Satellite Image-Based Spatial Analysis of Urban Air Quality Index

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Abstract

Accurate air quality assessments are essential for understanding exposure to pollution and supporting environmental policy decisions. This study presents a comprehensive methodology for estimating air quality index (AQI) using satellite data and Google Earth Engine (GEE). The research process begins with identifying shortcomings in current approaches to air quality monitoring and reviewing relevant literature on satellite-based pollutant estimation and AQI calculation. To simplify the analysis, a dedicated application has been developed in GEE to enable dynamic selection of study areas and integration of satellite column density data. To estimate surface concentrations at ground level, the pollutant columns extracted from the satellite are processed through molecular weight conversion and atmospheric scaling. The concentration is then standardised from mol/m² to µg/m³ to facilitate the calculation of the AQI. For key air pollutants, individual air quality indicators are generated to provide insight into spatial patterns of air quality in the study area. This methodology demonstrates a scalable and reproducible approach to satellite-based air quality monitoring and provides the basis for future improvements, including higher-resolution datasets, predictive modelling, and integration with terrestrial measurements.

1. Introduction

Air quality measurements are crucial for protecting human health and the environment, as ambient air pollution is a leading global risk factor, contributing to millions of premature deaths annually (WHO, 2021). Pollutants such as particulate matter (PM_5), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), carbon monoxide (CO), and ozone (O_3) are linked to serious health issues, including respiratory diseases and mortality (WHO, 2011; US EPA, 2011). Continuous monitoring enables timely health warnings and protects vulnerable groups.

Additionally, air quality measurements help safeguard ecosystems and natural resources, as pollutants can damage crops, reduce productivity, and harm aquatic ecosystems (US EPA, 2023; EEA, 2022). Ground-level ozone, for example, impairs plant growth, while acid deposition negatively impacts biodiversity.

Accurate air quality data also support evidence-based policymaking, enabling governments to set standards, regulate emissions, and manage urban planning (WHO, 2021; EEA, 2022). Overall, systematic air quality monitoring is essential for safeguarding public health and ensuring environmental sustainability.

1.1 Air Quality

Air quality is crucial to the maintenance of ecosystems, as all living things depend on a balanced mix of gases in the atmosphere, such as oxygen and carbon dioxide. Poor air quality damages ecosystems, damages plant productivity and contributes to climate change through increased greenhouse gases. In recent decades, air pollution in the Indian subcontinent has increased as a result of rapid industrialisation, urbanisation and vehicle emissions and coal-fired power generation (Guttikunda and Jawahar, 2014). The region has some of the highest pollutant levels in the world, with 21 of the top 30 most polluted cities (IAQA, 2020) causing significant health risks, including respiratory and cardiovascular diseases (WHO, 2021). Addressing these challenges requires scientific research and effective pollution-control policies, such as emission standards and sustainable transport. The air quality index (AQI) communicates the level of pollution and associated health risks, but in developing regions, on-the-ground monitoring is often limited. Remote sensing by satellites can improve the assessment of air pollutants and support air quality management (Van Donkelaar et al., 2019). Improving air quality in the Indian sub-continent is US critical environmental and public health challenge that requires a comprehensive approach to monitoring and control.

1.2 Types of Air Pollutants

Air pollutants are classified as primary and secondary. Primary pollutants such as sulphur dioxide (SO_2), nitrogen oxides (NO_2), carbon monoxide (CO), particulate matter (PM), and volatile organic compounds (VOCs) are emitted directly by activities such as burning fossil fuels, industrial processes, and fires (US EPA, 2023; WHO, 2021). Natural sources also contribute to the formation of primary pollutants such as inorganic gases, PM_{10} and $PM_{2.5}$, hydrocarbons, benzene, and radon, which is radioactive. In contrast, secondary pollutants such as ground-level ozone (O_3) are formed by chemical reactions between primary pollutants, often mediated by sunlight (see Seinfeld and Pandis, 2016; US EPA, 2023).

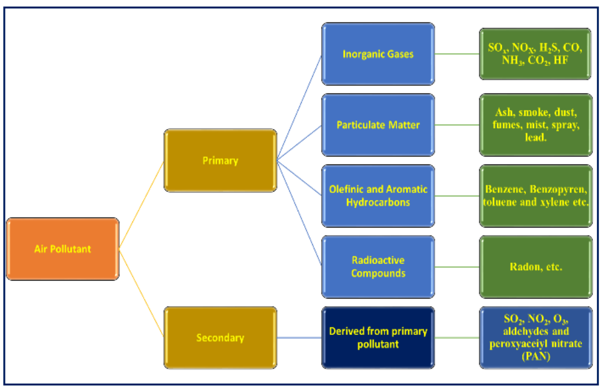

Figure 1. Type of Pollutant.

Air quality monitoring uses ground-based stations, passive sampling, mobile systems, and satellites, each of which has unique advantages for pollution control strategies (IPCC, 2021). The primary pollutants can be further divided into several types:

1.3 Monitoring air pollutants

Air pollutants can be monitored by a number of techniques, each with its own strengths and limitations when applied in isolation. The integration of multiple monitoring approaches often provides a more comprehensive and synchronized understanding of the distribution, transformation, and patterns of exposure (WHO 2021; IPCC, 2021).

Ground-Based Monitoring: Ground-based monitoring involves the direct measurement of air pollutants using instruments installed on fixed or mobile platforms. These methods provide very precise and reliable data, which is particularly valuable for regulatory compliance and public health protection.

Continuous Air Quality Monitoring Stations (CAAQMS): Continuous ambient air quality monitoring (CAAQM) stations measure key pollutants like sulfur dioxide (SO_2), nitrogen dioxide (NO_2), carbon dioxide (CO), ozone (O_3), particulate matter ($PM_{2.5}$), and sometimes volatile organic compounds (VOCs). They provide high-resolution data, essential for assessing short-term pollution events and daily air quality index (AQI) reports (US EPA, 2023). Common instruments include chemical-based analyzers (for NO), UV fluorescence analyzers (for SO_2), non-dispersive infrared analyzers (for CO), and beta-amplitude monitors (U.S. EPA, 2023).

Manual Sampling Methods: These methods collect air samples using filters or sorbent tubes. High-volume and gravimetric methods analyze particles, while gaseous samples undergo chromatographic or spectroscopic analyses. Although accurate, these methods require laboratory processing, limiting their use for real-time monitoring (WHO, 2021).

Mobile Monitoring Units: Mobile monitoring devices attached to vehicles allow spatial mapping of pollution in urban areas. These systems help to identify pollution hotspots, emissions from transport and variations in pollutant concentrations at street level. Mobile platforms are particularly useful for exposure assessment in cities and for micro-scale air quality studies (Apte et al., 2017).

Low-Cost Sensors and IoT Devices: Low-cost sensors and IoT devices are increasingly used for localized air quality monitoring. These affordable sensors provide near-real-time data and are popular in citizen science projects and Smart Cities. While they may be less accurate than regulatory instruments, their widespread use enhances community awareness and participatory monitoring (Snyder et al., 2013).

Remote Sensing Techniques: Remote sensing techniques use satellite or airborne sensors to monitor the air pollution in a large geographical area (Sharma et al., 2025). These approaches are particularly valuable in regions where there are no dense monitoring networks on the ground.

Satellite-Based Monitoring: Satellite-based monitoring uses instruments such as MODIS (Moderate Resolution Imaging Spectroradiometer), Ozone Monitoring Instrument (OMI), and Troposition Observatory Imaging Spectro-Radiometer (TROPOMI). These instruments measure trace gases such as NO_2, SO_2, CO, methane (CH_4), and aerosol optical depth (AOD), which can be used to estimate the particulate matter concentration at the surface (Van Donkelaar et al., 2019). Satellite observations provide a wide spatial coverage and allow analysis of long-term trends at the regional and global levels. However, they may be constrained by cloud coverage, vertical resolution and indirect surface concentration estimates (IPCC, 2021).

Airborne Remote Sensing: Aerial remote sensing, carried out by aircraft or unmanned aerial vehicles (drones), offers a higher spatial resolution and targeted measurements than satellites. These systems are particularly effective for local studies, mapping industrial emissions and emergency assessment (WHO, 2021).

Lidar (Light Detection and Ranging): Lidar (Light Detection and Ranging) technology uses laser pulses to detect aerosols and certain gases in the atmosphere by measuring the reflected signals. Lidar systems can produce detailed vertical profiles of pollutant concentrations, allowing researchers to study the dynamics of the boundary layer, aerosol transport and the vertical mixing process. This technique significantly improves the understanding of the dispersion of pollution from the ground to higher altitudes (IPCC, 2021).

In conclusion, while each monitoring method - ground, mobile, low cost, satellite, airborne or LIDAR - has its own inherent advantages and limitations, their combined use makes for a more reliable and integrated assessment of air quality. Such a synergistic framework improves the reliability of environmental monitoring, supports the reporting of AQI and reinforces evidence-based strategies for the management of air pollution.

2. Research Synthesis

Advances in satellite remote sensing and ground-based air quality monitoring have improved atmospheric measurements, but challenges remain in using satellite data to derive accurate pollutant-specific Air Quality Indices (AQI). Satellites like Sentinel-5P with TROPOMI and Aura with OMI provide high-quality column-integrated measurements of trace gases. However, converting these measurements to reliable surface-level concentrations for AQI calculations is still complex and uncertain (Levelt et al., 2018; Veefkind et al., 2012).

Column–Surface Concentration Mismatch: Most satellite instruments measure column-integrated pollutant concentrations (e.g., total ozone, tropospheric NO_2) while AQI systems require near-surface concentrations in µg/m³ or ppb. The vertical distribution of pollutants is influenced by boundary layer dynamics and atmospheric conditions. Converting satellite data to surface concentrations involves chemical transport models, statistical regression, or machine learning, which introduces uncertainties. There is currently no universally accepted method for this conversion (Lamsal et al., 2008; Goldberg et al., 2019).

Limited Accuracy for Particulate Matter Estimation: Particulate matter ($PM_{2.5}$ and PM_{10}) is a key component of AQI frameworks but is not directly measured by polar-orbiting trace gas sensors. Instead, PM concentrations are inferred from Aerosol Optical Depth (AOD) data from MODIS on Terra and Aqua, which reflect total aerosol loading rather than ground-level concentrations. The relationship between AOD and surface $PM_{2.5}$ is variable, influenced by factors like aerosol composition, humidity, and land use, making conversion models region-specific and limiting their standardized use in AQI reporting (van Donkelaar et al., 2010; Hoff and Christopher, 2009).

Insufficient Temporal Resolution for AQI Standards: AQI calculations require averaging pollutant concentrations over specific time intervals (e.g., 1-hour for NO_2 and SO_2, 8-hour for O_3, 24-hour for $PM_{2.5}$). Most polar-orbiting satellites, such as

Sentinel-5P, provide only one daily overpass at a fixed local time, and factors like cloud cover and retrieval errors often lead to data gaps. This limits the ability to detect short-term pollution episodes essential for AQI determination. Thus, integrating satellite observations with ground-based data and models is necessary but methodologically complex (Veefkind et al., 2012).

Inconsistent Validation Across Regions: Satellite-derived pollutant estimates need validation against ground-based monitoring networks, which are unevenly distributed globally. While North America, Europe, and parts of East Asia have dense coverage, many developing regions are poorly monitored. This bias limits understanding of satellite retrieval performance in areas where it is most needed and introduces uncertainty into global AQI modelling efforts (Martin, 2008).

L***ack of Standardized Satellite-Based AQI Framework:*** Current regulatory AQI systems use surface-level pollutant concentrations in µg/m³ or ppb. Although satellite-derived column densities can be modelled to estimate surface concentrations, there is no standardized guideline for incorporating satellite data into official AQI calculations. This lack of a harmonized framework limits the use of satellite data in regulatory air quality reporting.

Uncertainty Quantification and Error Propagation: Many studies show correlations between satellite-derived and ground-based pollutant measurements, but there is often insufficient quantification of uncertainty related to retrieval algorithms, atmospheric corrections, and meteorological variability. A systematic framework for estimating air quality indices (AQI) using satellite data, especially for multi-pollutant systems, is still lacking.

Limited Integration of Advanced Data Fusion Techniques: Recent research has examined machine learning, bayesian data assimilation, and hybrid modelling that integrates satellite observations, ground data, meteorological variables, land-use features, and chemical transport models. However, scalable frameworks for operational AQI estimation using multi-source data across different regions are still lacking. It is crucial to develop standardized and adaptable data fusion systems for better reliability and policy implementation.

The main research gap is the lack of a reliable, standardized method to convert satellite-derived atmospheric concentrations—measured in Dobson Units or column number densities—into accurate surface-level concentrations (µg/m³) for pollutant-specific AQI estimation. Addressing this requires advancements in vertical profile modelling, uncertainty quantification, data fusion, and regulatory harmonization. This study is focused on changing satellite-derived atmospheric concentrations, which can be measured in Dobson Units or column number density, into exact surface-level concentrations (µg/m³).

3. Methodology, Data Used and Air Pollution Standards

The methodology for assessing the air quality index (AQI) using remote sensing and spatial analysis integrates advanced satellite-derived atmospheric measurements with geospatial modelling techniques to estimate pollutant concentrations and calculate the spatial and temporal AQI. This framework allows for comprehensive assessment, visualization, and monitoring of air quality trends in a variety of geographical areas, including areas with limited terrestrial monitoring infrastructure. Satellite data is available to measure air quality, and various agencies and countries have their own air quality standards.

3.1 Methodology

The methodology (Figure 2) for air quality assessment using satellite data and Google Earth Engine (GEE) is structured in a series of steps: identifying research gaps, producing results for specific air quality pollutants, and proposing future directions.

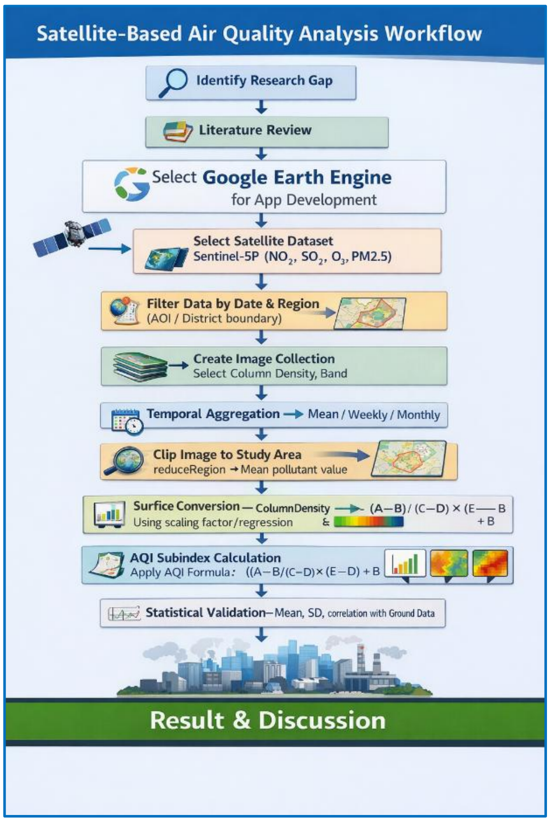

Figure 2. Methodology

The study begins with a thorough review of the existing literature on air quality monitoring, including both satellite and terrestrial measurements. This process highlights limitations of existing methods, such as limited high-resolution spatial coverage, inconsistent data, and a lack of integration with computational tools such as Google Earth Engine (GEE). A systematic review of relevant studies was conducted to gain an insight into the methods used to convert satellite column density data to surface pollutant concentrations. The focus is on identifying the most appropriate satellite datasets, scaling factors, molecular-weight conversion methods, and methods for calculating air-quality indices. A custom application has been developed on the GEE platform to automate data processing, visualization, and AQI calculation. The application enables dynamic selection of study areas, time filtering, and integration of multiple satellite datasets for comprehensive air quality analysis. The study area is defined by the administrative borders imported into the GEE. This approach ensures that any subsequent analysis is confined to the area of interest. The relevant satellite products, such as Sentinel-5P for nitrogen dioxide (NO_2) and ozone (O_3), and MODIS or VIIRS for particulate matter (PM), are selected as appropriate. Column density data are filtered by date and location, and the corresponding ranges of target pollutants are extracted for further analysis. To reflect ground-level concentrations, the processing of column density data must be adjusted using atmospheric correction models or boundary-layer assumptions. These steps link column density measurements to pollutant concentrations in the real world. To comply with the AQI standards, the surface concentration was converted from mol/m² to µg/m³, taking into account molecular weights and boundary-layer height. Using the converted pollutant concentrations, the Air Quality Index (AQI) is calculated based on standard breakpoints, such as those set by the US EPA or CPCB. The AQI offers a categorical assessment of air pollution severity for each pollutant. The individual AQI values are generated for each pollutant (NO_2, SO_2, $PM_{2.5}$, O_3, etc.) to facilitate analysis of specific pollutants and identify the main contributors to air quality degradation. The results are interpreted to identify spatial and temporal patterns in air quality. Limitations of the current approach are discussed, and recommendations for future improvements—such as higher-resolution datasets, integration of ground-based monitoring, and predictive modelling

3.2 Data Used

Assessing air quality through remote sensing requires knowledge of satellite platforms that monitor atmospheric composition. In recent decades, various space agencies have launched Earth observation missions to track air pollution globally and regionally (Sharma et al., 2025). This research estimates surface concentrations of the main pollutants: SO2, NO2, O3, CO, and CH4 using satellite imagery, primarily using the Sentinel-5P data for its high resolution and day coverage. The study aims to convert satellite measurements into surface concentrations (µg/m³) for AQI calculations. Creating spatially coherent AQI maps to address the limitations of sparse ground monitoring networks.

Satellite-based air quality monitoring within the Copernicus framework relies on atmospheric composition products from the Sentinel-5P mission. These datasets provide trace gas measurements in column density units, which represent the vertically integrated amount of the pollutant from Earth's surface to the upper atmosphere. These observations are widely used to map pollution distributions, identify emission hotspots, and estimate air quality indices (AQIs) in regions with limited terrestrial monitoring.

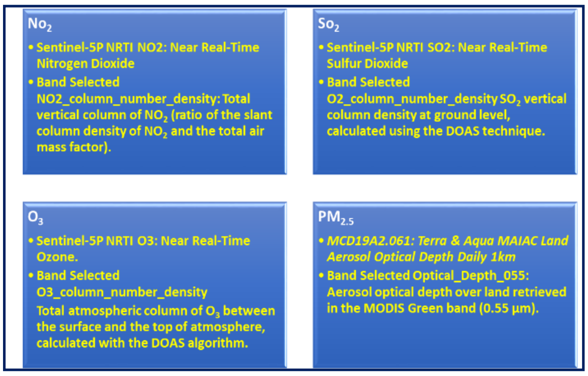

Figure 3. Data Used

Satellite Data Source: The main source of air quality data is Copernicus, the European Earth Observation Initiative, which provides open satellite data for environmental monitoring. The Sentinel-5P satellite, which carries the TROPOMI sensor, gathers observations of atmospheric trace gases. The TROPOMI system provides higher-resolution global measurements of the main air pollutants, such as nitrogen dioxide (NO_2), sulphur dioxide (SO_2), ozone (O_3), carbon dioxide (CO), methane (Mg) and aerosols, which can be analysed in real time on cloud computing platforms such as Google Earth Engine.

Specific column density bands are selected for air quality assessment because they quantify the atmospheric load of each pollutant.

Nitrogen Dioxide (NO_2): The tropospheric NO2 column density band measures NO_2 in the troposphere, the most important atmospheric layer for human exposure and urban emissions. This band is widely used to assess pollution from transport and industry.

Sulphur Dioxide (SO_2): The SO_2 column number density band represents the total SO_2 content of the atmosphere. Additional altitude-specific retrievals help to distinguish surface emissions from volcanic or stratospheric plumes.

Ozone (O_3): The O3 column number density band provides a total ozone column and supports regional analysis of photochemical smog and the atmospheric chemical composition.

Carbon Monoxide (CO): The CO_column Number Density range reflects combustion-related pollution and is useful for studying biomass combustion and long-distance transport.

Aerosols (PM Proxy): Sentinel-5P does not directly measure particulate matter (PM2.5), but studies use the absorption rate index band as a proxy for estimating PM2.5 using regression, scaling factors, or machine-learning models.

The column density is the vertically integrated quantity of the pollutant and is usually expressed in mol/m². Since the calculation of AQI requires surface concentrations (µg/m³), these satellite measurements are converted by means of scaling factors: Chemical Transport Modelling, Calibration with ground monitoring stations, and meteorological corrections. This conversion bridges the gap between satellite data and the regulatory air quality standards.

3.3 Air Pollution Standards

Air pollution standards are regulatory limits set to control concentrations of the main air pollutants, with the primary objective of protecting human health and the environment. These standards are developed and enforced by national environmental authorities, such as the US Environmental Protection Agency (US EPA), and follow at international level the WHO's scientific advice. Regulatory frameworks are usually based on epidemiological and toxicological evidence linking exposure to pollutants to adverse health outcomes, including respiratory disease, cardiovascular disease and early death (WHO, 2021; US EPA, 2023).

Air quality standards generally focus on key pollutants such as particulate matter ($PM_{2.5}$ and PM_{10}.), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), carbon dioxide (CO), ozone (O_3) and lead (Pb). These pollutants have been selected on the basis of their prevalence, toxicity and documented impact on vulnerable groups such as children, elderly and persons with pre-existing respiratory or cardiovascular diseases. For example, fine particles ($PM_{2.5}$) penetrate deep into the lungs and bloodstream, while exposure to ozone is associated with acute respiratory irritation and reduced lung function (WHO, 2021).

The standards are usually expressed as maximum permitted concentrations over specified averaging periods, which vary according to the health effects of the pollutant. For pollutants such as ozone and sulphur dioxide, which may cause acute health effects, short-term exposure limits (e.g., 1 hour or 8 hours) are usually used. Long-term limits (e.g. annual average values) are often used for pollutants such as PM2.5 and nitrogen dioxide, reflecting cumulative risks associated with chronic exposure. These averaging periods are the basis for national AQI systems,

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which translate the measured concentrations into health categories for public communication.

Air quality standards vary between countries and organisations due to differences in regional sources of pollution, climatic conditions, socio-economic considerations, and evolving scientific knowledge. In 2021, the World Health Organisation updated its global guidelines on air quality, providing revised health reference levels for key pollutants. These guidelines are not legally binding but represent scientifically based concentration limits below which the health risks are substantially reduced (WHO, 2021). For example, the WHO's 2021 annual median $PM_{2.5}$ guideline has been reduced to 5 µg per m³, reflecting stronger evidence for adverse health effects at previously accepted levels.

Continuous review and revision of air pollution standards is essential, as new research is continuously improving our understanding of the relationship between exposure and response and the health burden of air pollution. Updating the legislation ensures that standards remain in line with current scientific knowledge and promotes long-term protection of public health and environmental sustainability.

Pollutant	Averaging Time	AQG Level (WHO, 2021)
$PM_{2.5}$ (fine particles)	Annual mean 24-hour 15 µg/m³	5 µg/m³
PM_{10} (coarse particles)	Annual mean24-hour 45 µg/m³	15 µg/m³
Ozone (O_3)	Peak season average[(b)] 8-hour - 100 µg/m³	60 µg/m³
Nitrogen dioxide (NO_2)	Annual mean 24-hour 25 µg/m³	10 µg/m³
Sulfur dioxide (SO_2)	24-hour	40 µg/m³
Carbon monoxide (CO)	24-hour	4 mg/m³

Table 1. WHO 2021 Air Quality Guideline Levels

Indian Standards by CPCB - Following the Stockholm Conference on the Human Environment in 1972, the Indian Government enforced the Air (Prevention and Control of Pollution) Act in 1981, which gave the Indian Central Pollution Control Board (CPCB) the power to establish national air quality guidelines. To prevent, control, and mitigate air pollution, the CPCB launched the first national ambient air quality standards in 1982, updated them in 1994, and again in 2009, which are now applicable at the national level (Munoth, N., Sharma, N., 2021). The CPCB and several national pollution control boards (SPBs) are the organisations responsible for developing and maintaining air quality standards. All these agencies are under the authority of the Ministry of Environment and Forests (MoEF, India).

4. Result and Discussion

The study shows that NO2, SO2, O3, and PM2.5 concentrations derived from satellite data can effectively support the estimation of the air quality index at the district level by applying methods such as time filtering, spatial aggregation, and appropriate conversion from column to surface measurements. By integrating observations from space borne monitoring missions such as Sentinel-5P, which provide measurements of trace gases (NO_2, SO_2, and O_3) and products derived from satellites for the estimation of $PM_{2.5}$. Together, these elements contribute to a comprehensive picture of the overall state of air quality.
The results show that satellite measurements of pollution capture spatial variability across different regions is effective. They highlight high-emission areas, such as urban industrial clusters, and cleaner hinterland areas. By aggregating data over time, a researcher can smooth short-term fluctuations, making regional estimates more reliable. After converting to surface concentrations and using standard methods to interpolate air quality thresholds, the resulting AQI values align with expected emission and dispersion patterns.

Integrating these datasets within a geospatial cloud computing environment enables automated, scalable, and reproducible analyses. Cloud-based platforms facilitate the efficient handling of large, multi-temporal datasets, dynamic boundary-based extraction, and real-time visualization of Air Quality Index (AQI). This significantly alleviates the computational limitations often faced in traditional desktop-based processing.

4.1 Satellite-Derived Pollutant Distribution using Google Earth Engine: The air quality assessment was carried out using satellite data files processed in Google Earth Engine (GEE), a cloud-based geo-spatial platform that allows for extensive analysis of the environment. The column densities of pollutants (e.g., NO_2, SO_2, CO) obtained from the European Space Agency Sentinel-5P products were converted into surface concentrations using mean or Regression coefficients derived from ground-based monitoring observations.

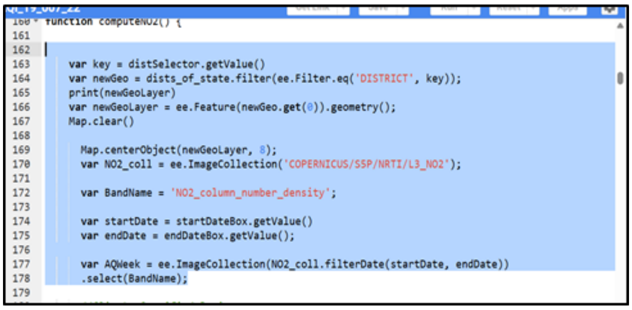


Figure 4. Fetch the Satellite image column density

The study area is dynamically selected using an interactive district selector (distSelector)(Figure 4). The name of the selected district (key) is retrieved from the user interface. The district boundary is filtered from a preloaded administrative boundary dataset (dists_of_state) using the DISTRICT attribute.

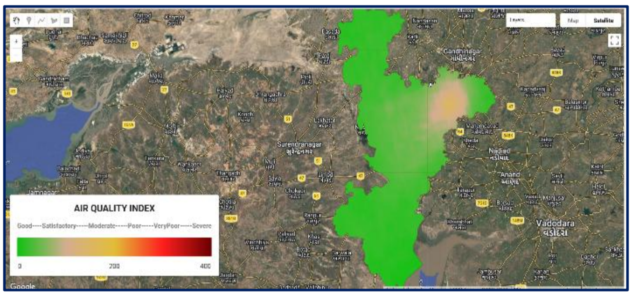


Figure 5. District level Pollution Map

The first matching feature is converted into a geometry (newGeoLayer). The map is then cleared and centred over the selected district at zoom level 8. This process enables region-specific air pollution analysis by allowing the spatial aggregation of satellite-derived pollutant concentrations within administrative boundaries (Figure 5).

Conversion to Surface Concentration: Satellite products provide vertical column densities rather than surface concentrations. To solve this issue, GEE has devised a statistical transformation model that combines column density, a scale factor, a regression model, and surface concentration (R2 = XX and RMSE = XX mg per m^2). Column Density → Scaling Factor / Regression Model → Surface Concentration. This conversion method ensures uniform units (e.g. mol/m² to µg/m³) and improves the policy's interpretation for decision-making.

In this study, a scaling factor was used to convert satellite measurements into estimated surface concentrations. The data set used column density values (e.g. mol/m²) from European Space Agency satellites such as Sentinel-5P. Although these data sets provide spatially continuous coverage, they represent the integrated pollutant burden across the entire atmospheric column and not the actual concentrations at ground level.

Data were averaged over the selected period and study area to obtain representative values. Time averaging (e.g., weekly or monthly) reduces short-term variability, and spatial aggregation ensures that the concentration reflects conditions within a defined boundary rather than individual pixels.

Scaling factors or regression models are used to estimate surface concentrations once column means are obtained. This step accounts for atmospheric mixing, the boundary-layer height, and the vertical distribution of pollutants, enabling conversion of column measurements into ground-level estimates, which are more relevant for assessing human exposure.

$$Surface\ \text{Concentration} = Satellite\ Column\ density \times MolecularWeight \times ScalingFactor \times 1000 \quad (1)$$

Equation 1 provides a simplified, physics-based approach to converting satellite-derived pollutant concentrations to surface-level concentrations expressed in micrograms per cubic meter (µg per m³), accounting for the effects of the planetary boundary layer (PBL), vertical distribution, and atmospheric mixing (e.g., NO, SO, PM-related AOD.

```
Map.centerObject(newGeoLayer, 8);
var NO2_coll = ee.ImageCollection('COPERNICUS/S5P/NRTI/L3_NO2');

var BandName = 'tropospheric_NO2_column_number_density';

var startDate = startDateBox.getValue()
var endDate = endDateBox.getValue();

var AQWeek = ee.ImageCollection(NO2_coll.filterDate(startDate, endDate))
.select(BandName);

//Clip to Specified Region
var NO2_mean = AQWeek.mean().clip(newGeoLayer);

// clipped image transfered to another variable for reduce region analysis
var meanNO2Image = ee.Image(NO2_mean);
  //  Define constants

var molWeight = 46;        // NO2 molecular weight in g/mol
var scaleFactor = 0.8;     // Example scaling factor to convert column → surface

// Compute surface concentration (µg/m³)
var NO2_surface = meanNO2Image.multiply(molWeight)   // mol/m² → g/m²
                    .multiply(scaleFactor) // adjust to near-surface
                    .multiply(1000)       // g → µg
                    .rename('NO2_surface');

// Reduce the region. The region parameter is the Feature geometry.
var meanNO2 = NO2_surface.reduceRegion({
  reducer: ee.Reducer.mean(),
  geometry: newGeoLayer,
  scale: 1000, // approximate Sentinel-5P resolution
  maxPixels: 1e9,
  bestEffort: true
});

// Mean NO2 conc. values multiply by 1000
var meanNO2_value = ee.Number(meanNO2.get(BandName)).multiply(1);
var e = meanNO2_value;
print('Value of "e" is',e);
```

Figure 6. code for Surface Concentration

Using the above code (Figure 6), it is possible to perform basic measurements, which lead to the conversion of the column density observed by the satellite into surface concentration, which leads to a better understanding of air quality. Consider the molecular weights of the main pollutants: nitrogen dioxide (NO_2) at 46 g mol, sulphur dioxide (SO_2) at 64 g mol, ozone (O_3) at 48g mol and carbon dioxide (CO) at 28 g mol. Molecular mass is the mass of the pollutant gas in grams per mole (g/mol), which is represented by the mole mass value. In order to achieve cleaner air, satellite sensors can provide key information on pollutant concentrations ranging from molecules per square metre (mol/m²) to molecules per square inch (molecules/cm²). To really understand the impact of these data, scientists convert these measurements into micrograms per cubic metre (µg/m³), a key step in calculating air quality index and understanding the health effects of air pollution in our communities.

The resulting concentrations are finally converted to the appropriate units for calculating the Air Quality Index (AQI). Adjustments and standardisation of units ensure compliance with AQI thresholds and enable classification of pollutant concentrations into standard air-quality categories for interpretation and decision-making.

4.2 AQI Computation and Classification: The air quality index (AQI) is a numerical scale that provides the public with a simple way of communicating the level of air pollution. It translates complex air pollutant concentrations into a single number, which is then broken down into categories representing health hazards. Key pollutants commonly used in the calculation of the AQI: $PM_{2.5}$ (PM < 2.5 micrometres), PM2.5 (PM < 10 micrometers), NO_2 (nitrogen dioxide), SO_2 (sulphur dioxide), CO_2 (carbon dioxide), O_2 (oxygen).

AQI Computation Formula: The linear stepwise interpolation method is used to calculate the AQI.

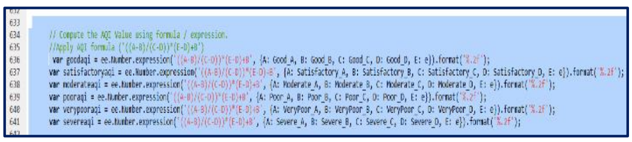
$$AQI = \frac{I_{hi} - I_{lo}}{C_{hi} - C_{lo}} \cdot (C - C_{lo}) + I_{lo} \quad (2)$$

Equation 1 AQI Formula

Where:

C	Observed pollutant concentration
C_{lo}	Lower breakpoint concentration (for the corresponding AQI category)
C_{hi}	Upper breakpoint concentration
I_{lo}	Lower AQI value of the category
I_{hi}	Upper AQI value of the category

Equation 2 above has been implemented in the following code to accurately calculate the air quality index (AQI) for specific pollutants.



```
// Compute the AQI Value using Formula / expression.
//Apply AQI formula ('((A-B)/(C-D))*(E-D)+B')
 var goodaqi = ee.Number.expression('((A-B)/(C-D))*(E-D)+B', {A: Good_A, B: Good_B, C: Good_C, D: Good_D, E: e}).format('%.2f');
var satisfactoryaqi = ee.Number.expression('((A-B)/(C-D))*(E-D)-B', {A: Satisfactory_A, B: Satisfactory_B, C: Satisfactory_C, D: Satisfactory_D, E: e}).format('%.2f');
var moderateaqi = ee.Number.expression('((A-B)/(C-D))*(E-D)+B', {A: Moderate_A, B: Moderate_B, C: Moderate_C, D: Moderate_D, E: e}).format('%.2f');
var pooraqi = ee.Number.expression('((A-B)/(C-D))*(E-D)+B', {A: Poor_A, B: Poor_B, C: Poor_C, D: Poor_D, E: e}).format('%.2f');
var verypooraqi = ee.Number.expression('((A-B)/(C-D))*(E-D)+B', {A: VeryPoor_A, B: VeryPoor_B, C: VeryPoor_C, D: VeryPoor_D, E: e}).format('%.2f');
var severeaqi = ee.Number.expression('((A-B)/(C-D))*(E-D)+B', {A: Severe_A, B: Severe_B, C: Severe_C, D: Severe_D, E: e}).format('%.2f');
```

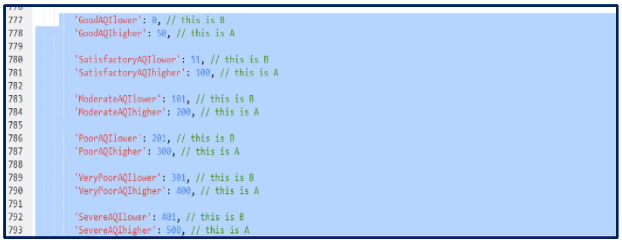
Figure 7. AQI Computation

This implementation takes into account different parameters and standardised thresholds for each pollutant, ensuring that the calculated AQI effectively reflects the current atmospheric conditions. The code (Figure 7) processes real-time data input, calculates AQI values based on a defined formula and provides information on the level of air pollution associated with each specific pollutant. AQI values are also classified by category.

AQI Classification: The AQI is divided into six main categories, each corresponding to a level of health-related impact. Different countries may have slightly different ranges, but the concepts are similar. Here is a standard classification used by India's CPCB and the US EPA

AQI Range	Category	Health Implications
0–50	Good	Air quality is satisfactory and there is little or no risk from air pollution.
51–100	Satisfactory / Moderate	The air quality is acceptable; some pollutants may be of concern to very sensitive persons.
101–200	Moderate / Unhealthy for Sensitive Groups	Health effects may be seen in sensitive groups (children, the elderly, people with respiratory problems). The general population is less affected.
201–300	Unhealthy	Everyone can experience health effects; vulnerable groups may experience more severe effects.
301–400	Very Unhealthy	Health warning; everyone may experience more serious health effects.
401–500	Hazardous	Health warnings of emergencies; whole populations at risk.

Table 2 AQI Range as per CPCB and EPA



```
'GoodAQIlower': 0, // this is B
'GoodAQIhigher': 50, // this is A

'SatisfactoryAQIlower': 51, // this is B
'SatisfactoryAQIhigher': 100, // this is A

'ModerateAQIlower': 101, // this is B
'ModerateAQIhigher': 200, // this is A

'PoorAQIlower': 201, // this is B
'PoorAQIhigher': 300, // this is A

'VeryPoorAQIlower': 301, // this is B
'VeryPoorAQIhigher': 400, // this is A

'SevereAQIlower': 401, // this is B
'SevereAQIhigher': 500, // this is A
```

Figure 8. Code for AQI Categorise

The above code in Figure 8 has a category (Table 2) for the AQI pollutant value and its refutation in the map in Figure 10, where the AQI values are classified into categories and the boundary is given for classification and calculation. It is essentially a scale used to categorize the AQI into health categories such as good, moderate, or severe.

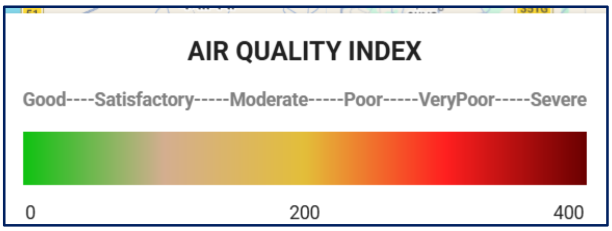


Figure 9. AQI colour ramp widget

The air quality index (AQI) is displayed in Figure 9 as a colourful widget that visually displays the levels of air pollution and its associated health effects. On the horizontal scale, low AQI values (approximately 0) are shown on the left, while high values (above 400) are shown on the right, indicating dangerous air conditions.

The gradients allow users to quickly identify the purity or pollution of the air based on its colour. Each colour is associated with a unique health category. A green level (0-50) means the air is clear and free of health hazards, making it suitable for outdoor activities. The Satisfactory (51 to 100) category, which is usually yellow, is a category which represents acceptable air quality, but may still cause minor breathing difficulties to sensitive persons.

The Moderate (101-200) range, shown in orange, shows the visible levels of pollution which may irritate vulnerable groups such as children, older people and people with respiratory diseases. Higher AQI levels indicate an increased health risk. The poor (201-300) category, shown in red, indicates that a wider range of people may experience respiratory discomfort and prolonged outdoor exposure is discouraged. Significant health effects and an increased risk of respiratory disease are indicated in Very Poor (301-400), often shown in purple. Finally, the Severe (>400) category, shown in dark brown, indicates the presence of hazardous air quality which may affect even healthy people and lead to dangerous outdoor activities.

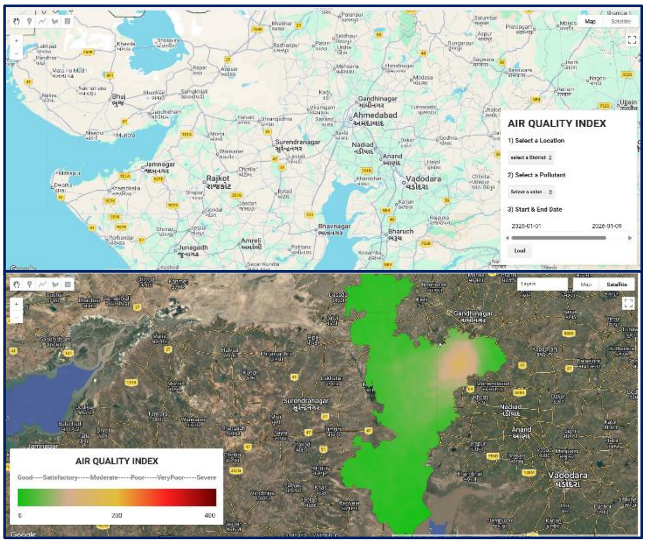


Figure 10. Application Visualisation

As a visualisation tool (Figure 10), the AQI legend is key for translating pollutant concentrations into easily understandable categories, thereby promoting public awareness, environmental monitoring, and air quality management decisions.

5. Conclusion and Future Work

The study effectively demonstrated the use of satellite-derived column density data and Google Earth Engine (GEE) to assess air quality and to calculate the air quality index for each pollutant in the selected study area. The results reveal distinct spatial and temporal patterns of pollution, showcasing hotspots and variations in pollutant concentrations over time. The Study effectively demonstrates the use of satellite-derived column density data and Google Earth Engine (GEE) for assessing air quality and calculating the individual pollutant Air Quality Index (AQI) within the selected study area. This study is significant as it addresses the existing gap in converting satellite-derived concentrations - measured in Dobson Units or column number densities - into near surface-level concentrations (µg/m³) for pollutant-specific pollutant AQI estimation. This study contributes towards improving the reliability of satellite-based air quality assessment by integration of satellite observations with analytical conversion approaches and cloud-based processing.

However, some limitations are noted. While satellite data provides broad spatial coverage, it may not fully capture fine-scale variations near emission sources. Additionally, uncertainties in atmospheric correction and molecular weight conversion can affect accuracy.

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Several improvements are recommended for future work. The use of higher resolution satellite data sets and the integration of ground monitoring stations can increase the spatial and temporal accuracy. Moreover, integrating predictive modelling techniques, such as machine learning and chemical modelling, could enable real-time air quality prediction. Extending the methodology to cover more pollutants, the overall AQI calculation and different geographical areas would further validate and generalise the approach and provide a robust framework for satellite-based air quality monitoring and decision making, as well as a user-friendly application for locating AQI as well as a validation matrix.

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