effects caused by air pollution.

According to the World Health Organization, air pollution is "*contamination of the indoor and outdoor environment by chemical, physical or biological agent that modifies the natural characteristics of the atmosphere*" [9]. Air pollutants have been broadly classified as primary and secondary pollutants [10] [11]. Primary air pollutants originate from their sources and are released directly into the atmosphere, while secondary air pollutants are created when primary pollutants react with other substances, like ozone. Examples of primary pollutants include nitrogen dioxide (NO_2), carbon monoxide (CO), Sulphur dioxide (SO_2), and total suspended particles (TSP). On the other hand, ozone (O_3) and particulate matter (PM) are examples of secondary pollutants [12].

Air pollution sources are of four main categories. They include; mobile, stationary, area, and natural sources [13] [14]. Mobile sources refer to vehicular emissions as well as from airplanes while stationary air pollution sources include emissions from power plants, industries, factories, and oil refineries among other fixed stations. Area sources include agricultural areas and cities while natural causes include wind-blown dust, wildfires, and volcanoes as examples [15].

In a publication by the United Nations Environment Programme (UNEP) titled Air Pollution Hurts the Poorest Most, (n.d [16]), it was highlighted that negligence by citizens in most developing countries in upholding regulations around air pollution has led to many recorded deaths associated with atmospheric pollution. In most developing countries, ambient air pollution is mostly attributed to industrialization and urbanization which poses a serious health threat to their ever-growing population [1] [17] [18].

Similarly, Nairobi's population is more affected by ambient air pollution than those in other parts of the country [19]. With 4.4 million residents as of 2019, Nairobi is the most populous city in the nation and one of the fastest-growing cities in the world [20]. It also experiences intense traffic situations with a high prevalence of old, unmaintained vehicles running on low-quality fuel with high Sulphur content, which contribute largely to the unclean atmospheric conditions [21]. The increasing population in Nairobi faces health threats caused by air pollutants and as such, it calls for management strategies to be put in place. Nevertheless, before the said strategies are set, it is important to acquire location-based information on air pollution occurrences. One such way is through mapping the air quality situation.

2. Situational Analysis of Air Quality in Nairobi County

Nairobi County experiences rapid industrialization and urbanization [22]. Nairobi County's air quality is deteriorating at a startling rate. Studies done specifically in the slums of Nairobi have uncovered unhealthy levels of pollution for sensitive groups such as children, who do not have fully developed lungs to contain the detrimental effects of PM particles [23] [24]. These areas experience high population density [25]. Similarly, Nairobi's traffic situation has been considered a prime mobile source of air pollution [26] [27]. The increase in motorized transport in the city has played a part in contributing to vehicular air pollution [28]. According to current registration rates, the number of vehicles in Nairobi alone is expected to exceed 1.35 million by 2030. With this number of vehicles moving in and out of Nairobi's Central Business District (CBD), traffic snarl-ups are apparent. Nairobi's air pollution problem is exacerbated by smoke from factories, industries, and other plants in addition to vehicle emissions [29] [30]. As it stands, the Nairobi air pollution problem has not been sufficiently addressed despite it being a major environmental disaster [31].

In Nairobi County, the majority of air quality stations currently utilize low-cost sensors (LCS), a cost-effective option chosen for their affordability [19]. However, the utilization of such sensors introduces certain challenges regarding data accuracy and reliability due to occasional defects that may occur as reported on the Nairobi IQAir website (https://www.iqair.com/kenya/nairobi). LCS used in air quality monitoring is affected by environmental factors, necessitating costly periodic calibration to ensure data accuracy [32]. Reference monitors, also referred to as high-accuracy monitors, are costly devices that can cost up to US $100,000 and are utilized for regulatory purposes in many countries [33] [34].

The adoption of various mechanisms especially by bodies such as Kenya's National Environmental Management Authority (NEMA) is essential in coming up with policies and regulations on air pollution and enforcing them. Kenya, as of 2021, lacks a standalone national policy on air pollution, but it addresses this issue through broader environmental policies. The Environmental Management and Coordination (EMCA) Regulations were implemented by the Environment Minister in 2014 to address the problem of air pollution and to establish acceptable air pollution limits for areas used for residential, industrial, and occupational purposes.

These standards have been Kenya's main concern in containing the issue of air pollution in the country. However, initiatives on the issuance of air quality monitors and the creation of publicly available air quality data have been slow [19]. According to a NEMA statement, as of 2010, only two designated laboratories were listed as being capable of monitoring air quality, which is insufficient for the needs of the nation. Additionally, only a small number of designated laboratories are capable of monitoring emissions on behalf of industries [35]. It is for these reasons that the Government of Kenya has been unable to enforce the regulations.

It is safe to conclude that the quality of the measurement and the number of monitoring stations in Nairobi are not sufficient to accurately depict the air pollution situation over the entire county. It is practically impossible to fit monitoring stations everywhere as it would be a laborious and expensive undertaking. Nairobi alone would be economically unviable if more air quality monitoring stations were to be set up. A generalized representation of air quality information can be a means to solve this problem, especially by the use of remotely sensed data that offer a synoptic view.

3. Spatial Indicators for Air Quality Mapping

Various spatial indicators have made it possible to visualize the air quality situation in an area. For instance, aerosol optical thickness which is an indicator of atmospheric pollutant concentration, has been used in air quality studies as a measurement of pollution [36]. The retrieval of aerosol optical depth, extraction of API values, visibility studies quantified in terms of atmospheric turbidity, and identification of suitable Pseudo Invariant Targets (PITs) in satellite images are common spatial indicators used for air quality mapping that rely on remotely sensed images [37].

An understanding of some of the main causes of air pollution is required to map air quality accurately. The Air Quality Action Plan 2019-2023 report, **Table 1** gives a summary of the components of air pollution.

4. Remote Sensing for Air Quality Mapping

The use of remotely sensed data to evaluate air quality has been the subject of numerous studies. The widespread recommendation of remote sensing is primarily attributed to its synoptic characteristic, providing a comprehensive view of a vast area, its high temporal resolution, allowing for frequent monitoring over time, and the continuous surface representation of imageries [39]. In studies where ground monitoring stations are few or nonexistent, remote sensing data has been used to fill in the existing gaps, especially for rural air quality mapping endeavors [40].

It became evident that air pollution could be mapped using remote sensing when the Measurement of Air Pollution from Satellite (MAPS) instrument, which was launched in 1981 on the space shuttle Columbia, provided the first measurements of high concentrations of CO over the continents of Asia, Africa, and South America [41]. The Total Ozone Mapping Spectrometer (TOMS) and Stratospheric Aerosol and Gas Experiment (SAGE) instruments on the Nimbus 7 satellite measured tropospheric ozone, demonstrating the global nature of air pollution [42]. These were among the earliest attempts to map air quality at a global scale using remotely sensed imageries.

Satellite sensors orbiting in outer space can map aerosols. Examples provided by both Lelieveld *et al.* [43] and Kaufman *et al.* [44], portrayed the worldwide

Table 1. Air pollutants and their impact on health and the environment.

Emission	Description	Sources	Harmful Effects
Carbon monoxide (CO)	Incomplete conversion of fuels containing carbon releases carbon dioxide (CO), a colorless, odorless toxic gas that can also be produced industrially and used to create both organic and inorganic chemical products.	<u>Human-caused sources</u> Burning of wood for cooking fuel and heat, burning of fossil fuels for transportation or power generation, and agricultural burning. <u>Organic resources</u> Methane and non-methane hydrocarbon oxidation, emissions from plants and the ocean, and forest fires.	<u>Impacts on health</u> Carbon monoxide poisoning symptoms include headache, weakness, nausea, dizziness, and fainting. Severe cases may also include coma and respiratory failure that results in death.
Nitrogen oxides (NO_X)	Nitric oxide (NO) and nitrogen dioxide (NO_2) are combined to form the term NOX. While NO is a colorless, tasteless gas, NO_2 is a potent oxidant that is yellowish-orange to reddish-brown in color and has an overpowering rotten egg smell.	<u>Human-caused sources</u> Fossil fuel combustion in power generating units and automobiles, mostly on roads. <u>Organic resources</u> Lighting, wildfires, and soil microbial activity.	<u>Impacts on health</u> • Reasons for Irritation of the eyes and lungs. • May increase the likelihood of developing or exacerbating respiratory conditions. <u>Effects on the environment</u> • Hastens the eutrophication process. • Increases the acidity of freshwater ecosystems and soils. • Causes haze to form in the air, which reduces visibility.
Ozone (O_3)	It is a colorless, unstable, toxic gas with strong oxidizing abilities that is produced when NOx and VOCs combine in the presence of sunlight.	VOC and NOx are secondary pollutants.	<u>Impacts on health</u> cause cardiovascular and respiratory issues. <u>Environmental effects</u> Particularly vulnerable vegetation and ecosystems that are affected include forests, parks, wildlife refuges, and wilderness areas.
Sulphur dioxide (SO_2)	SO_2 is a colorless, non-flammable gas with a strong, disagreeable smell.	<u>Human-caused sources</u> Fossil fuels are burned to generate electricity and power industries, ships, and rail cars. <u>Organic resources</u> Fires, phytoplankton, and volcanoes.	<u>Impact on health</u> Irritates the throat, nose, and eyes while having an impact on the respiratory system. <u>Effects on the environment</u> • Reduces the rate of plant growth. • Hastens the withering and early demise of plants. • Damages and stains stone and other materials, including statues. • May cause haze to form in the air, which may reduce visibility.
Particulate matter (PM_{10}, $PM_{2.5}$)	A mixture of solid and liquid droplets that are visible to the unaided eye in the atmosphere is referred to as particulate matter (PM). PM can take many forms, such as smoke, soot, dust, and dirt. Pollutants classified as primary or secondary can be PM. PM10 is the term for particles that are too small to breathe in. PM2.5 is the term for fine inhalable particles with a diameter of less than 2.5 µm.	<u>Human-caused sources</u> Emissions from fugitive dust during construction, power plants, automobile engines, domestic heating and cooking, and mining and quarrying. <u>Natural resources.</u> Natural material erosion, soil suspension by wind, and sea spray composition.	<u>Impacts on health</u> Cardiovascular and respiratory issues (primarily linked to $PM_{2.5}$). <u>Effects on the environment.</u> • Particles containing sulfur and nitrogen have the potential to cause soil and water to become acidic. • Excessive dust deposition on vegetation can hinder growth and have an adverse effect on plant health.

(Modified from source: Nairobi City County, 2019 pg. 11-12 [38]).

distribution of both naturally occurring and man-made aerosols, collected from a Moderate-Resolution Imaging Spectrometer (MODIS) on the TERRA satellite.

Air pollution as a phenomenon would be more understood by use of satellite imageries as was in the case of El-Askary [45], where AOD was retrieved from satellite data confirming dust and air pollution events in Cairo, Egypt. In the study conducted by El-Nadry *et al.* [46], in mapping the air quality of the North African region, they concluded that satellite data would suffice where ground recording stations were not set up. Also from their study, they exploited the use of TROPOMI among other data sources such as MODIS, which was documented to be the first study to ever exploit data by Sentinel-5P in the northern part of Africa.

More researchers are developing different approaches to depict and comprehend the state of air pollution in African nations, such as employing artificial neural networks and machine learning techniques [47] [48].

5. Mapping Air Quality for Nairobi County

5.1. Area of Study Description

Kenya's capital and largest city is Nairobi. It is situated at 1˚9'S, 1˚28'S, 36˚4'E, and 37˚10'E (**Figure 1**). The city is located roughly 200 kilometers south of the Equator, covering 696 square kilometers in total, and rises to an altitude of about 1700 meters above sea level. Nairobi County consists of 17 administrative sub-counties, which are as follows: Kamukunji, Kasarani, Kibra, Langata, Makadara, Mathare, Roysambu, Ruaka, Starehe, and Westlands. South and North Dagoretti, Embakasi Central, Embakasi East, Embakasi North, Embakasi South, and Embakasi West. As of 2019, the estimated population of Nairobi County was 4.3 million, which is growing at a 4% annual rate [49]. Rapid urbanization has been linked to Nairobi County's exponential population growth as more people are drawn to the area in quest of job opportunities [50]. Kenya's capital is one of the developing cities where the majority of people reside in areas with polluted air [51]. Air pollution in Nairobi is a major problem, with mobile sources being the main source of pollutants [52]. Apart from the transient sources, Nairobi's air pollution has also been caused by pollution from stationary sources [29]. Despite this, Nairobi does not have an inventory of air quality, and studies that are limited to certain pollutants are insufficient to determine the county's overall level of atmospheric quality [38].

5.2. Data Sources and Collection

The primary data used was Landsat imageries as outlined in **Table 2**. Details of the Landsat types and band characteristics are well documented in published journals [53].

Nairobi county boundary shapefile was obtained from the Independent Electoral and Boundaries Commission (IEBC) database in shapefile format (.shp).

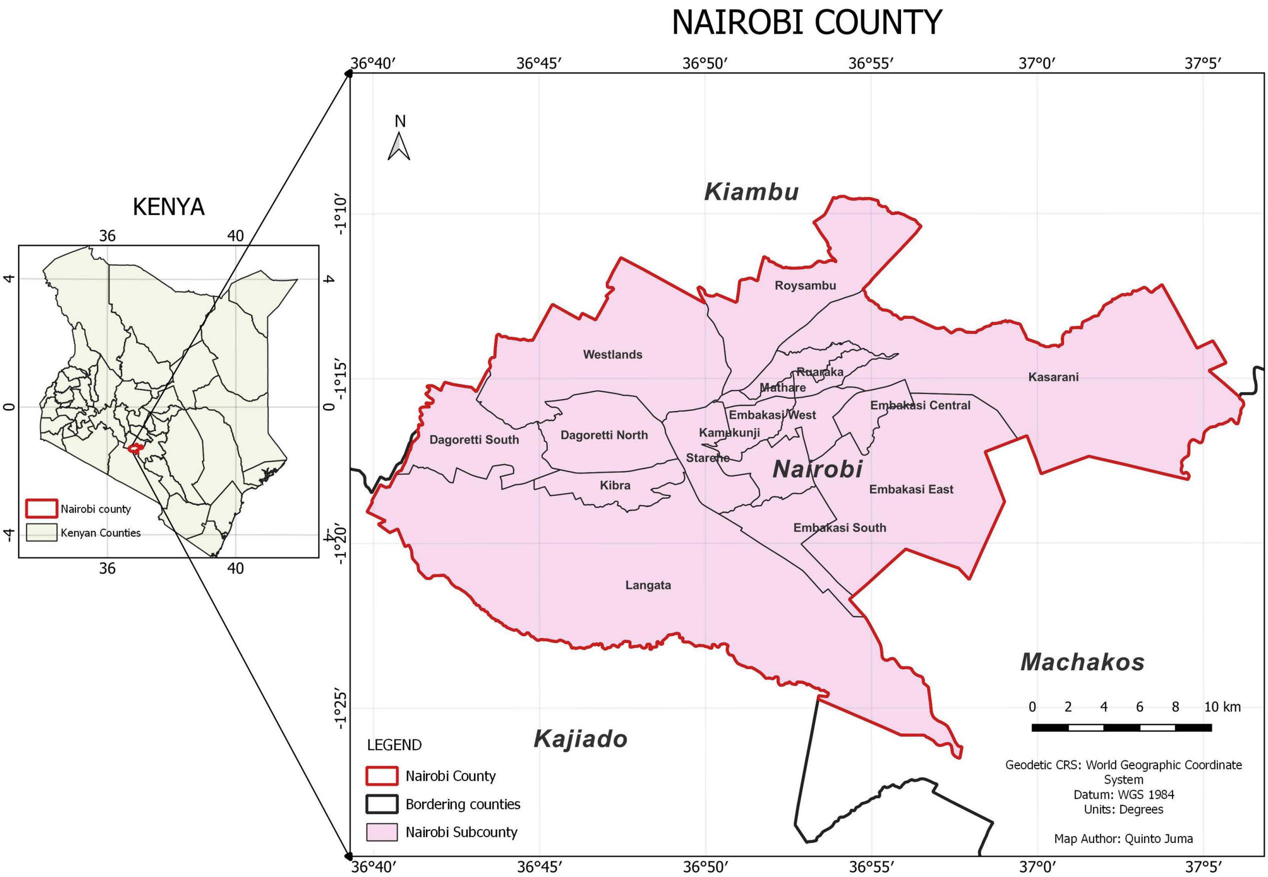

Figure 1. Study area map of Nairobi County.

Table 2. Landsat imagery characteristics used for mapping air quality in Nairobi County.

No.	Image ID	Time	Date	Spatial resolution (m)	Path/row	Cloud cover %
1	LANDSAT/LT05/C01/T1_TOA	07:33:29	19/08/2010 (Tuesday)	30	168/061	Less than 3
2	LANDSAT/LE07/C01/T1_SR	07:32:05	10/02/2002 (Sunday)	30	168/061	Less than 3
3	LANDSAT/LC08/C01/T1_SR	07:43:05	29/01/2018 (Monday)	30	168/061	Less than 3
4	LANDSAT/LC08/C01/T1_SR	07:44:53	15/11/2013 (Friday)	30	168/061	Less than 5
5	LANDSAT/LC08/C01/T1_SR	07:43:04	25/02/2016 (Thursday)	30	168/061	Less than 1
6	LANDSAT/LC08/C01/T1_SR	07:43:11	20/02/2020 (Saturday)	30	168/061	Less than 2

Source: Google Earth Engine catalog.

5.3. Procedure for Mapping Air Quality for Nairobi County

The study utilized Landsat imagery from three different epochs (2000, 2010, and 2018) acquired from the Google Earth Engine (GEE) cloud server (Figure 2). Simple JavaScript codes were employed to access and retrieve the images, which were subsequently filtered based on cloud metadata, date, and the geographical extent of the area of interest (Nairobi). These filtered images were then exported to a common Google Drive and later saved on the personal computer storage for

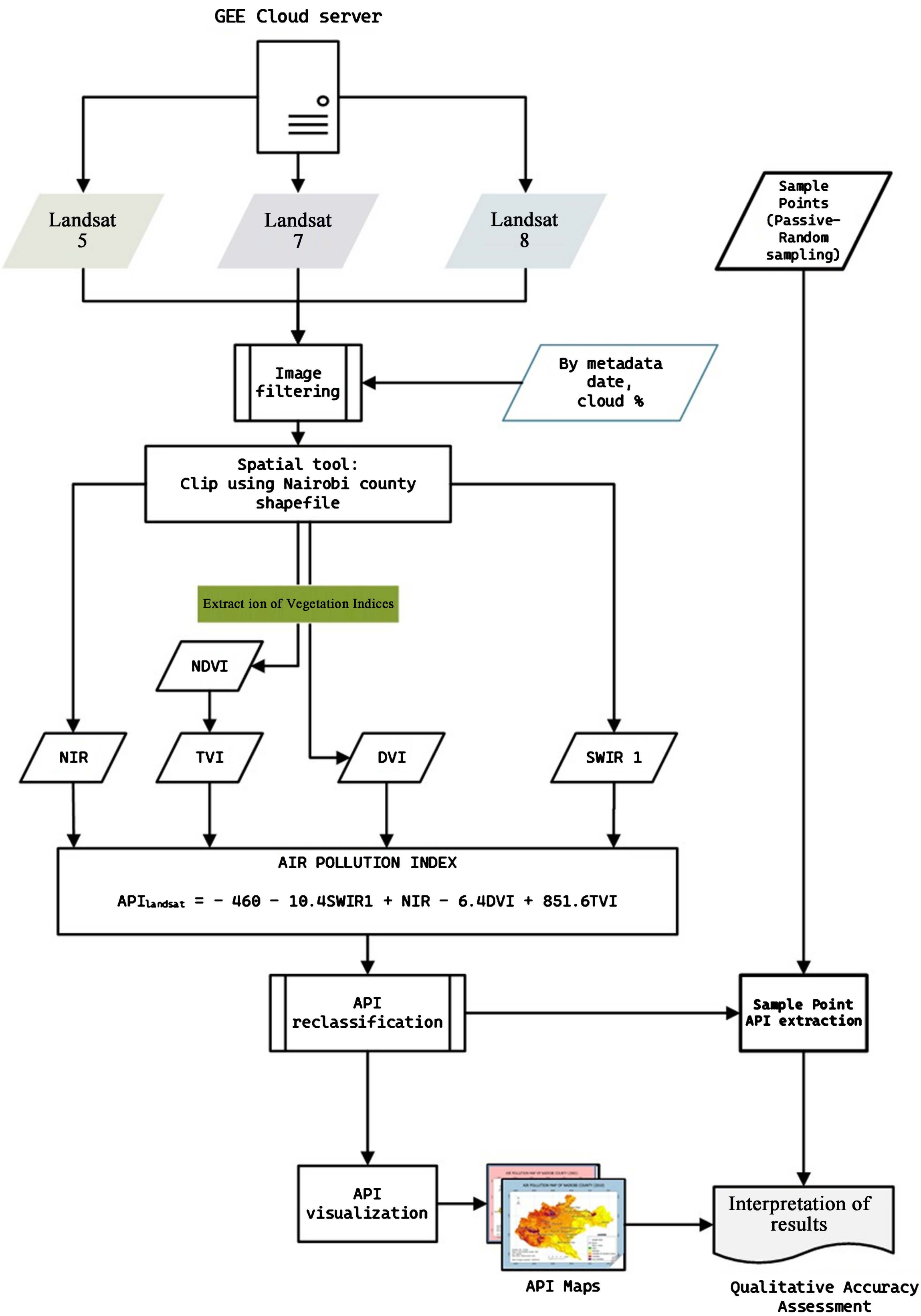

Figure 2. A systematic flowchart describing the processes taken in mapping air quality in Nairobi County from Landsat imagery acquisition, processing, extraction of vegetation indices, and computation of air pollution index (API) and visualization of air pollution maps.

further analysis.

In the subsequent steps, the acquired Landsat images were integrated into the QGIS interface [54]. Vegetation indices, namely the Normalized Difference Vegetation Index (NDVI), Transformed Vegetation Index (TVI), and Difference Vegetation Index (DVI), were computed using the QGIS raster calculator. Additionally, the Air Pollution Index (API) classification was computed using the raster calculator tool in QGIS.

For qualitative accuracy assessment, five (5) sample points were drawn from each class representing residential, industrial, green spaces, and traffic hotspots, based on a passive-random sampling in Google Earth Pro software. These sample points were overlaid with the classified API rasters, and API values were extracted from each raster using the raster extraction tool in QGIS. To adhere to the API classification chart used in the study, the calculated API rasters were then reclassified.

Finally, a qualitative accuracy assessment was conducted for each of the sample stations, and deductions were drawn from the obtained API values. This comprehensive process allowed for an in-depth analysis of air quality dynamics in Nairobi and enabled the drawing of valuable conclusions based on the classified imagery and sampled data.

5.3.1. Sampling Data

The data that formed part of the qualitative accuracy assessment approach was sampled across Nairobi County using a passive-quasi-random sampling technique.

5.3.2. Extraction of Vegetation Indices

This was done by the use of QGIS raster calculator. The following vegetation indices were extracted.

1) NVDI (Normalized Difference Vegetation Index) [55]:

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{RED}) / (\mathrm{NIR} + \mathrm{RED}) \tag{1}$$

2) TVI (Transformed Vegetation Index) [56]: served to transform the values from NDVI into a normal distribution:

$$\mathrm{TVI} = \mathrm{sqrt}(\mathrm{NDVI} + 0.5) \tag{2}$$

3) DVI (Difference Vegetation Index) [57]:

$$\mathrm{DVI} = \rho\mathrm{NIR} - \rho\mathrm{RED} \tag{3}$$

API was obtained from the radiometric reflectance values of NIR and SWIR1[1] and the vegetation indices (*i.e.*, DVI, TVI).

The API function is as follows [58]:

$$\mathrm{API}_{\mathrm{Landsat}} = -460 - 10.4\,\mathrm{SWIR1} + \mathrm{NIR} - 6.4\,\mathrm{DVI} + 851.6\,\mathrm{TVI} \tag{4}$$

5.3.3. API Classification and Visualization

After the API was computed for every Landsat imagery used, they were reclassi-

[1]SWIR1: Short Wave Infrared Red 1 band (Band 6 for Landsat 8 and Band 5 for Landsat 7).

fied as shown in Table 3.

The sample points were then overlaid on every classified imagery. This was done to give reference and aid in the interpretation of the spatial visualization. The overlaid sample points were then used to extract API values using the bi-linear interpolation method and the results were tabulated. The *raster-to-point* tool in QGIS was exploited and later the results were saved as CSV files.

6. Results

6.1. Air Pollution Information from Landsat 7 Imagery

Varying API values were recorded in Nairobi county in the year 2002 (Landsat 7 imagery) across different sample categories. In the residential category, Karen had the lowest API value (50.36472), while Parklands had the highest (121.6216) Karen exhibited the most favorable air quality category ("good"[2]), while Parklands had the least desirable air quality ("unhealthy for sensitive groups").

Kamulu and Ruai were observed to fall under "moderate" air quality with API values of 100.4715 and 92.50559 respectively. Among traffic hotspots, Roysambu stage showed moderate pollution (90.0007), while Koja Bus Station, Railways Bus Station, and Lusaka Road had higher API values. Bamburi Limited was visually observed to have relatively better air quality ("moderate"[3]) with the lowest API value in the industrial category (81.39734), while Industrial Area, EABL, and Acme Limited showed higher API values. Green spaces presented mixed results in comparison to the visual observations, with Ngong Race Course indicating more favorable air quality ("good") with the lowest API value (41.48645), while Bomas of Kenya and Marurui recorded higher API values.

Ref: Table A1 (annexed).

Figure 3 shows the air pollution categorized in API values as highlighted in Table 3. The result is from the extraction of API values from the Landsat 7 scene for Nairobi County in the year 2002.

6.1. Air Pollution Information from Landsat 5 Imagery

The investigation revealed that residential areas exhibited comparatively lower

Table 3. Air Pollution Index classification scheme.

NO.	Class	API	Symbology
1	Good	<50	
2	Moderate	51 - 100	
3	Unhealthy for sensitive groups	101 - 150	
4	Unhealthy	151 - 200	
5	Very unhealthy	201>	

Modified excerpt. Source: [59].

[2]"good" indicates that air quality is considered satisfactory, and air pollution poses little or no risk to the general population.

[3]"moderate" in the AQI signifies that air quality is acceptable; however, there may be some health concerns for a few sensitive individuals who are unusually sensitive to air pollution.

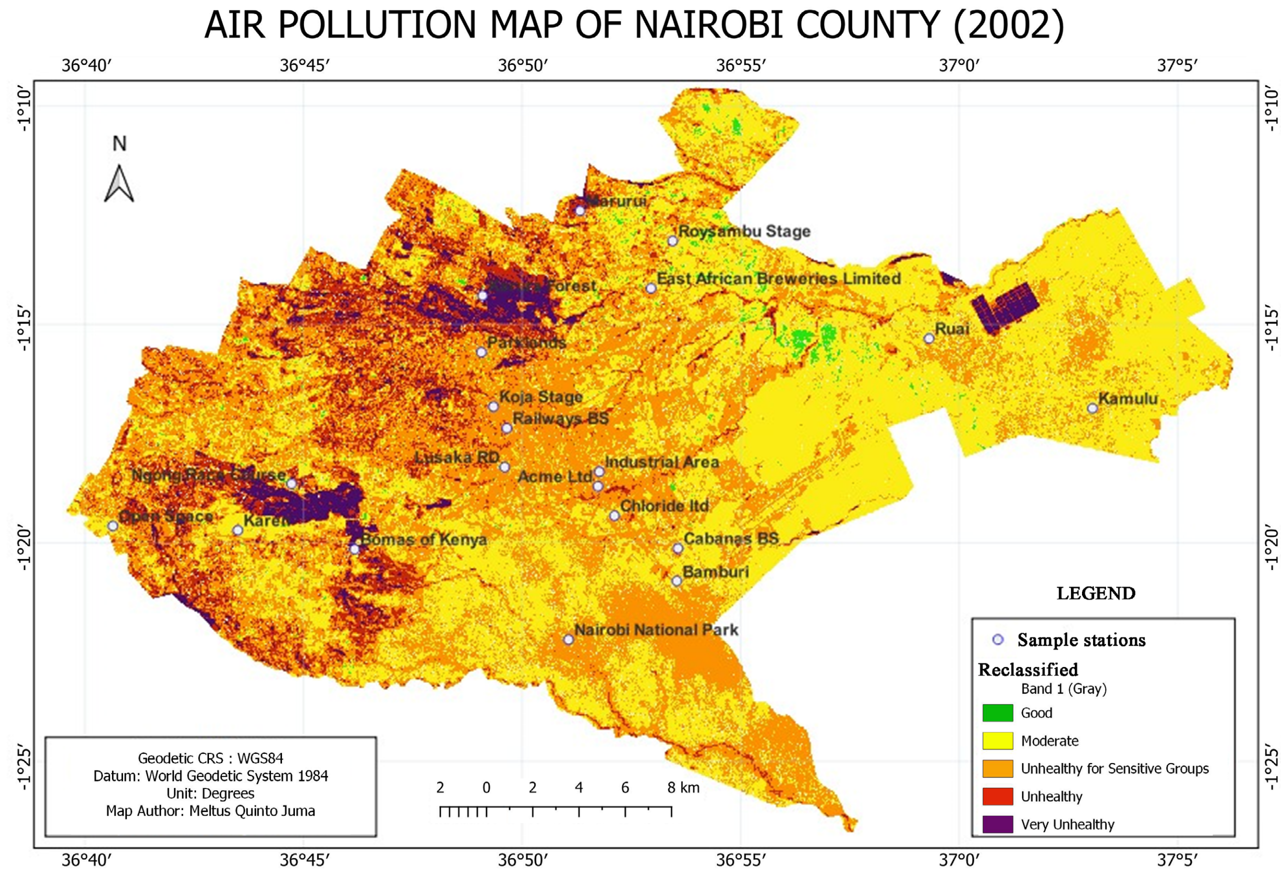

Figure 3. A map showing the air pollution (API) categorization in 2002 for Landsat 7 sample imagery.

levels of air pollution, whereas traffic hotspots and industrial zones displayed elevated pollution levels. Contrary to expectations, green spaces demonstrated higher pollution levels when compared to residential areas. The majority of API values across the sampled areas fell within the classification of "unhealthy for sensitive groups."[4]

The results depict varying air pollution levels across different areas in Nairobi. Residential areas displayed an average API value below 100, while Parklands exhibited the highest pollution at 139.764. Traffic hotspots and industrial zones consistently had higher pollution levels, with API values above 115 (traffic hotspot average: 125.1828) and EABL recorded the highest industrial API value at 132.4025. Intriguingly, green spaces also showed elevated pollution, with API values exceeding other areas (e.g., Nairobi National Park: 93.56007, Karura forest: 114.90893, Marurui: 168.5034) ref: Table A1 (annexed).

Figure 4 shows the distribution of air pollution over Nairobi County in 2010. Landsat 5 imagery was used as the primary data.

6.2. Air Pollution Information from Landsat 8 Imagery

Figure 5 shows results obtained using four different Landsat 8 imageries to

[4]"Unhealthy for sensitive groups" is an air pollution classification indicating heightened health risks for individuals with pre-existing respiratory or cardiovascular conditions, the elderly, young children, and those with compromised immune systems [59].

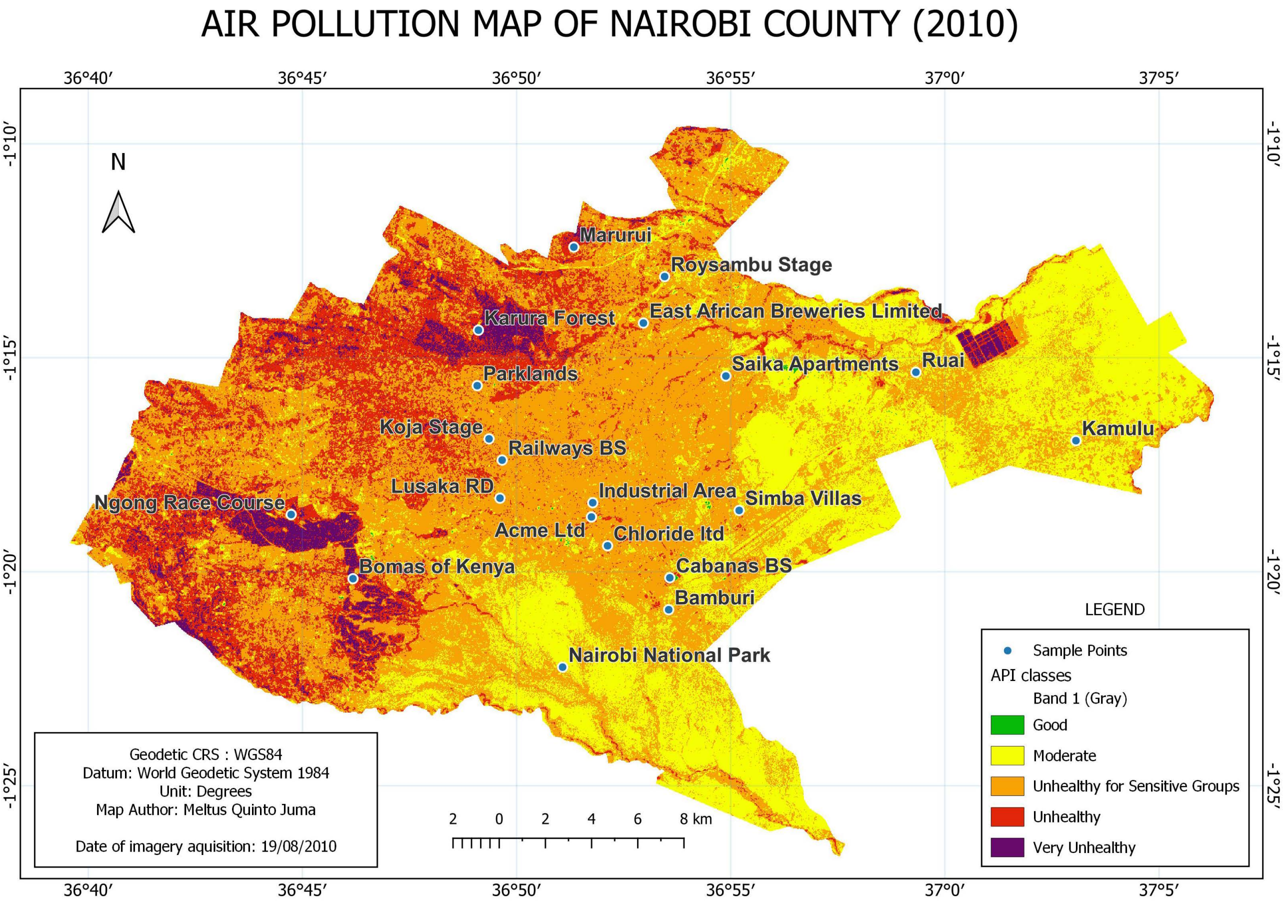

Figure 4. A map showing the air pollution index (API) categorization in 2010, Landsat 5 sample imagery.

represent the extracted API values. A different color scheme (sequential) was used for the classification rather than that described in Table 3.

Amongst the API values obtained from the image samples, none of them made logical sense as most of the sample points registered negative values. The API code provided proved indifferent to the use of Landsat 8 imagery.

Normalization of API values for Landsat 8 *imagery, year* 2018

A sample API data for Landsat 8 for the year 2018 as shown in Figure 5, was normalized using the expression illustrated herein and later reclassified according to Table 3.

Stretching the data to 8-bit

$smin = 0; smax = 255$

$(x - min(x)) * (smax - smin)/(max(x) - min(x)) + smin$

$NewRaster = (OldRaster - -1) * 255/(1 - -1) + 0$

source: (online)

API representation and values for normalized sample Landsat 8 imagery (2018).

Figure 6 shows the result obtained from normalizing the API values to fit the 8-bit value range.

The values obtained after the normalization of the data for the 20 sample

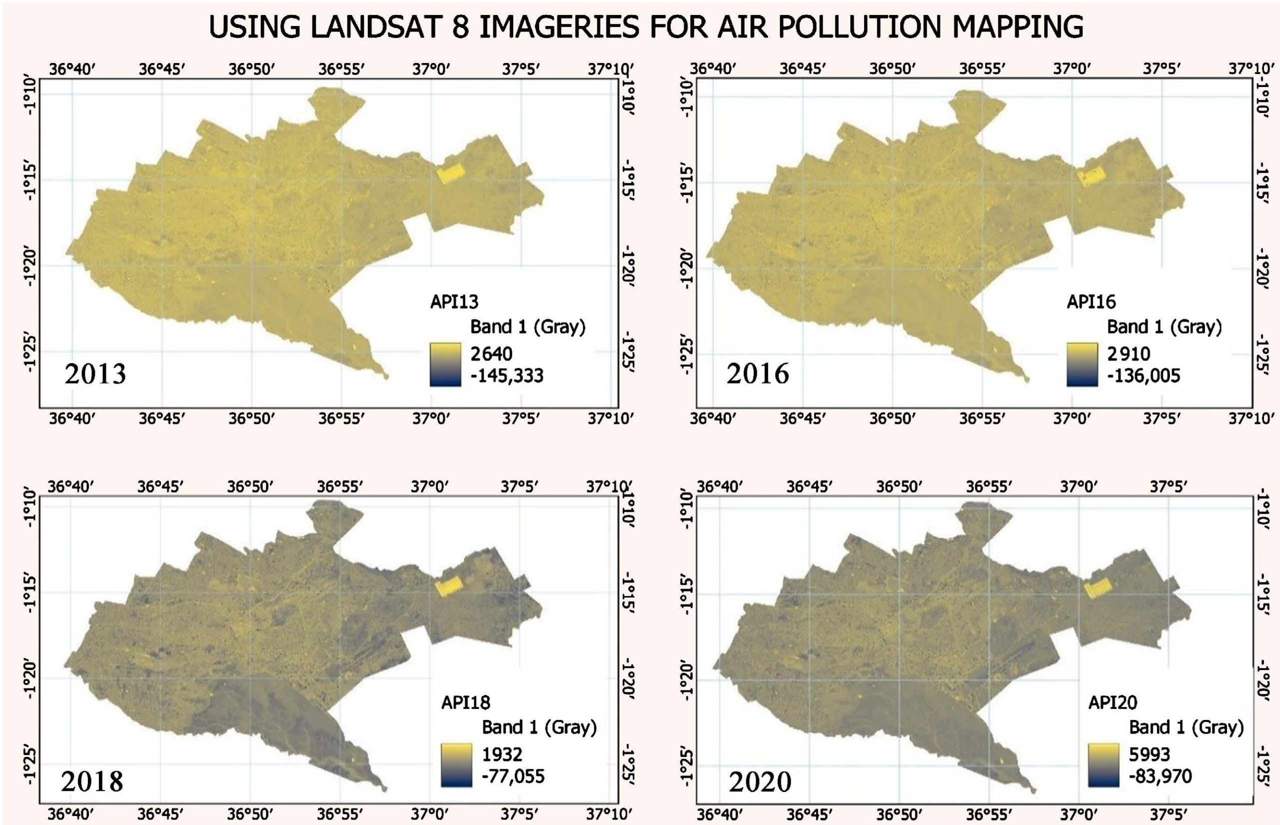

Figure 5. Using Landsat 8 imageries for air pollution index (API) representation.

stations ranged from 106.3265 to 185.7503 as shown in Table A1 (annexed) implying that the 20 samples fall under unhealthy for sensitive groups and unhealthy categories.

7. Discussions of the Results

7.1. Discussions of API Classified Imagery from Landsat 7 for the Year 2002

Residential areas like Karen exhibited lower API values, potentially due to the surrounding green space in the area. In contrast, Parklands' higher API value can be linked to its proximity to the CBD, with interconnecting residential roads having increased traffic congestion during peak hours. The moderate API values in Kamulu and Ruai, both residential regions, suggest a moderate level of pollution, potentially influenced by moderate traffic density and limited industrial activities.

The variations in API values among traffic hotspots can be attributed to several potential reasons. Roysambu stage's moderately polluted air could be due to a combination of moderate traffic congestion and limited industrial activities in the area. Koja Bus Station and Railways Bus Station showing similar API values in the "unhealthy for sensitive groups" category may result from their proximity to major roadways, leading to higher vehicular emissions and air pollution. Lusaka Road's highest API value in the same category could be attributed to heavy traffic flow and with its location being nearer to the industrial area, contributing

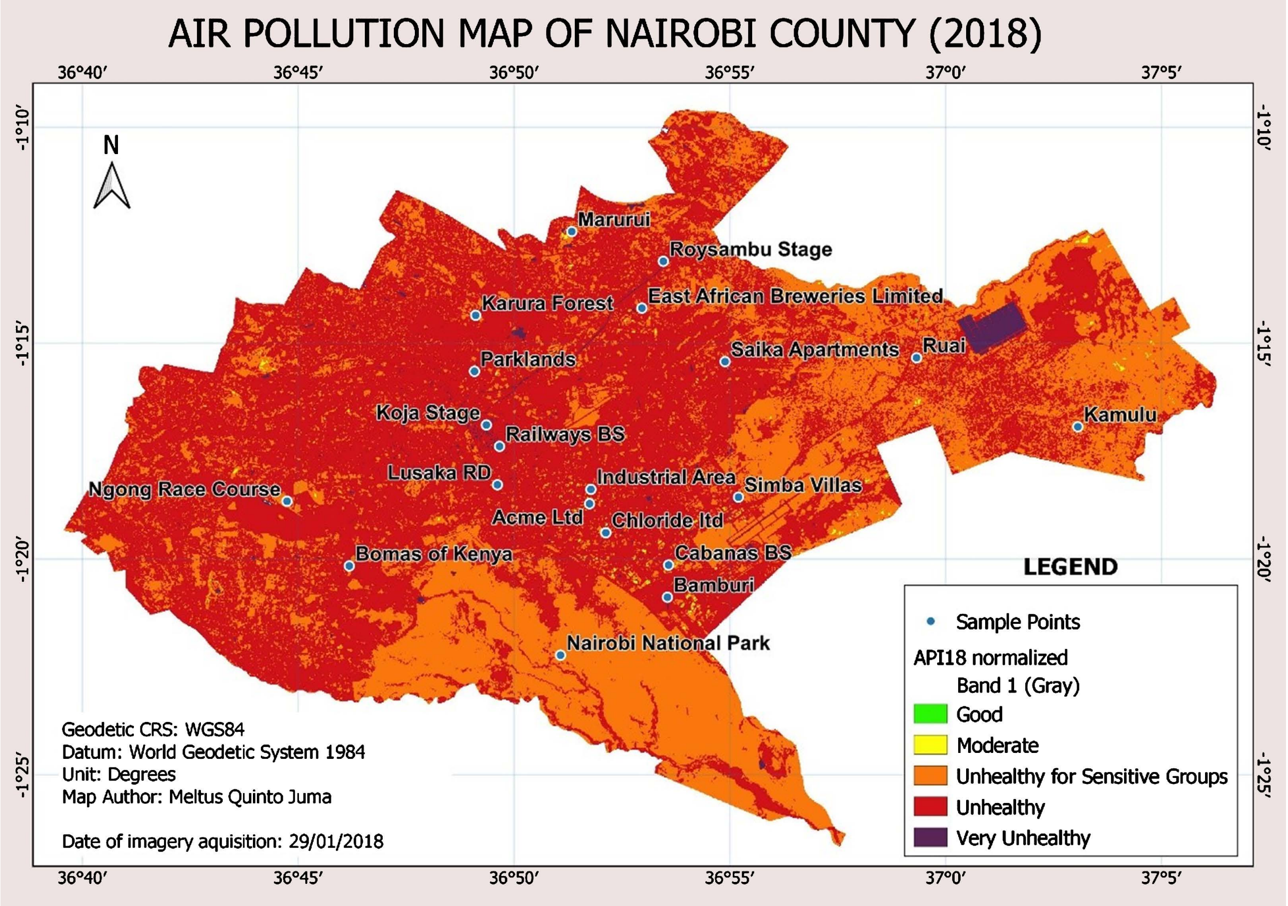

Figure 6. Air pollution index (API) categorization map for Landsat 8 in the year 2018-normalized API values.

to increased pollutant concentrations.

In the industrial sample type, Bamburi Limited recorded the lowest API value, showing moderate pollution, while the Industrial Area had the highest API value, placing it in the category of "unhealthy for sensitive groups." EABL and Acme Limited also fell under the latter category, indicating significant air pollution levels associated with industrial activities.

Unlike the air pollution representation in Landsat 5 API classified imagery (Figure 4), Landsat 7 API classified image 2002, is partially in line with the assumptions made for green spaces. The assumption being that greener spaces are likely to register lower API values as compared to other sample types. Ngong Race Course's lower API value may be due to its open space nature with limited vehicular traffic and hardly any industrial activities. The moderate API values for the Open Space sample from Karen and Karura Forest could be influenced by vegetation and far distance from pollution sources. Conversely, higher API values at Bomas of Kenya and Marurui indicate potential nearby pollution sources affecting their air quality.

7.2. Discussions of API Classified Imagery from Landsat 5 for the Year 2010

Landsat API classified imagery for the year 2010 provided valuable information on air pollution levels across the different areas in Nairobi. Notably, residential regions exhibited comparatively lower pollution levels in contrast to traffic hotspots and industrial zones. However, it was observed that Parklands, despite being primarily a residential area, displayed the highest API value, signifying "unhealthy for sensitive groups" air quality. This phenomenon could be attributed to its proximity to the CBD of Nairobi, which also demonstrated similar pollution standards. Additionally, the traffic congestion experienced at road intersections within the Parkland area could serve as a contributing factor to the observed high API value.

Regarding traffic hotspots, the extracted API values consistently exceeded 115, with Koja Stage and Railways Bus Station displaying comparable high values. On the other hand, Roysambu Stage had a slightly lower API value within this category. The location of the Lusaka Road junction near Nyayo Stadium near industrial areas and heavy traffic flow might account for its higher API value. All traffic hotspot values fell within the "unhealthy for sensitive groups" category, highlighting the potential health risks associated with these areas.

The API values corresponding to the sampled areas with industrial activities accurately reflected the state of air pollution in these regions. EABL recorded the highest API value, closely followed by Industrial Area, Acme Ltd, and Chloride Ltd. Conversely, Bamburi demonstrated the lowest API value within this category. Bamburi, being a sub-outlet for the cement plant in Athi River, primarily dealing with cement supplies rather than manufacturing, appeared to have a positive influence on its lower API value. However, despite its location in a relatively polluted area, all industrial area API values fell under the "unhealthy for sensitive groups" category.

Conversely, the API values for green spaces presented mixed results, differing from the initial assumption that such areas would have lower pollution levels. The general impression from the extracted values indicated an unhealthy pollution level for the sampled green spaces. Even though Nairobi National Park registered the lowest API value, surpassing that of Karura Forest and Marurui, it was still higher than Simba Villas. This discrepancy raises questions about the API formula, potentially due to the influence of high vegetation indices values, since the methodology adopts vegetation as a pseudo invariant target.

7.3. Discussions of API Classified Imagery from Landsat 8 for the Year 2018

The values obtained after the normalization of the data for the 20 sample stations implied that the 20 samples fall under unhealthy for sensitive groups and unhealthy categories. These remarks are, however, not likely due to the different characteristics in the sample types. The values slightly differ from each other. Green spaces and residential sample types were expected to bring huge disparities as compared to traffic hotspots and industrial sample sites, which was not the case.

7.4. Practical Implications and Limitations of the Study

The study presents valuable insights into Nairobi County's air quality using Landsat imagery to extract API values, enabling effective monitoring and targeted improvement strategies. The findings emphasize the significance of considering air quality in urban planning, particularly in high-pollution areas, and its implications on public health. The spatial data facilitates health impact assessments, identifying vulnerable populations in need of targeted interventions. Policymakers can utilize the API data to develop regulations and implement pollution-reducing measures.

However, the study faces limitations due to the temporal and spatial resolution constraints of Landsat imagery, potentially overlooking short-term fluctuations and fine-scale variations. The API formula's suitability, especially when applied to Landsat 8 imagery, warrants further investigation. The absence of ground truthing through on-site air quality measurements may affect result reliability. Moreover, the study does not consider potential land-use changes, which could influence air pollution patterns over time. Nonetheless, it lays the foundation for future research and policy interventions to address air pollution in the region, emphasizing the importance of integrating remote sensing and ground-based data for comprehensive air quality assessments.

8. Conclusion

The application of remote sensing technology to map air quality in Nairobi County has provided valuable insights, particularly in regions where ground-based monitoring stations are scarce, a common challenge in many developing countries. The cost-effectiveness and comprehensive spatial coverage of this technology make it an invaluable tool for understanding pollution patterns. Our analysis revealed distinct pollution patterns, with residential areas exhibiting lower pollution levels compared to traffic hotspots and industrial zones. The consistent recording of high Air Pollution Index (API) values in traffic hotspots, exceeding 115 and categorized as "unhealthy for sensitive groups," underscores the need for targeted interventions in these areas. Green spaces' API values varied, contrary to initial assumptions, indicating challenges in the interpretation of pollution levels in these areas. To enhance the applicability of air quality assessments, we propose the recalibration of the API formula at smaller scales, such as the sub-county or ward level. This would enable a more focused approach, allowing us to discern the impact of air pollution on various land cover types more accurately. Furthermore, we recommend further research involving various sensors, including those on board Sentinel 2, to expand the scope and accuracy of air quality monitoring. This study advocates for the continued use of API as a standardized measure of air quality, providing a common metric for comparison and analysis.

Acknowledgments

The authors are grateful to Mr. Onyango Bernard, GIS Developer at the Food and Agriculture Organization, and Mr. Chiro Jelani from the National Environmental and Management Authority for their assistance.

Author Contribution

Quinto Juma Meltus: Conceptualization, methodology, software, data curation, writing, original draft preparation, visualization, investigation. Faith Njoki Karanja: Conceptualization and design of the study, supervision of the research, reviewing, writing and editing the manuscript, granting final approval of the version to be submitted.

Data Availability

We freely obtained the data from the Google Earth Engine catalog. Reach out to the corresponding author @ meltusquinto@gmail.com for data used in the study.

Funding Statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. Exclusively the authors funded the research.

Conflicts of Interest

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

References

[1] Balakrishnan, K., *et al.* (2019) The Impact of Air Pollution on Deaths, Disease Burden, and Life Expectancy across the States of India: The Global Burden of Disease Study 2017. *The Lancet Planetary Health*, **3**, E26-E39.

[2] Tibuakuu, M., Michos, E.D., Navas-Acien, A. and Jones, M.R. (2018) Air Pollution and Cardiovascular Disease: A Focus on Vulnerable Populations Worldwide. *Current Epidemiology Reports*, **5**, 370-378. https://doi.org/10.1007/s40471-018-0166-8

[3] Kinney, P.L. (2018) Interactions of Climate Change, Air Pollution, and Human Health. *Current Environmental Health Reports*, **5**, 179-186. https://doi.org/10.1007/s40572-018-0188-x

[4] WHO (2023) Air Pollution. https://www.who.int/health-topics/air-pollution#tab=tab_1

[5] Ghorani-Azam, A., Riahi-Zanjani, B. and Balali-Mood, M. (2016) Effects of Air Pollution on Human Health and Practical Measures for Prevention in Iran. *Journal of Research in Medical Sciences*, **21**, 65. https://doi.org/10.4103/1735-1995.189646

[6] (Tony) Cox, L.A. (2017) Socioeconomic and Air Pollution Correlates of Adult Asthma, Heart Attack, and Stroke Risks in the United States, 2010-2013. *Environmental Research*, **155**, 92-107. https://doi.org/10.1016/j.envres.2017.01.003

[7] Phung, D., *et al.* (2016) Air Pollution and Risk of Respiratory and Cardiovascular Hospitalizations in the Most Populous City in Vietnam. *Science of the Total Environment*, **557-558**, 322-330. https://doi.org/10.1016/j.scitotenv.2016.03.070

[8] Mokoena, K.K., Ethan, C.J., Yu, Y., Shale, K. and Liu, F. (2019) Ambient Air Pollu-

tion and Respiratory Mortality in Xi'an, China: A Time-Series Analysis. *Respiratory Research*, **20**, Article No. 139. https://doi.org/10.1186/s12931-019-1117-8

[9] WHO (2021) WHO Global Air Quality Guidelines: Particulate Matter (PM2.5 and PM10), Ozone, Nitrogen Dioxide, Sulfur Dioxide and Carbon Monoxide: Executive Summary. https://www.who.int/publications/i/item/9789240034433

[10] Kim, Y.P. and Lee, G. (2018) Trend of Air Quality in Seoul: Policy and Science. *Aerosol and Air Quality Research*, **18**, 2141-2156. https://doi.org/10.4209/aaqr.2018.03.0081

[11] Orru, H., Ebi, K.L. and Forsberg, B. (2017) The Interplay of Climate Change and Air Pollution on Health. *Current Environmental Health Reports*, **4**, 504-513. https://doi.org/10.1007/s40572-017-0168-6

[12] Huang, X., *et al.* (2021) Enhanced Secondary Pollution Offset Reduction of Primary Emissions during COVID-19 Lockdown in China. *National Science Review*, **8**, nwaa137. https://doi.org/10.1093/nsr/nwaa137

[13] Rafee, S.A.A., *et al.* (2017) Contributions of Mobile, Stationary and Biogenic Sources to Air Pollution in the Amazon Rainforest: A Numerical Study with the WRF-Chem Model. *Atmospheric Chemistry and Physics*, **17**, 7977-7995. https://doi.org/10.5194/acp-17-7977-2017

[14] Sevimoğlu, O. (1997) Assessment of Major Air Pollution Sources in Efforts of Long Term Air Quality Improvement in İstanbul. *Sakarya University Journal of Science*, **24**, 389-405. https://doi.org/10.16984/saufenbilder.586655

[15] NPS.Gov. Where Does Air Pollution Come from? Air (U.S. National Park Service). https://www.nps.gov/subjects/air/sources.htm

[16] Air Pollution Hurts the Poorest Most. https://www.unep.org/news-and-stories/story/air-pollution-hurts-poorest-most

[17] Burroughs Peña, M.S. and Rollins, A. (2017) Environmental Exposures and Cardiovascular Disease: A Challenge for Health and Development in Low- and Middle-Income Countries. *Cardiology Clinics*, **35**, 71-86. https://doi.org/10.1016/j.ccl.2016.09.001

[18] Mannucci, P.M. and Franchini, M. (2017) Health Effects of Ambient Air Pollution in Developing Countries. *International Journal of Environmental Research and Public Health*, **14**, 1048. https://doi.org/10.3390/ijerph14091048

[19] De Souza, P. (2020) Air Pollution in Kenya: A Review. *Air Quality, Atmosphere & Health*, **13**, 1487-1495. https://doi.org/10.1007/s11869-020-00902-x

[20] Kenya National Bureau of Statistics—Humanitarian Data Exchange. https://data.humdata.org/organization/kenya-national-bureau-of-statistics

[21] Kinney, P.L., *et al.* (2011) Traffic Impacts on $PM_{2.5}$ Air Quality in Nairobi, Kenya. *Environmental Science & Policy*, **14**, 369-378. https://doi.org/10.1016/j.envsci.2011.02.005

[22] Enoh, N. and Kipruto, J. (2015) Urban Air Quality in the City of Nairobi, Kenya: Application of Energy Dispersive X-Ray Fluorescence and Principal Component Analysis. http://erepository.uonbi.ac.ke/handle/11295/90202

[23] Egondi, T., Ettarh, R., Kyobutungi, C., Ng, N. and Rocklöv, J. (2018) Exposure to Outdoor Particles ($PM_{2.5}$) and Associated Child Morbidity and Mortality in Socially Deprived Neighborhoods of Nairobi, Kenya. *Atmosphere*, **9**, Article No. 351. https://doi.org/10.3390/atmos9090351

[24] Egondi, T., Muindi, K., Kyobutungi, C., Gatari, M. and Rocklöv, J. (2016) Measuring Exposure Levels of Inhalable Airborne Particles ($PM_{2.5}$) in Two Socially De-

prived Areas of Nairobi, Kenya. *Environmental Research*, **148**, 500-506. https://doi.org/10.1016/j.envres.2016.03.018

[25] Machiyama, K., Mumah, J.N., Mutua, M. and Cleland, J. (2019) Childbearing Desires and Behaviour: A Prospective Assessment in Nairobi Slums. *BMC Pregnancy Childbirth*, **19**, Article No. 100. https://doi.org/10.1186/s12884-019-2245-3

[26] Rastogi, M. (2021) A Review Paper on Traffic Pollution. *Asian Journal of Research in Business Economics and Management*, **11**, 118-123. https://doi.org/10.5958/2249-7307.2021.00050.5

[27] Ngo, N.S., Gatari, M., Yan, B., Chillrud, S.N., Bouhamam, K. and Kinney, P.L. (2015) Occupational Exposure to Roadway Emissions and inside Informal Settlements in Sub-Saharan Africa: A Pilot Study in Nairobi, Kenya. *Atmospheric Environment*, **111**, 179-184. https://doi.org/10.1016/j.atmosenv.2015.04.008

[28] Mukaria, S.M. (2017) Traffic Police Knowledge, Attitude and Practices Concerning Motor Vehicle Air Pollution at Key Nairobi Road Junctions. http://erepository.uonbi.ac.ke/handle/11295/102027

[29] Mulaku, G.C. and Kariuki, L.W. (2001) Mapping and Analysis of Air Pollution in Nairobi, Kenya. http://erepository.uonbi.ac.ke/handle/11295/55771

[30] Gatari, M.J., Boman, J. and Wagner, A. (2009) Characterization of Aerosol Particles at an Industrial Background Site in Nairobi, Kenya. *X-Ray Spectrometry*, **38**, 37-44. https://doi.org/10.1002/xrs.1097

[31] Faith Ndunge Mutua, C.K.D.M.N. (2021) Determination of PM_{10} and $PM_{2.5}$ Concentration in Ambient Air Samples in Nairobi City, Kenya (2016).

[32] Okafor, N.U., Alghorani, Y. and Delaney, D.T. (2020) Improving Data Quality of Low-Cost IoT Sensors in Environmental Monitoring Networks Using Data Fusion and Machine Learning Approach. *ICT Express*, **6**, 220-228. https://doi.org/10.1016/j.icte.2020.06.004

[33] Becker, R. and Henderson, V. (2015) Effects of Air Quality Regulations on Polluting Industries. *Journal of Political Economy*, **108**, 379-421. https://doi.org/10.1086/262123

[34] Concas, F., *et al.* (2021) Low-Cost Outdoor Air Quality Monitoring and Sensor Calibration. *ACM Transactions on Sensor Networks*, **17**, Article No. 2. https://doi.org/10.1145/3446005

[35] Doc, P. (2010) Gazzetted Laboratories. *Molecular Imaging*, No. 2, 1-4.

[36] Sifakis, N.I. and Soulakellis, N.A. (2000) Satellite Image Processing for Haze and Aerosol Mapping (SIPHA): Code Description and Presentation of Results. *The International Geoscience and Remote Sensing Symposium*, **1**, 222-224.

[37] Hadjimitsis, D.G., Retalis, A. and Clayton, C.R.I. (2002) The Assessment of Atmospheric Pollution Using Satellite Remote Sensing Technology in Large Cities in the Vicinity of Airports. *Water*, *Air and Soil Pollution*: *Focus*, **2**, 631-640.

[38] Nairobi City County (2019) Nairobi City County Air Quality Action Plan (2019-2023). https://www.eci-africa.org/wp-content/uploads/2019/05/Nairobi-Air-Quality-Action-Plan_Final_ECI_31.12.2018.pdf

[39] Nguyen, H.-H., Thi Thuy An, T., Tien Lam, L., Hai Hoa, N., Thai Son, L. and Van Hung, N. (2018) Using Landsat Imageries for Particle Pollution Mapping in Hanoi City. *Journal of Forestry Science and Technology*, No. 5, 53-61. https://earthexplorer.usgs.gov

[40] A Systems Approach to Air Pollution (ASAP)—African Centre for Technology Studies (ACTS).

https://www.acts-net.org/research/projects/a-systems-approach-to-air-pollution-asap

[41] Marsh, J.G., *et al.* (1988) A New Gravitational Model for the Earth from Satellite Tracking Data: GEM-T1. *Journal of Geophysical Research*: *Solid Earth*, **93**, 6169-6215. https://doi.org/10.1029/JB093iB06p06169

[42] Fishman, J., Minnis, P. and Reichle, H.G. (1986) Use of Satellite Data to Study Tropospheric Ozone in the Tropics. *Journal of Geophysical Research*: *Atmospheres*, **91**, 14451-14465. https://doi.org/10.1029/JD091iD13p14451

[43] Lelieveld, J., *et al.* (2002) Global Air Pollution Crossroads over the Mediterranean. *Science* (80-.), **298**, 794-799.

[44] Kaufman, Y.J., Tanré, D. and Boucher, O. (2002) A Satellite View of Aerosols in the Climate System. *Nature*, **419**, 215-223. https://doi.org/10.1038/nature01091

[45] El-Askary, H. (2006) Air Pollution Impact on Aerosol Variability over Mega Cities Using Remote Sensing Technology: Case Study, Cairo, Egypt. *Egyptian Journal of Remote Sensing and Space Science*, **9**, 31-40.

[46] El-Nadry, M., Li, W., El-Askary, H., Awad, M.A. and Mostafa, A.R. (2019) Urban Health Related Air Quality Indicators over the Middle East and North Africa Countries Using Multiple Satellites and AERONET Data. *Remote Sensing*, **11**, Article No. 2096. https://doi.org/10.3390/rs11182096

[47] Semlali, B.-E.B., El Amrani, C. and Denys, S. (2019) Development of a Java-Based Application for Environmental Remote Sensing Data Processing. *International Journal of Electrical and Computer Engineering*, **9**, 1978-1986. https://doi.org/10.11591/ijece.v9i3.pp1978-1986

[48] Kalajdjieski, J., *et al.* (2020) Air Pollution Prediction with Multi-Modal Data and Deep Neural Networks. *Remote Sensing*, **12**, Article No. 4142. https://doi.org/10.3390/rs12244142

[49] Kenya National Bureau of Statistics (2019) Kenya Population and Housing Census Volume 1: Population by County and Sub-County. https://www.knbs.or.ke/?wpdmpro=2019-kenya-population-and-housing-census-volume-i-population-by-county-and-sub-county

[50] Mundia, C. and Murayama, Y. (2013) Modeling Spatial Processes of Urban Growth in African Cities: A Case Study of Nairobi City. *Urban Geography*, **31**, 259-272. https://doi.org/10.2747/0272-3638.31.2.259

[51] Zhang, X., Chen, X. and Zhang, X. (2018) The Impact of Exposure to Air Pollution on Cognitive Performance. *Proceedings of the National Academy of Sciences of the United States of America*, **115**, 9193-9197. https://doi.org/10.1073/pnas.1809474115

[52] Odhiambo, G.O., Nairobi, K., Kinyua, A.M., Gatebe, C.K. and Awange, J. (2010) Motor Vehicles Air Pollution in Nairobi, Kenya. *Research Journal of Environmental and Earth Sciences*, **2**, 178-187. http://maxwellsci.com/print/rjees/v2-178-187.pdf

[53] Barsi, J.A., Lee, K., Kvaran, G., Markham, B.L. and Pedelty, J.A. (2014) The Spectral Response of the Landsat-8 Operational Land Imager. *Remote Sensing*, **6**, 10232-10251. https://doi.org/10.3390/rs61010232

[54] QGIS Version 3.28. https://www.qgis.org/en/site/

[55] Carlson, T.N., Perry, E.M. and Schmugge, T.J. (1990) Remote Estimation of Soil Moisture Availability and Fractional Vegetation Cover for Agricultural Fields. *Agricultural and Forest Meteorology*, **52**, 45-69. https://doi.org/10.1016/0168-1923(90)90100-K

[56] Zevenbergen, A.W., Rango, A., Ritchie, J.C., Engman, E.T. and Hawkins, R.H. (1988) Rangeland Runoff Curve Numbers As Determined from Landsat MSS Data. *International Journal of Remote Sensing*, **9**, 495-502.

[57] Tucker, C.J. (1979) Red and Photographic Infrared Linear Combinations for Monitoring Vegetation. *Remote Sensing of Environment*, **8**, 127-150. https://doi.org/10.1016/0034-4257(79)90013-0

[58] Mozumder, C., Reddy, K.V. and Pratap, D. (2013) Air Pollution Modeling from Remotely Sensed Data Using Regression Techniques. *Journal of the Indian Society of Remote Sensing*, **41**, 269-277. https://doi.org/10.1007/s12524-012-0235-2

[59] Costa, L.G., Cole, T.B., Dao, K., Chang, Y.C., Coburn, J. and Garrick, J.M. (2020) Effects of Air Pollution on the Nervous System and Its Possible Role in Neurodevelopmental and Neurodegenerative Disorders. *Pharmacology & Therapeutics*, **210**, Article ID: 107523. https://doi.org/10.1016/j.pharmthera.2020.107523

Annex

Table A1. Extracted Air Pollution Index (API) values for the various epochs over twenty sampled locations Nairobi County.

No.	Name	Description	2002	2010	Normalized API for 2018
1	Ngong Race Course	Green space	41.48645	181.7296	115.1822
2	Karura Forest	Green space	61.58703	114.90893	106.3265
3	Nairobi National Park	Green Space	107.884	93.56007	137.4614
4	Bomas of Kenya	Green Space	180.918	181.9981	170.8752
5	Marurui	Green space	136.1313	168.5034	150.5227
6	Koja Stage	Traffic hotspot	119.6478	124.9784	183.7041
7	Railways BS	Traffic hotspot	117.8752	128.4885	181.2698
8	Cabanas BS	Traffic hotspot	98.81324	119.593	179.5578
9	Lusaka RD	Traffic hotspot	136.0798	137.3874	184.5813
10	Roysambu Stage	Traffic hotspot	90.0007	115.4667	185.7503
11	Different sample location was taken for each raster (indicated in brackets)	Residential	50.36472 (Karen)	78.95782 (Simba Villas)	157.6298 (Simba Villas)
12	Parklands	Residential	121.6216	139.764	174.049
13	Kamulu	Residential	100.4715	101.0833	160.8781
14	Ruai	Residential	92.50559	96.46345	149.4228
15	Different sample location was taken for each raster (indicated in brackets)	Residential	84.02992 (Open space)	104.3313 (Saika Apartments)	159.6409 (Saika Apartments)
16	Chloride Ltd	Industrial	112.1357	126.2735	181.0678
17	Bamburi	Industrial	81.39734	106.2911	159.7568
18	Acme Ltd	Industrial	112.4192	126.6936	171.0387
19	Industrial Area	Industrial	120.5531	128.7915	176.4931
20	East African Breweries Limited (EABL)	Industrial	102.774	132.4025	175.1887