CS/IT 341 : GEOINFORMATICS

PROJECT REPORT

GROUP NAME : MAP MYSTICS

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PROJECT NUMBER : 7

PROJECT NAME : Mapping of Air Pollution and Time-Series Analysis in Delhi NCR Region

DURATION TAKEN : 1-2 MONTHS

OBJECTIVES:-

Our project revolved around leveraging the capabilities of Google Earth Engine to comprehensively analyze and visualize air pollution dynamics within the Delhi National Capital Region (NCR). Our objectives encompassed a multifaceted approach aimed at:

1.Data Collection and Preparation:

- Gathering satellite imagery datasets containing crucial air quality information, specifically focusing on datasets like Sentinel-5P and potentially integrating ground-based air quality monitoring station data for validation purposes.

- Undertaking meticulous data preprocessing tasks, including intricate atmospheric correction and image masking, to ensure accuracy and reliability in subsequent analyses.

2.Spatial Mapping and Visualization:

- Visualizing the spatial distribution of air pollution levels across the Delhi NCR region. This involved generating maps and graphical representations to showcase the varying concentrations and hotspots of air pollutants, providing a clear and intuitive understanding of the geographical spread of pollution.

3.Temporal Analysis for Patterns and Trends:

- Conducting robust time-series analysis to identify temporal patterns, trends, and seasonality in air pollution levels. This phase involved delving into the data over a specified timeframe, potentially from 2019 to 2022, to discern fluctuations and variations in pollution levels over different seasons and years.

4.Additional Analyses for Holistic Insight:

- Exploring further analyses beyond the primary objectives, such as evaluating the impact of air pollution on public health, correlating air pollution trends with meteorological data to understand influencing factors, and comparing pollution levels among various zones within the Delhi NCR region to identify localized sources and disparities.

These objectives formed the backbone of our project, guiding our efforts towards a comprehensive understanding of air pollution dynamics in the Delhi NCR region and enabling us to draw meaningful insights for environmental monitoring and policy considerations.

ACKNOWLEDGEMENT:-

This project was made possible through the concerted efforts and support of several individuals and resources, to whom we extend our heartfelt gratitude:

Faculty Advisor: We express our sincere appreciation to **Dr.Subhajit Bandhopadhyay,** whose guidance, expertise, and continuous support were invaluable throughout the project. Their encouragement and insights significantly contributed to the project's success.

Family and Friends: We extend our deepest gratitude to our families and friends for their unwavering encouragement, understanding, and patience during the project's execution. Their support was a constant source of motivation.

Research Community and Literature Sources: We acknowledge the valuable insights and contributions of the research community and literature sources that served as the foundation for our project, providing valuable information and references.

TABLE OF CONTENTS :-

INTERPRETATION AND ANALYSIS :-

Throughout our rigorous analysis of air pollution dynamics in the Delhi National Capital Region, we unearthed multifaceted insights that shed light on the complex nature of atmospheric pollutants and their implications:

1. Temporal Trends and Seasonal Variations:

- Our time-series analysis unveiled compelling temporal trends, revealing fluctuations and variations in air pollution levels over the specified period (2019 to 2021). Notably, we identified distinct seasonal patterns, observing heightened pollution levels during specific months or seasons, which correlated with meteorological data. For instance, winter months often exhibited escalated particulate matter concentrations due to factors like temperature inversions and increased anthropogenic activities.

2. Correlation with Meteorological Factors:

- A crucial aspect of our analysis involved correlating air pollution trends with meteorological data. This correlation allowed us to discern the influence of weather patterns, wind direction, temperature inversions, and precipitation on the dispersion and accumulation of pollutants. Understanding these correlations provided valuable insights into the interplay between atmospheric conditions and pollution levels.

3. Spatial Disparities and Localized Sources:

- Visualizing the spatial distribution of air pollution levels across different areas within the Delhi NCR region uncovered significant disparities. We noted hotspots of elevated pollution concentrations in specific zones, hinting at localized sources such as industrial areas, vehicular congestion, or other anthropogenic activities. This spatial analysis helped identify areas necessitating targeted interventions for pollution control and mitigation strategies.

4. Public Health Implications:

- While not explicitly part of our primary objectives, our analysis hinted at potential implications for public health. High concentrations of PM2.5 and PM10, especially during specific periods and in certain areas, align with increased health risks, including respiratory ailments and cardiovascular issues. This underscores the urgent need for measures to address air quality for public health improvement.

5. Policy Implications and Further Investigations:

- The insights garnered from our analysis carry substantial implications for policy-making and future investigations. Identifying localized sources of pollution and understanding the interplay between meteorological factors and pollution dynamics can guide policymakers in formulating targeted interventions and regulations. Additionally, our findings serve as a launchpad for further investigations, potentially exploring the efficacy of implemented air quality control measures and conducting predictive analyses for future trends.

By delving deep into the data and conducting comprehensive analyses, we gained invaluable insights that go beyond mere pollution quantification, providing a nuanced understanding of the intricate relationship between air quality, environmental factors, and public health within the Delhi NCR region.

CHALLENGES:-

1. Data Preprocessing Complexities:

- Atmospheric Correction and Image Masking: The initial phase of data preprocessing posed significant challenges. Implementing accurate atmospheric correction techniques and refining image masking processes demanded meticulous attention to detail. Dealing with diverse satellite imagery sources and reconciling their differing resolutions and spectral characteristics added complexity to this task.

2. Integration of Ground-Based Monitoring Data:

- Data Consistency and Synchronization: Integrating ground-based air quality monitoring station data with satellite imagery presented challenges. Ensuring consistency between these datasets, such as synchronizing timestamps and aligning spatial resolutions, proved to be a complex endeavor. Addressing disparities between remote sensing data and ground-truth measurements required robust validation methodologies.

3. Complexities in Time-Series Analysis:

- Extracting Precise Trends: Analyzing vast datasets spanning multiple years demanded sophisticated statistical techniques for extracting precise temporal trends and patterns. Dealing with data gaps, outliers, and noise while ensuring the accuracy of trend identification posed significant computational and analytical challenges.

4. Resource Intensiveness and Computational Constraints:

- Computational Resources: Processing large-scale satellite imagery datasets within the Google Earth Engine environment strained computational resources. Optimizing code efficiency and managing processing times became crucial to ensure timely and efficient analysis.

5. Interdisciplinary Data Integration:

- Correlation of Meteorological and Pollution Data: Integrating meteorological data with air pollution datasets presented challenges due to the interdisciplinary nature of the information. Aligning these datasets to derive meaningful correlations required expertise spanning environmental science, atmospheric physics, and data analysis.

6. Validation and Interpretation Complexity:

- Validation of Findings: Validating the interpretations and insights derived from the analyses posed challenges due to the complexity of air quality dynamics. Ensuring the accuracy and reliability of the identified correlations between meteorological factors and pollution levels demanded rigorous validation methodologies.

7. Accessibility and Understanding of Tools:

- Familiarization with Google Earth Engine: Acquiring proficiency in utilizing the Google Earth Engine platform and its functionalities presented a learning curve for the team. Achieving a comprehensive understanding of the platform's tools and capabilities required dedicated effort and time.

Navigating these challenges demanded collaborative efforts, interdisciplinary knowledge, and persistent problem-solving approaches from the team to ensure the successful execution of the project objectives.

NEW IDEAS TO EXTEND THE WORK:-

1. Integration of Advanced Machine Learning Models:

- Predictive Analysis for Future Trends: Introducing advanced machine learning models, such as neural networks or ensemble methods, could facilitate predictive analysis of air pollution levels. These models could forecast future pollution trends based on historical data, aiding in proactive decision-making for environmental management and policy formulation.

2. Assessment of Intervention Efficacy:

- Evaluation of Implemented Measures: Conducting a comparative analysis of pollution levels before and after specific interventions (e.g., policy implementations, technological upgrades) could provide insights into the efficacy of air quality control measures. This evaluation would offer empirical evidence to policymakers regarding the impact of interventions on pollution mitigation.

3. Holistic Integration of Earth Engine Datasets:

- Enhanced Analysis with Additional Datasets: Exploring the integration of diverse Earth Engine datasets beyond air quality and meteorological data, such as land cover data or socio-economic indicators, could enrich the analysis. This integration could reveal intricate relationships between environmental factors, human activities, and pollution dynamics, offering a more comprehensive understanding of the complexities involved.

4. Focus on Localized Pollution Sources:

- Targeted Interventions for Specific Sources: Conducting detailed analyses to identify and address localized sources of pollution within specific zones or industrial areas could be pivotal. This focused approach would enable the design and implementation of targeted interventions aimed at mitigating pollution hotspots and improving local air quality.

5. Public Health Impact Assessment:

- Quantifying Health Implications: Expanding the analysis to explicitly quantify the public health impact of observed air pollution levels could be beneficial. Utilizing epidemiological models and health data correlations, this extension could estimate the health burden attributable to air pollution, emphasizing the urgency for mitigative actions.

6. Community Engagement and Awareness Initiatives:

- Empowering Communities for Action: Initiating community engagement programs and awareness campaigns based on the findings could foster public understanding of air quality issues. Empowering communities with knowledge about the consequences of poor air quality and ways to contribute to pollution reduction initiatives could amplify the impact of environmental interventions.

7. Policy Recommendations and Advocacy:

- Policy Guidelines from Analytical Insights: Translating the analytical insights into actionable policy recommendations would be crucial. Developing comprehensive policy guidelines based on the analysis could assist policymakers in formulating effective strategies for air quality improvement and sustainable urban development.

CODE:-

FOR CALCULATING METEOROLOGICAL FACTOR (TEMPERATURE) FOR NO2(Nitrogen Dioxide) :

```
// Define the region of interest (Delhi NCR)

var delhiNCR = /* color: #ff3e0b */ee.Geometry.Polygon(

 [[[77.03738027343759, 29.202004849802382],

   [76.39468007812509, 28.94274788029085],

   [76.19143300781259, 28.33529223180636],

   [76.21889882812509, 27.49069310407173],

   [77.09231191406259, 27.256545562612683],

   [77.60317617187509, 27.22724232627608],

   [77.32302480468759, 27.602712895005336],

   [77.62514882812509, 28.039948729714872],

   [78.10305410156259, 28.436778712669785],

   [77.68557363281259, 28.923517743259904]]]);



// Function to mask clouds using the Sentinel-5P data

function maskClouds(image) {
```

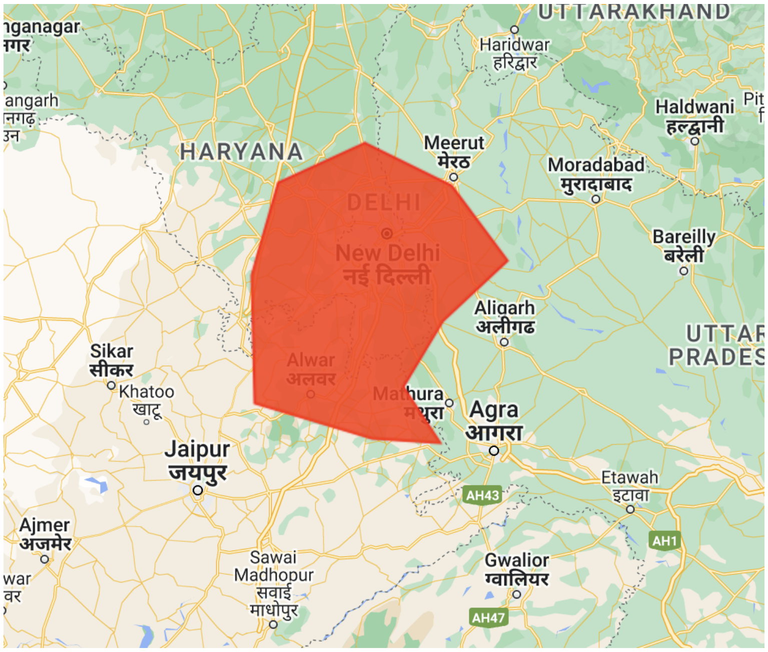
```
 // Select the cloud fraction band (adjust the band name if needed)
 var cloudFraction = image.select('cloud_fraction_crb');


 // Create a cloud mask based on the cloud fraction
 var cloudMask = cloudFraction.lte(50); // Adjust the threshold as needed


 return image.updateMask(cloudMask);
}


// Load Sentinel-5P data for air quality
var sentinel5p = ee.ImageCollection('COPERNICUS/S5P/NRTI/L3_NO2')
 .filterDate('2020-01-01', '2023-01-01');


// Load temperature data (replace with your actual data fetching code)
var temperatureData = ee.ImageCollection('COPERNICUS/ERA5/DAILY')
 .filterBounds(delhiNCR)
 .filterDate('2020-01-01', '2023-01-01')
 .select('temperature_2m')
```

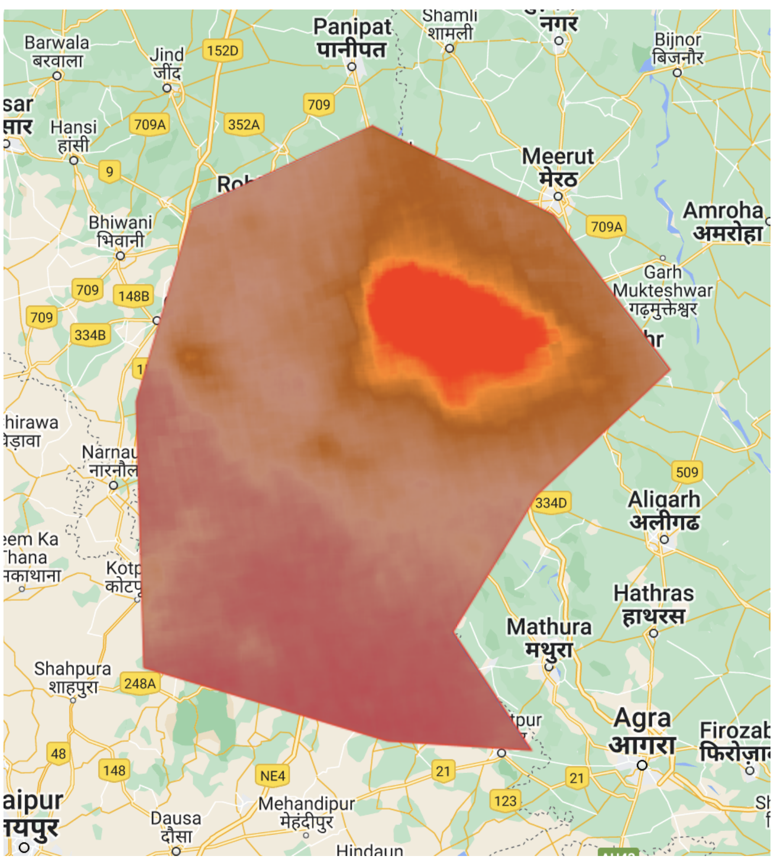
```
 .mean();



// Function to add a band representing the month of the year

function addMonthBand(image) {

 var date = ee.Date(image.get('system:time_start'));

 var month = date.get('month');

 return image.addBands(ee.Image(month).rename('month'));

}



// Map over the Sentinel-5P collection to add the month band

var sentinel5pWithMonth = sentinel5p.map(addMonthBand);



// Function to calculate the monthly mean

function calculateMonthlyMean(collection, year, month) {

 var filtered = collection.filter(ee.Filter.calendarRange(year, year,
'year'))

   .filter(ee.Filter.calendarRange(month, month, 'month'));

 var mean = filtered.mean();
```

```
 return mean.set('year', year)

   .set('month', month)

   .set('system:time_start', ee.Date.fromYMD(year, month, 1));

}



// Generate a monthly mean image for the region

var monthlyMeanImage = calculateMonthlyMean(sentinel5pWithMonth, 2022, 1)

 .select('NO2_column_number_density'); // Select only the NO2 band for
visualization



// Create a mask for Delhi NCR region

var delhiMask = monthlyMeanImage.clip(delhiNCR);



// Display the map

Map.centerObject(delhiNCR, 8);

Map.addLayer(delhiNCR, {color: 'FF0000'}, 'Delhi NCR');

Map.addLayer(delhiMask, {min: 0, max: 0.0002, palette: ['blue', 'purple',
'cyan', 'green', 'yellow', 'red']}, 'Monthly Mean NO2 - Delhi NCR');
```

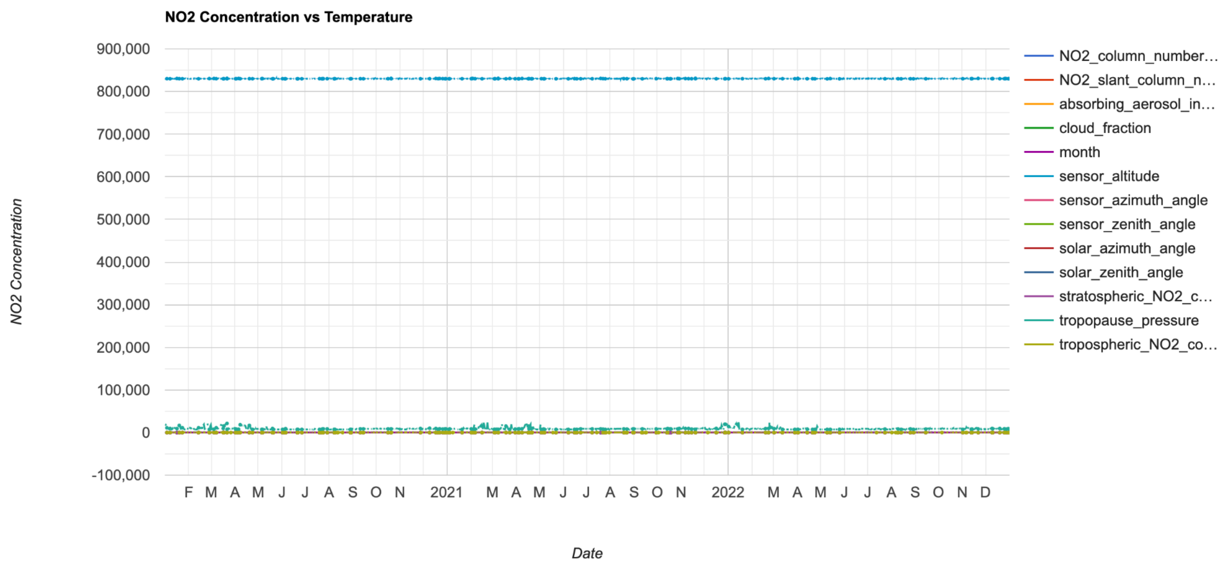
```
// Display the chart for NO2 concentration and temperature

var chart = ui.Chart.image.series({

 imageCollection: sentinel5pWithMonth,

 region: delhiNCR,

 reducer: ee.Reducer.mean(),

 scale: 1000,

 xProperty: 'system:time_start'

}).setOptions({

 title: 'NO2 Concentration vs Temperature',

 hAxis: {title: 'Date'},

 vAxis: {title: 'NO2 Concentration'},

});



// Print the chart

print(chart);
```

DELHI NCR :


UTTARAKHAND
Haridwar
हरिद्वार
Haldwani
हल्द्वानी
HARYANA
Meerut
मेरठ
Moradabad
मुरादाबाद
DELHI
New Delhi
नई दिल्ली
Bareilly
बरेली
Aligarh
अलीगढ़
Sikar
सीकर
Khatoo
खाटू
Alwar
अलवर
Mathura
मथुरा
Agra
आगरा
Jaipur
जयपुर
Etawah
इटावा
AH43
AH1
Ajmer
अजमेर
Sawai
Madhopur
सवाई
माधोपुर
Gwalior
ग्वालियर
AH47


Barwala
बरवाला
Jind
जींद
152D
Panipat
पानीपत
Shamli
शामली
Bijnor
बिजनौर
Hansi
हांसी
709A
352A
709
9
Meerut
मेरठ
Amroha
अमरोहा
Bhiwani
भिवानी
709A
Garh
Mukteshwar
गढ़मुक्तेश्वर
709
148B
709
334B
509
334D
Aligarh
अलीगढ़
Hathras
हाथरस
Mathura
मथुरा
Shahpura
शाहपुरा
248A
Agra
आगरा
48
148
NE4
21
123
21
Mehandipur
मेहंदीपुर
Dausa
दौसा

GRAPH :


NO2 Concentration vs Temperature
900,000
800,000
700,000
600,000
500,000
400,000
300,000
200,000
100,000
0
-100,000
NO2 Concentration
F M A M J J A S O N 2021 M A M J J A S O N 2022 M A M J J A S O N D
Date
NO2_column_number…
NO2_slant_column_n…
absorbing_aerosol_in…
cloud_fraction
month
sensor_altitude
sensor_azimuth_angle
sensor_zenith_angle
solar_azimuth_angle
solar_zenith_angle
stratospheric_NO2_c…
tropopause_pressure
tropospheric_NO2_co…

FOR CO(CARBON MONOXIDE) :

```
// Calculate CO concentration (in mol/m² or µg/m²) for any study area
using Time series chart Analysis (Dataset: Sentinel-5P NRTI CO)



// Note:

// CO (carbon monoxide) column number density refers to the concentration
of CO molecules present in a vertical column of the Earth's atmosphere.

// It is typically measured in units of molecules per square meter (mol/m²)
or micrograms per square meter (µg/m²).

// 1. Import countries boundaries

// 2. Import Sentinel 5P NRTI NO2

 var collection = ee.ImageCollection('COPERNICUS/S5P/NRTI/L3_CO')

.filterBounds(geometry)

.select('CO_column_number_density')

.filterDate('2021-01-01', '2021-12-31');



// 3. Set visualization parameters

var band_viz = {

min: 0,
```

```
max: 0.05,

palette: ['black', 'blue', 'purple', 'cyan', 'green', 'yellow', 'red']

};



// 4. Display & visualize the layer

Map.addLayer(collection.mean().clip(countries), band_viz, 'S5P CO');





// 5. Import sentinel-5P NRTI CO



//In this part, you define the start and end dates for the analysis.

//Then, you retrieve the Sentinel-5P NRTI CO ImageCollection, filter it
based on the specified geometry (study area),

//date range, and select the 'CO_column_number_density' band.

//Additionally, a mapping function is used to set a 'month' property on
each image to facilitate further processing.



var start_time = '2020-01-01'
```

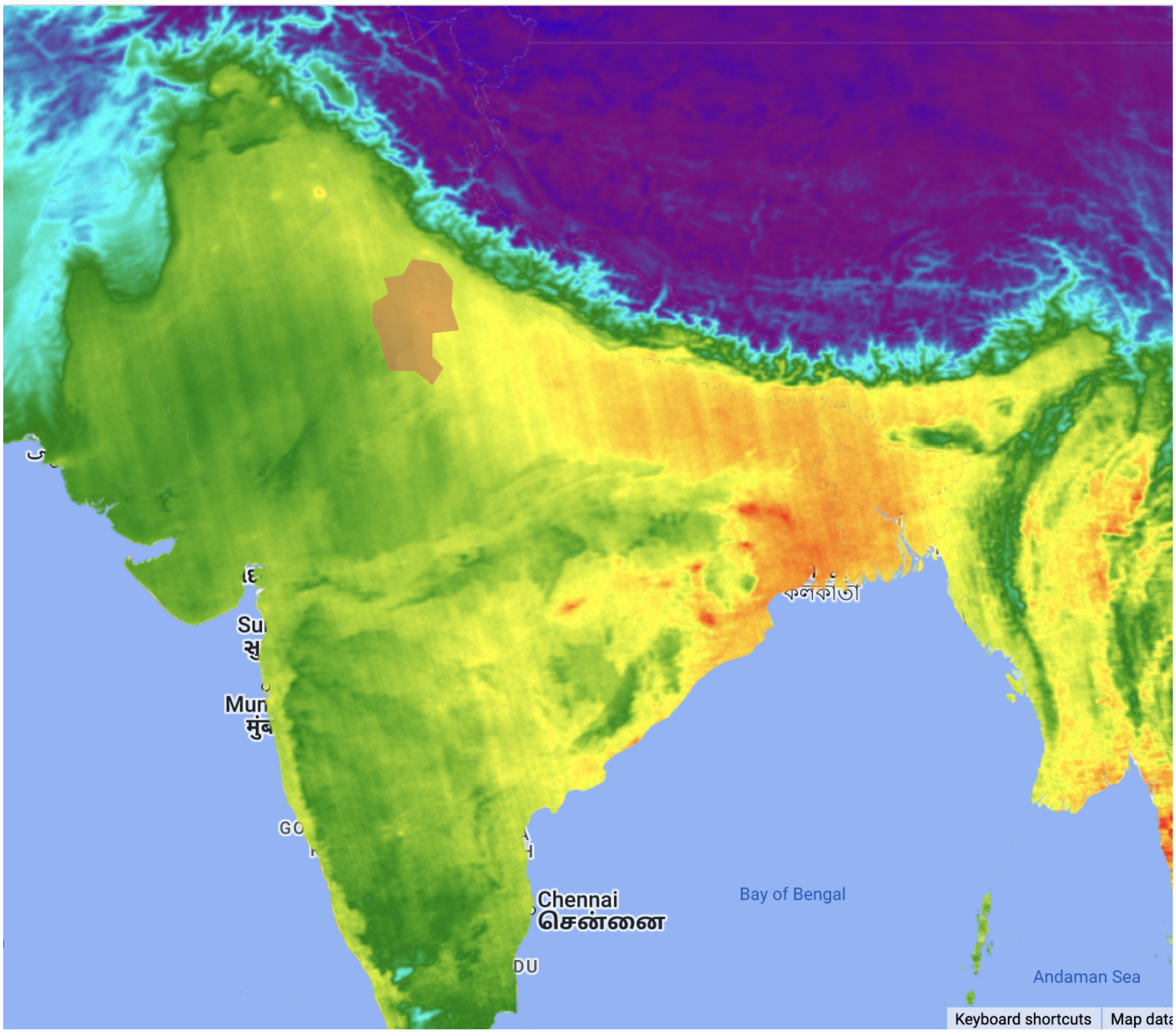
```
var end_time = '2020-12-31'



var CO_collection = ee.ImageCollection('COPERNICUS/S5P/NRTI/L3_CO')

.filterBounds(geometry)

.filterDate(start_time,end_time)

.select('CO_column_number_density')

.map(function(a){

return a.set('month', ee.Image(a).date().get('month'))

})



print(CO_collection)



// 6. Calculate the mean CO concentration for each month



//Here, you extract the distinct months present in the collection using
aggregate_array

//and distinct. Then, you map over the months and calculate the mean CO
concentration
```

```
//for each month using filterMetadata and mean. The resulting monthly mean
images
//are stored in a new ImageCollection called CO_final.


var months = ee.List(CO_collection.aggregate_array('month')).distinct()
print(months)


var CO_monthly_conc = months.map(function(x){
return CO_collection.filterMetadata('month', 'equals',
x).mean().set('month', x)
})
var CO_final = ee.ImageCollection.fromImages(CO_monthly_conc)



// 7. Create a time series chart


var chart = ui.Chart.image.series(CO_final, geometry,ee.Reducer.mean(),
5000,'month')
.setOptions({
```

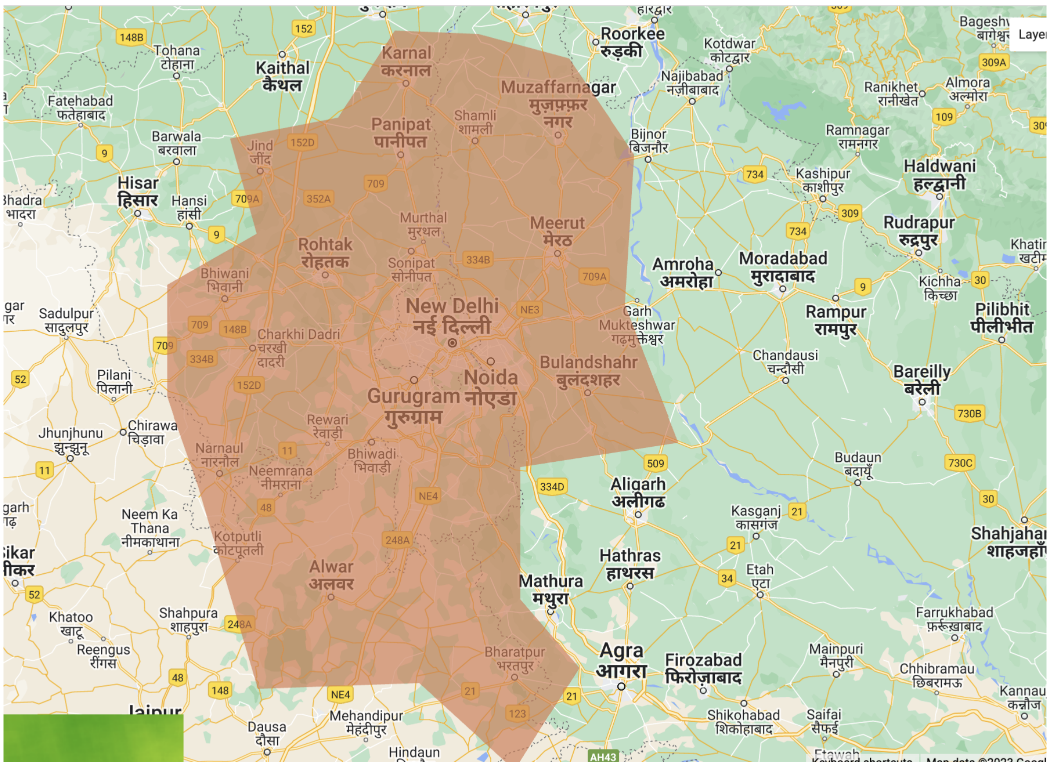
```
title: 'CO Concentration',

vAxis: {title: 'Concentration(μg/m²)'},

hAxis: {title: 'Month'}

})

print(chart)



//Finally, you create a time series chart using ui.Chart.image.series,
passing the

//CO_final ImageCollection, study area (geometry), the reducer
(ee.Reducer.mean()), a

//scale (5000), and the X-axis variable ('month'). Additional options like
the chart title and axis

//titles are specified using setOptions. The resulting chart is printed to
the console using print(chart).
```

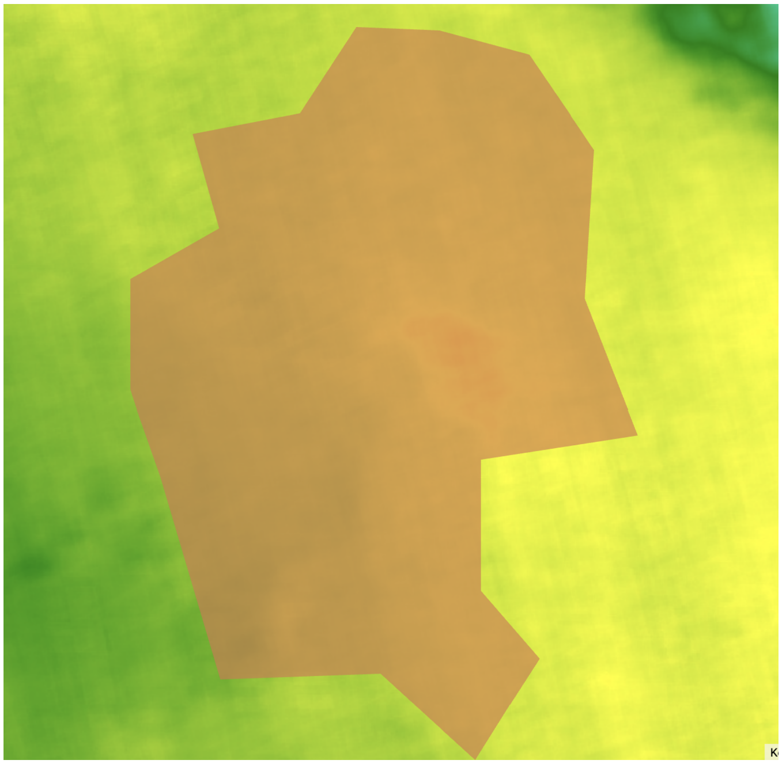
MAP FOR 2019 :

OVERALL INDIA :

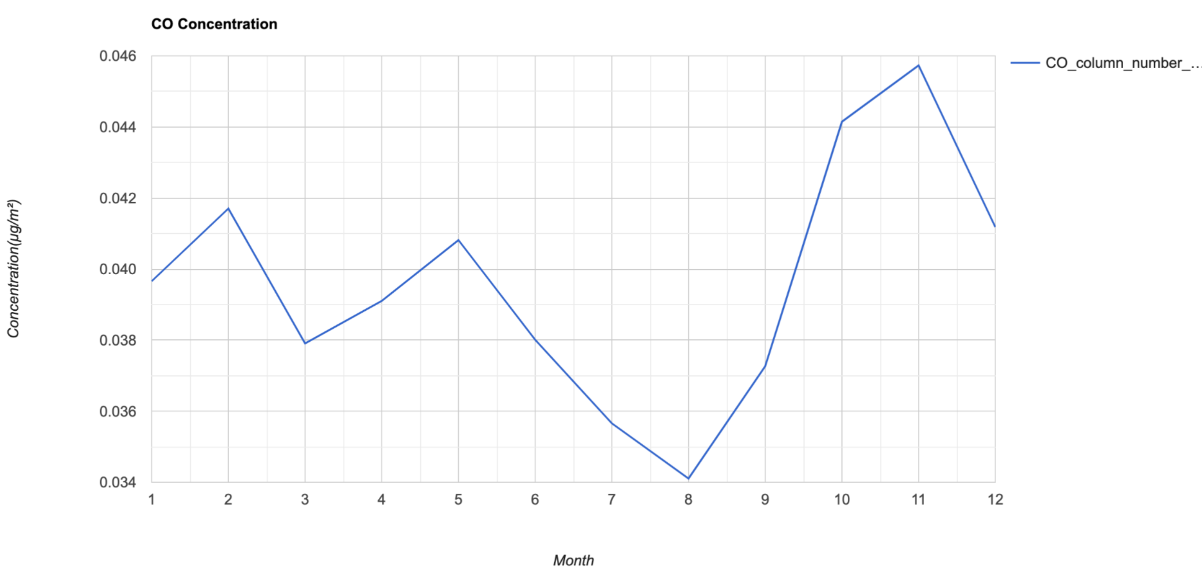


DELHI NCR :


Karnal
करनाल
Kaithal
कैथल
Tohana
टोहाना
Fatehabad
फतेहाबाद
Barwala
बरवाला
Hisar
हिसार
Hansi
हांसी
Roorkee
रुड़की
Kotdwar
कोटद्वार
Najibabad
नज़ीबाबाद
Muzaffarnagar
मुज़फ़्फ़रनगर
Shamli
शामली
Panipat
पानीपत
Jind
जींद
Bijnor
बिजनौर
Ranikhet
रानीखेत
Almora
अल्मोरा
Ramnagar
रामनगर
Haldwani
हल्द्वानी
Kashipur
काशीपुर
Rudrapur
रुद्रपुर
Murthal
मुरथल
Rohtak
रोहतक
Meerut
मेरठ
Sonipat
सोनीपत
Bhiwani
भिवानी
Amroha
अमरोहा
Moradabad
मुरादाबाद
Kichha
किच्छा
Rampur
रामपुर
Pilibhit
पीलीभीत
New Delhi
नई दिल्ली
Sadulpur
सादुलपुर
Charkhi Dadri
चरखी दादरी
Garh Mukteshwar
गढ़मुक्तेश्वर
Chandausi
चन्दौसी
Bulandshahr
बुलंदशहर
Noida
नोएडा
Gurugram
गुरुग्राम
Pilani
पिलानी
Bareilly
बरेली
Jhunjhunu
झुंझुनू
Chirawa
चिड़ावा
Rewari
रेवाड़ी
Narnaul
नारनौल
Bhiwadi
भिवाड़ी
Neemrana
नीमराना
Budaun
बदायूँ
Aligarh
अलीगढ
Neem Ka Thana
नीमकाथाना
Kasganj
कासगंज
Kotputli
कोटपूतली
Alwar
अलवर
Hathras
हाथरस
Mathura
मथुरा
Etah
एटा
Farrukhabad
फ़र्रुख़ाबाद
Khatoo
खाटू
Shahpura
शाहपुरा
Reengus
रींगस
Bharatpur
भरतपुर
Agra
आगरा
Firozabad
फ़िरोज़ाबाद
Mainpuri
मैनपुरी
Chhibramau
छिबरामऊ
Dausa
दौसा
Mehandipur
मेहंदीपुर
Hindaun
Shikohabad
शिकोहाबाद
Saifai
सैफई

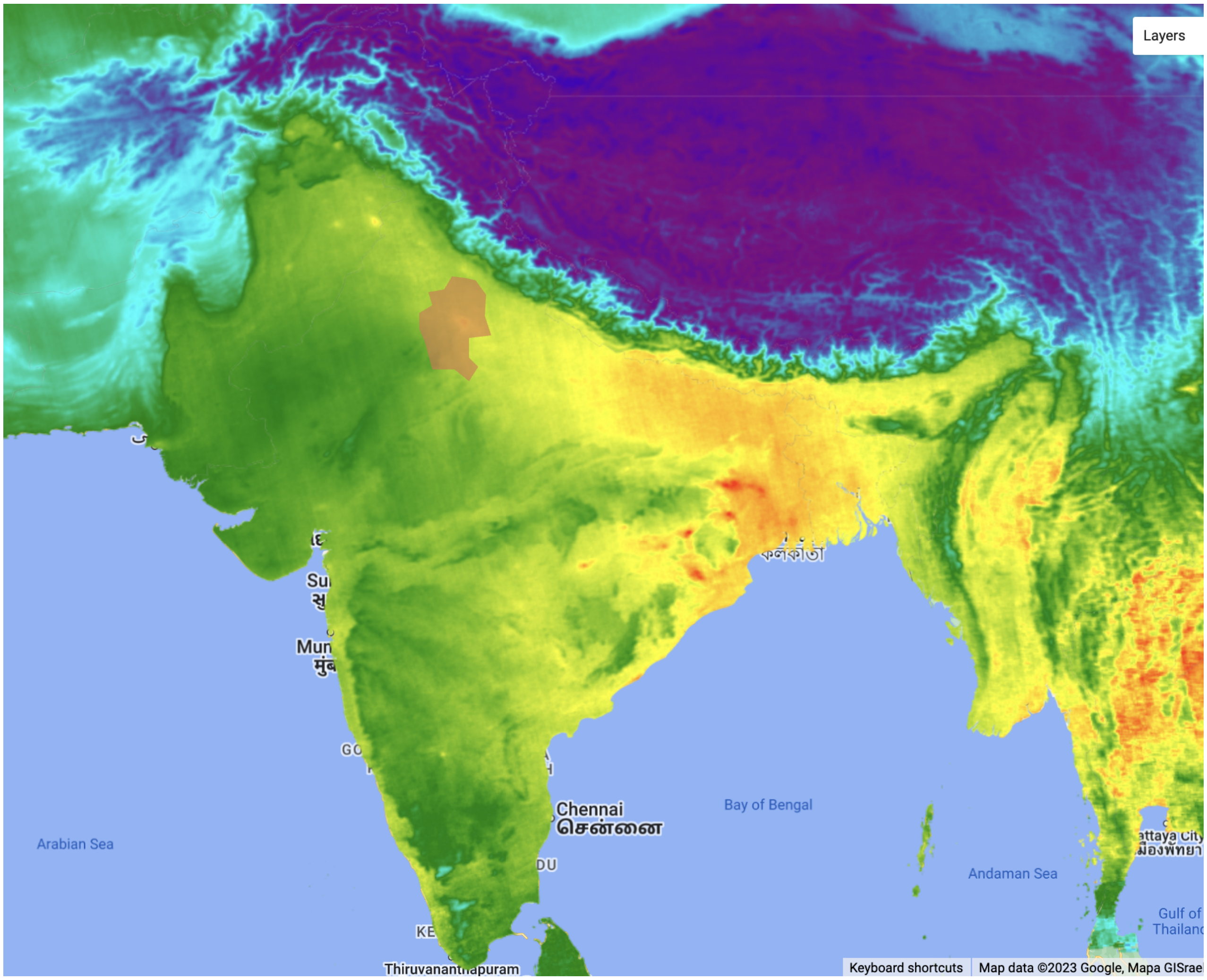


GRAPH :

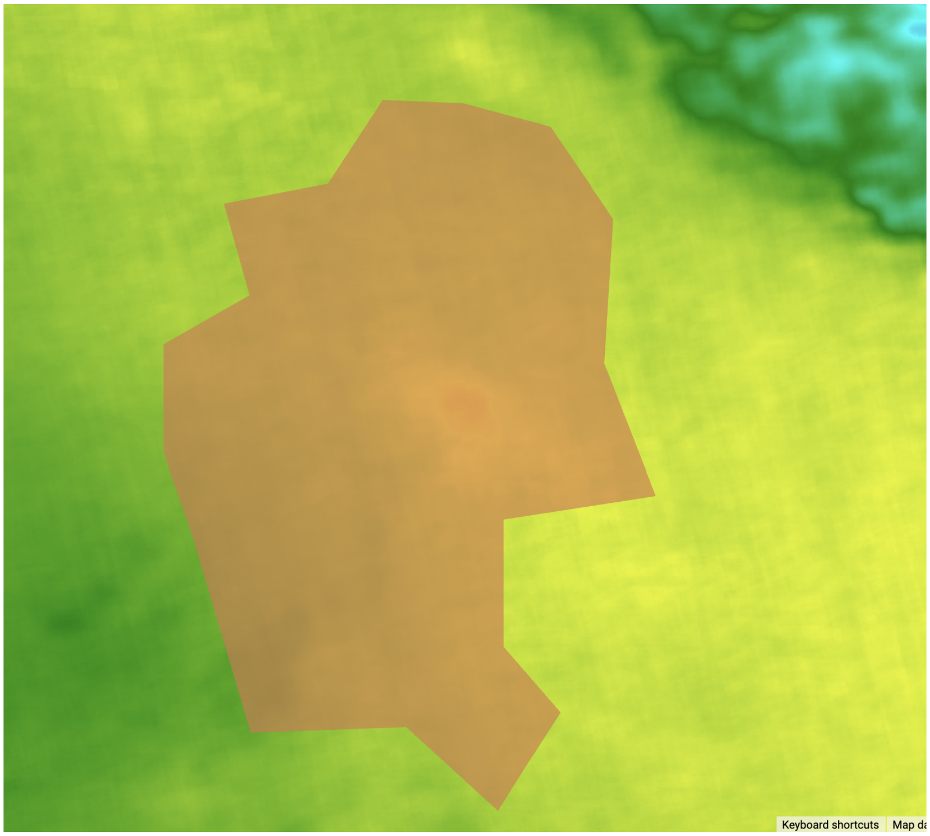

CO Concentration
Concentration(μg/m²)
0.046
0.044
0.042
0.040
0.038
0.036
0.034
1
2
3
4
5
6
7
8
9
10
11
12
Month
CO_column_number_...

MAP FOR 2020 :

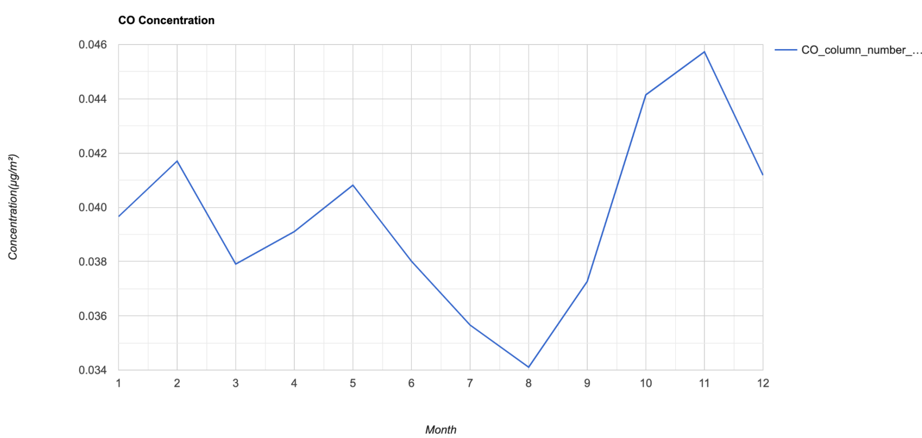
OVERALL INDIA :



DELHI NCR :

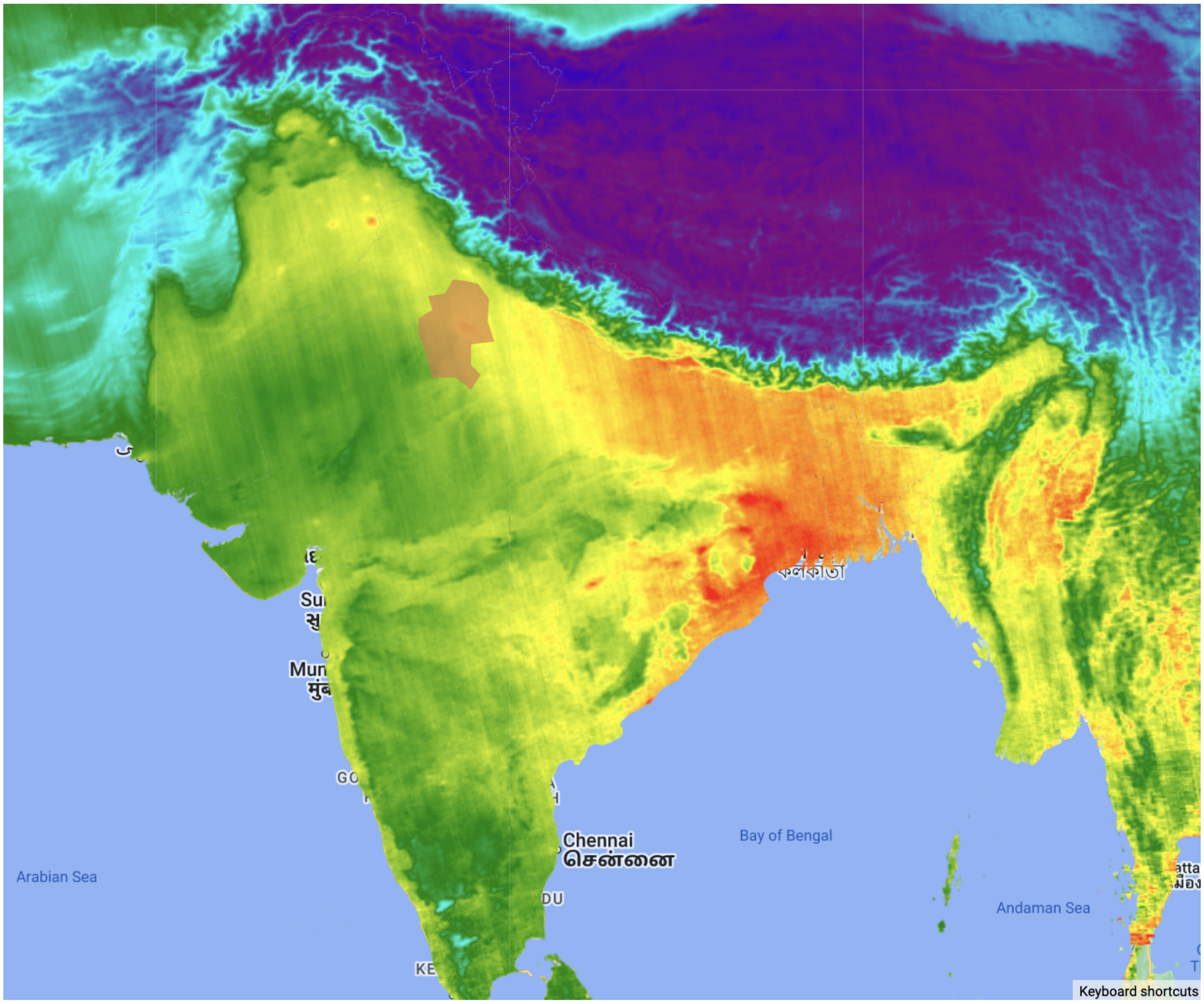


GRAPH :

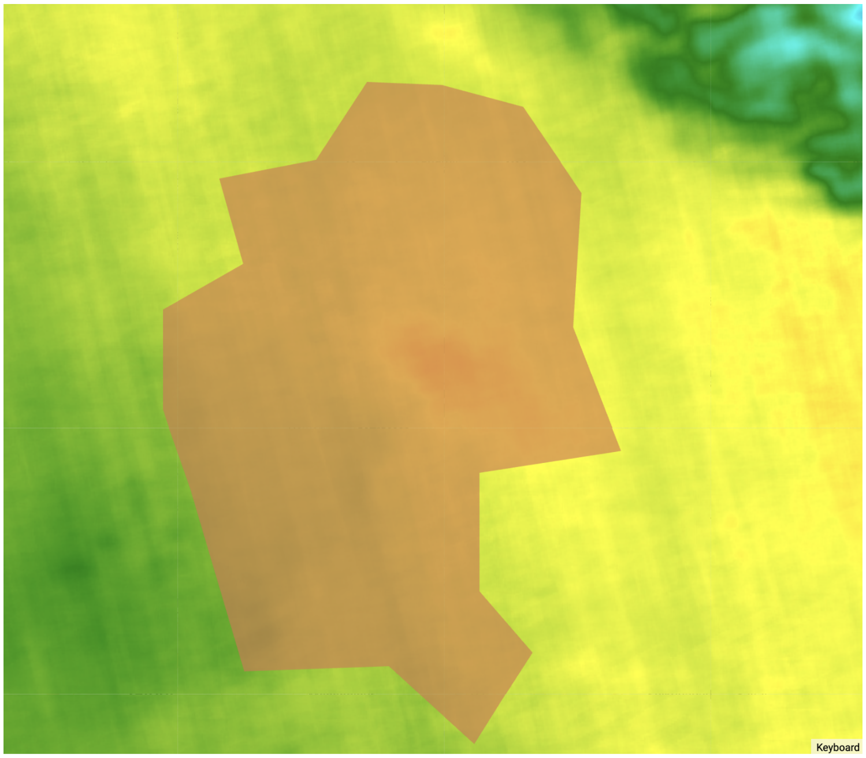


MAP FOR 2021 :

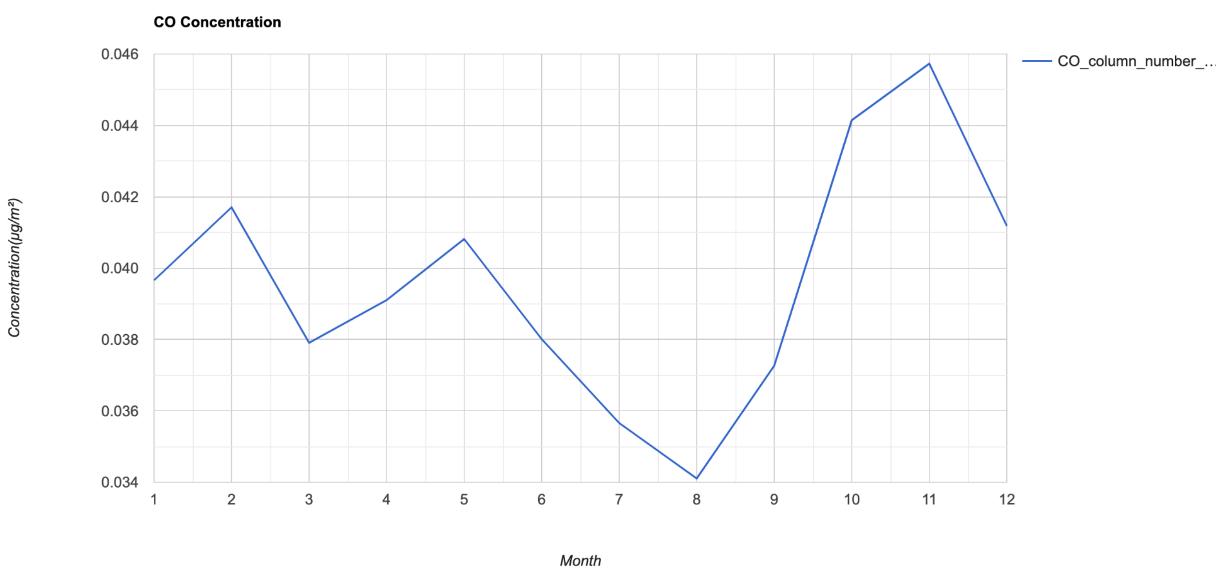
OVERALL INDIA :



DELHI NCR :



GRAPH :



FOR NO2(NITROGEN DIOXIDE) :

```
// Define the time frame

var startDate = '2019-01-01';

var endDate = '2019-12-31';



// Load Sentinel-5P data for nitrogen dioxide (NO2)

var collection = ee.ImageCollection('COPERNICUS/S5P/NRTI/L3_NO2')

 .select('tropospheric_NO2_column_number_density')

 .filterBounds(delhiNCR)

 .filterDate(startDate, endDate);




// Function to mask clouds and aerosols

function maskClouds(image) {

 var cloudMask = image.select('tropospheric_NO2_column_number_density');

 var mask = cloudMask.lte(0.1); // Example threshold for cloud masking

 return image.updateMask(mask);
```

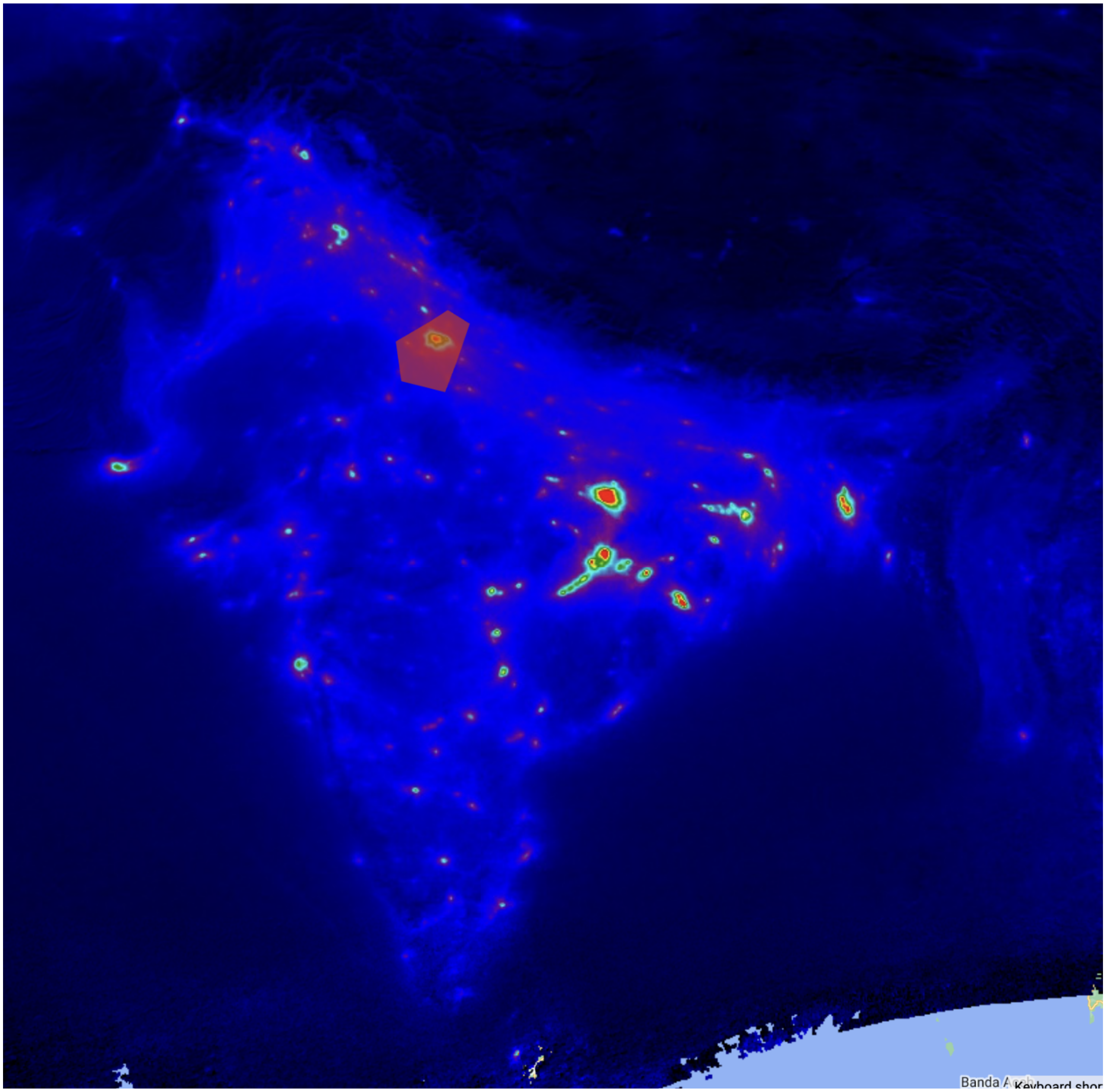
```
}



// Apply cloud masking to the collection

var filteredCollection = collection.map(maskClouds);



// Display the map of NO2 concentration

var no2Vis = {

 min: 0,

 max: 0.0002,

 palette: ['black', 'blue', 'purple', 'cyan', 'green', 'yellow', 'red']

};

Map.addLayer(filteredCollection.mean(), no2Vis,
'tropospheric_NO2_column_number_density');



// Function to calculate mean NO2 concentration (tropospheric) per image

function calculateMean(image) {

 var mean = image.reduceRegion({

   reducer: ee.Reducer.mean(),
```

```
  geometry: delhiNCR,

  scale: 1000

 });

 return image.set('date', image.date().format('YYYY-MM-dd')).set('mean',
mean.get('tropospheric_NO2_column_number_density'));

}



// Map the mean NO2 concentration over time

var timeSeries = filteredCollection.map(calculateMean);



// Chart the time series data

var chart = ui.Chart.image.seriesByRegion({

 imageCollection: timeSeries,

 regions: delhiNCR,

 reducer: ee.Reducer.mean(),

 scale: 1000,

 xProperty: 'date',

 seriesProperty: 'mean'
```

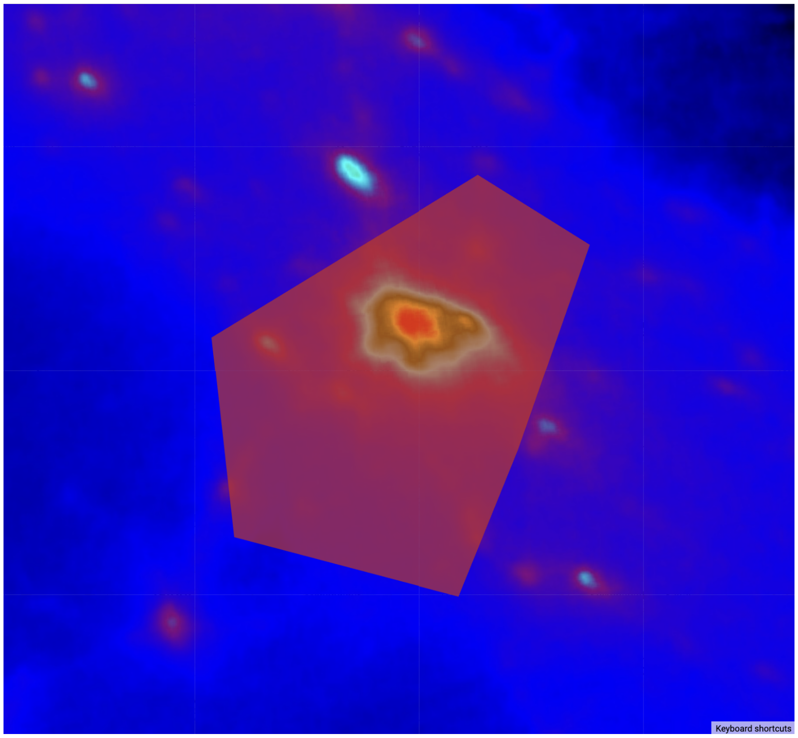
```
}).setOptions({

 title: 'Mean NO2 Concentration Over Time',

 hAxis: {title: 'Date'},

 vAxis: {title: 'NO2 Concentration (mol/m²)'}

});



// Display the chart

print(chart);
```

MAP FOR 2019 :

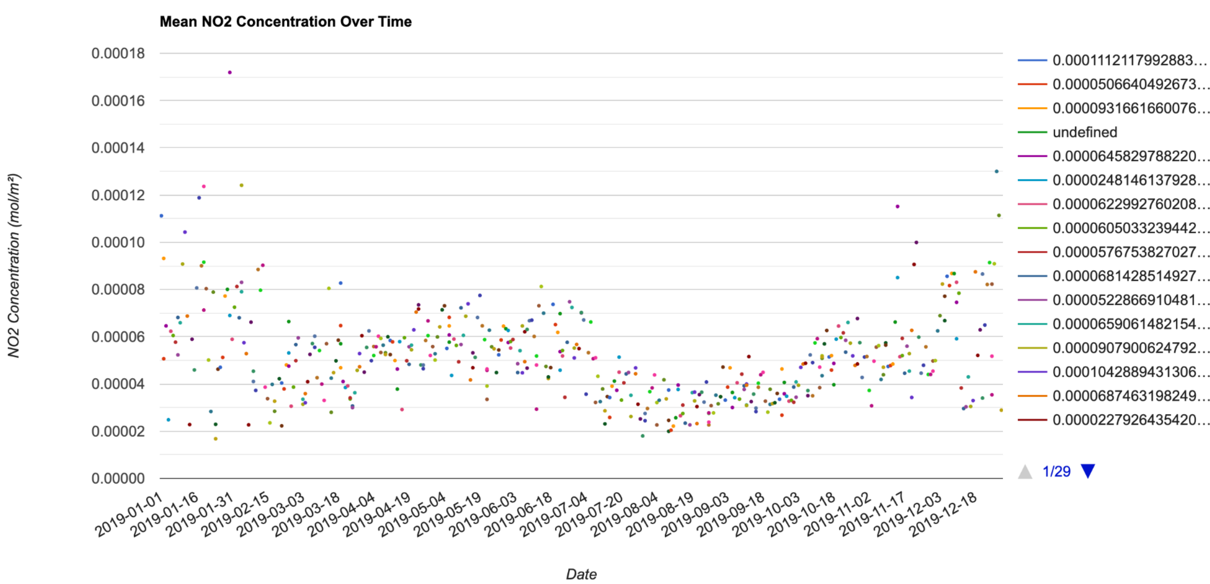
INDIA :



DELHI NCR :

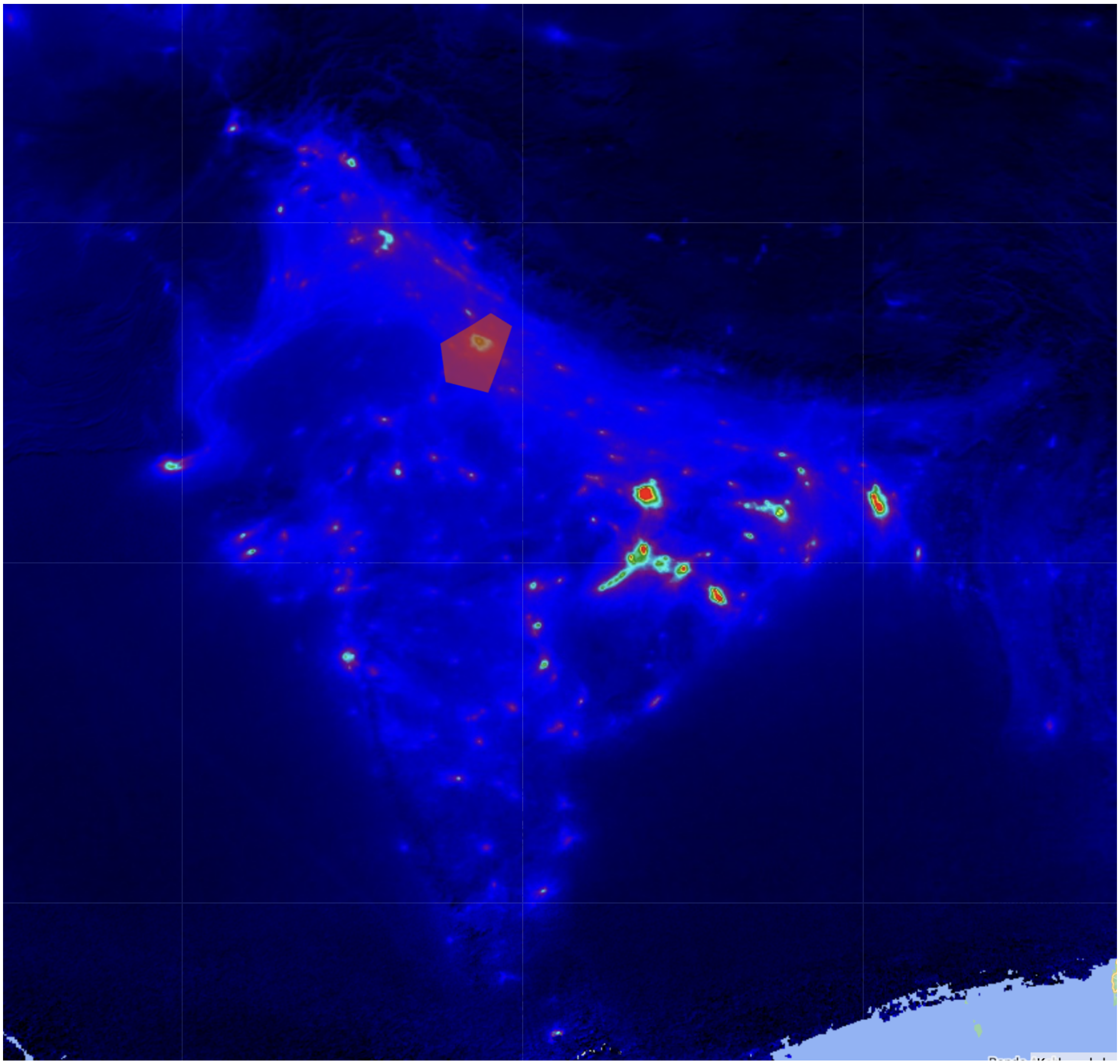


GRAPH :

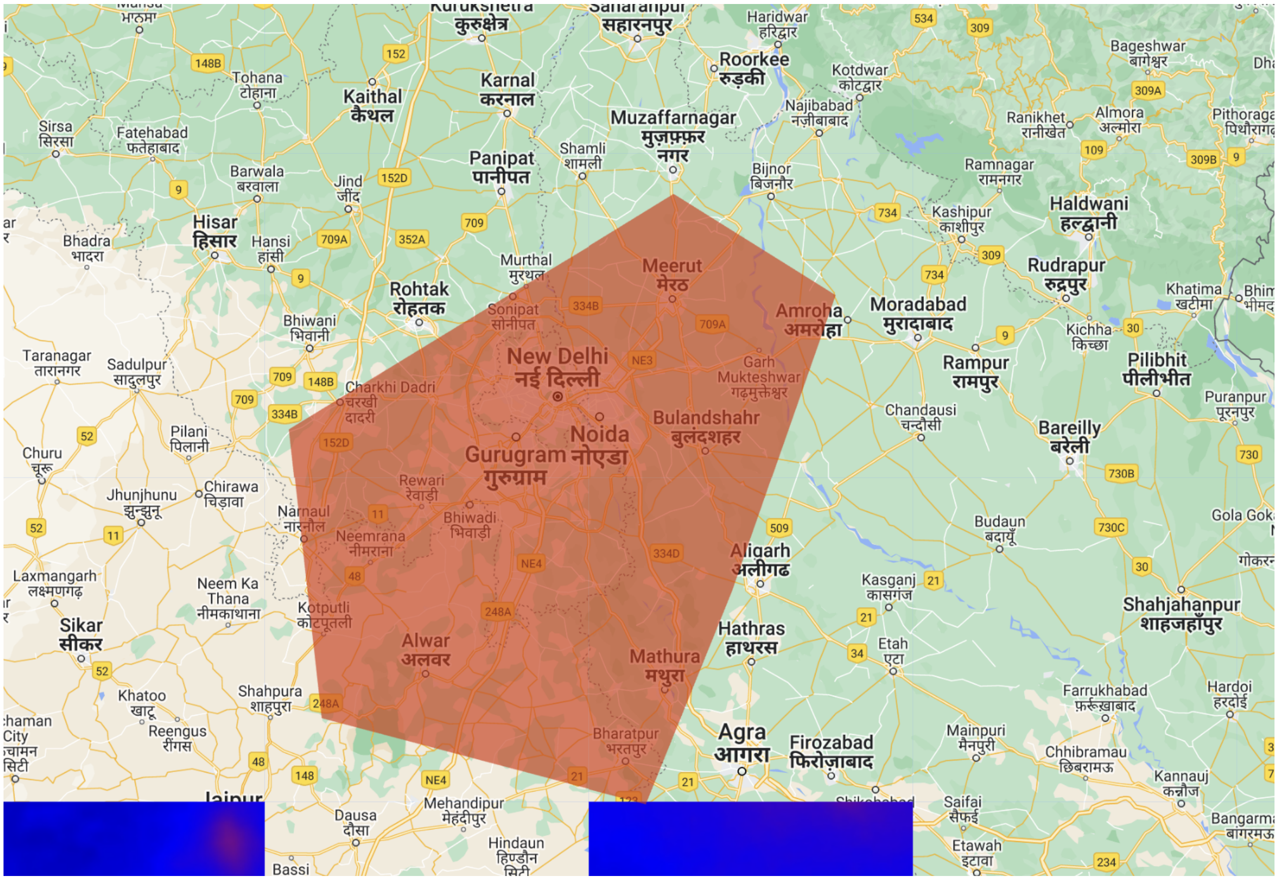


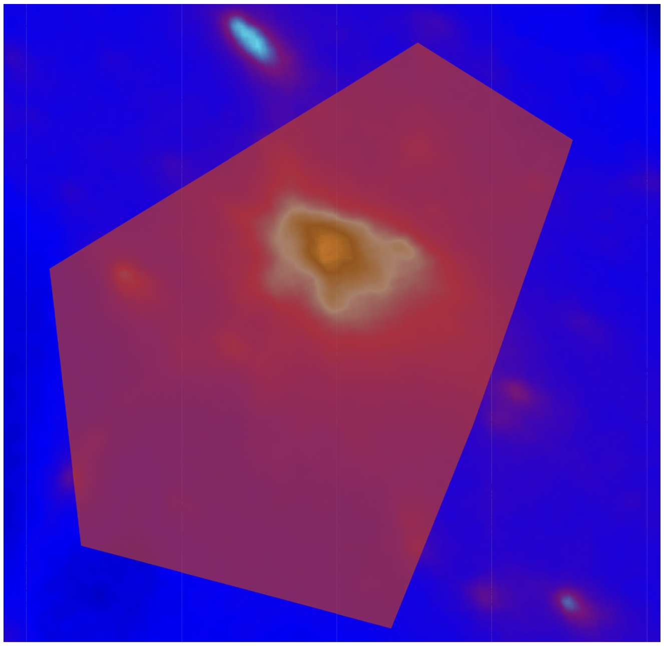
MAP FOR 2020 :

INDIA :

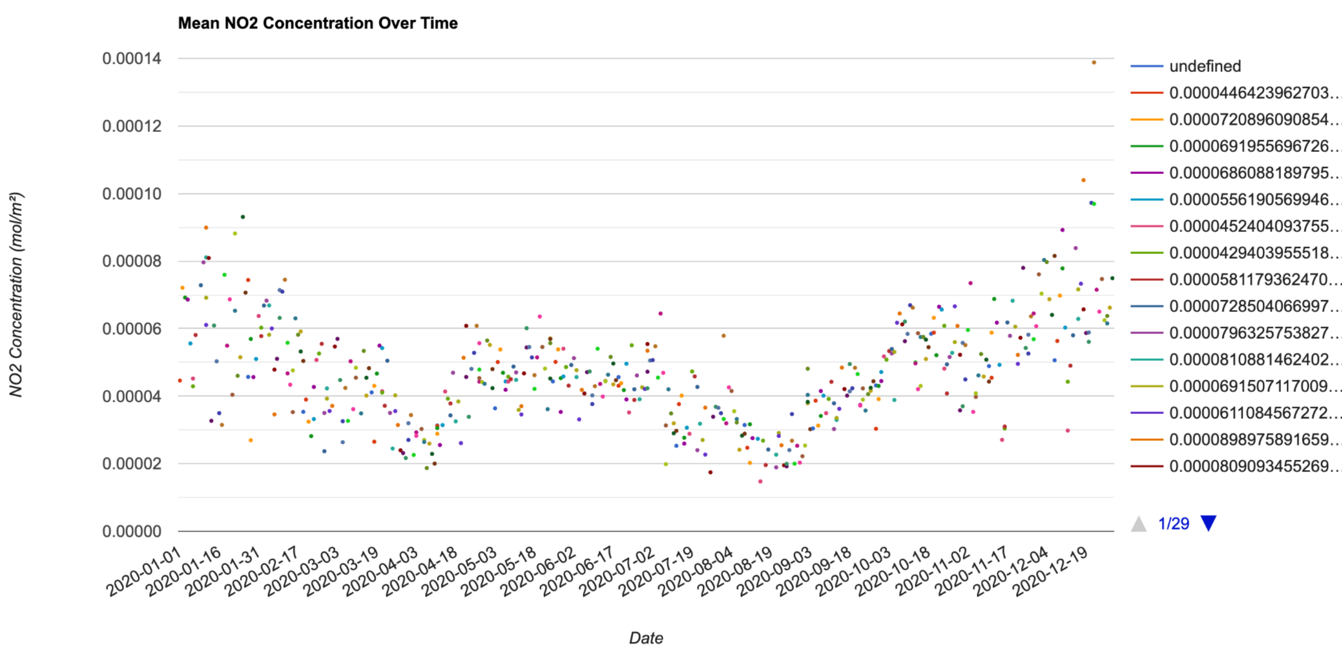


DELHI NCR :


Kurukshetra
कुरुक्षेत्र
Saharanpur
सहारनपुर
Haridwar
हरिद्वार
Roorkee
रुड़की
Kotdwar
कोटद्वार
Bageshwar
बागेश्वर
Tohana
टोहाना
Kaithal
कैथल
Karnal
करनाल
Najibabad
नज़ीबाबाद
Ranikhet
रानीखेत
Almora
अल्मोरा
Pithoragarh
Sirsa
सिरसा
Fatehabad
फतेहाबाद
Muzaffarnagar
मुज़फ़्फ़र
नगर
Shamli
शामली
Panipat
पानीपत
Barwala
बरवाला
Jind
जींद
Bijnor
बिजनौर
Ramnagar
रामनगर
Haldwani
हल्द्वानी
Hisar
हिसार
Hansi
हांसी
Bhadra
भादरा
Kashipur
काशीपुर
Murthal
मुरथल
Meerut
मेरठ
Rudrapur
रुद्रपुर
Rohtak
रोहतक
Sonipat
सोनीपत
Amroha
अमरोहा
Moradabad
मुरादाबाद
Khatima
खटीमा
Bhiwani
भिवानी
Kichha
किच्छा
Taranagar
तारानगर
Sadulpur
सादुलपुर
New Delhi
नई दिल्ली
Garh
Mukteshwar
गढ़मुक्तेश्वर
Rampur
रामपुर
Pilibhit
पीलीभीत
Charkhi Dadri
चरखी
दादरी
Puranpur
पूरनपुर
Pilani
पिलानी
Noida
नोएडा
Bulandshahr
बुलंदशहर
Chandausi
चन्दौसी
Bareilly
बरेली
Churu
चूरू
Gurugram
गुरुग्राम
Rewari
रेवाड़ी
Chirawa
चिड़ावा
Jhunjhunu
झुन्झुनू
Narnaul
नारनौल
Bhiwadi
भिवाड़ी
Neemrana
नीमराना
Budaun
बदायूँ
Gola Gokarannath
Aligarh
अलीगढ
Laxmangarh
लक्ष्मणगढ़
Neem Ka
Thana
नीमकाथाना
Kasganj
कासगंज
Shahjahanpur
शाहजहाँपुर
Kotputli
कोटपूतली
Sikar
सीकर
Alwar
अलवर
Hathras
हाथरस
Etah
एटा
Mathura
मथुरा
Khatoo
खाटू
Shahpura
शाहपुरा
Farrukhabad
फ़र्रुखाबाद
Hardoi
हरदोई
Chaman
City
Reengus
रींगस
Agra
आगरा
Firozabad
फ़िरोज़ाबाद
Mainpuri
मैनपुरी
Bharatpur
भरतपुर
Chhibramau
छिबरामऊ
Kannauj
कन्नौज
Mehandipur
मेहंदीपुर
Saifai
सैफई
Dausa
दौसा
Bangarmau
बांगरमऊ
Hindaun
हिण्डौन
Etawah
इटावा
Bassi



GRAPH :


Mean NO2 Concentration Over Time
0.00014
0.00012
0.00010
0.00008
0.00006
0.00004
0.00002
0.00000
NO2 Concentration (mol/m²)
2020-01-01
2020-01-16
2020-01-31
2020-02-17
2020-03-03
2020-03-19
2020-04-03
2020-04-18
2020-05-03
2020-05-18
2020-06-02
2020-06-17
2020-07-02
2020-07-19
2020-08-04
2020-08-19
2020-09-03
2020-09-18
2020-10-03
2020-10-18
2020-11-02
2020-11-17
2020-12-04
2020-12-19
Date
undefined
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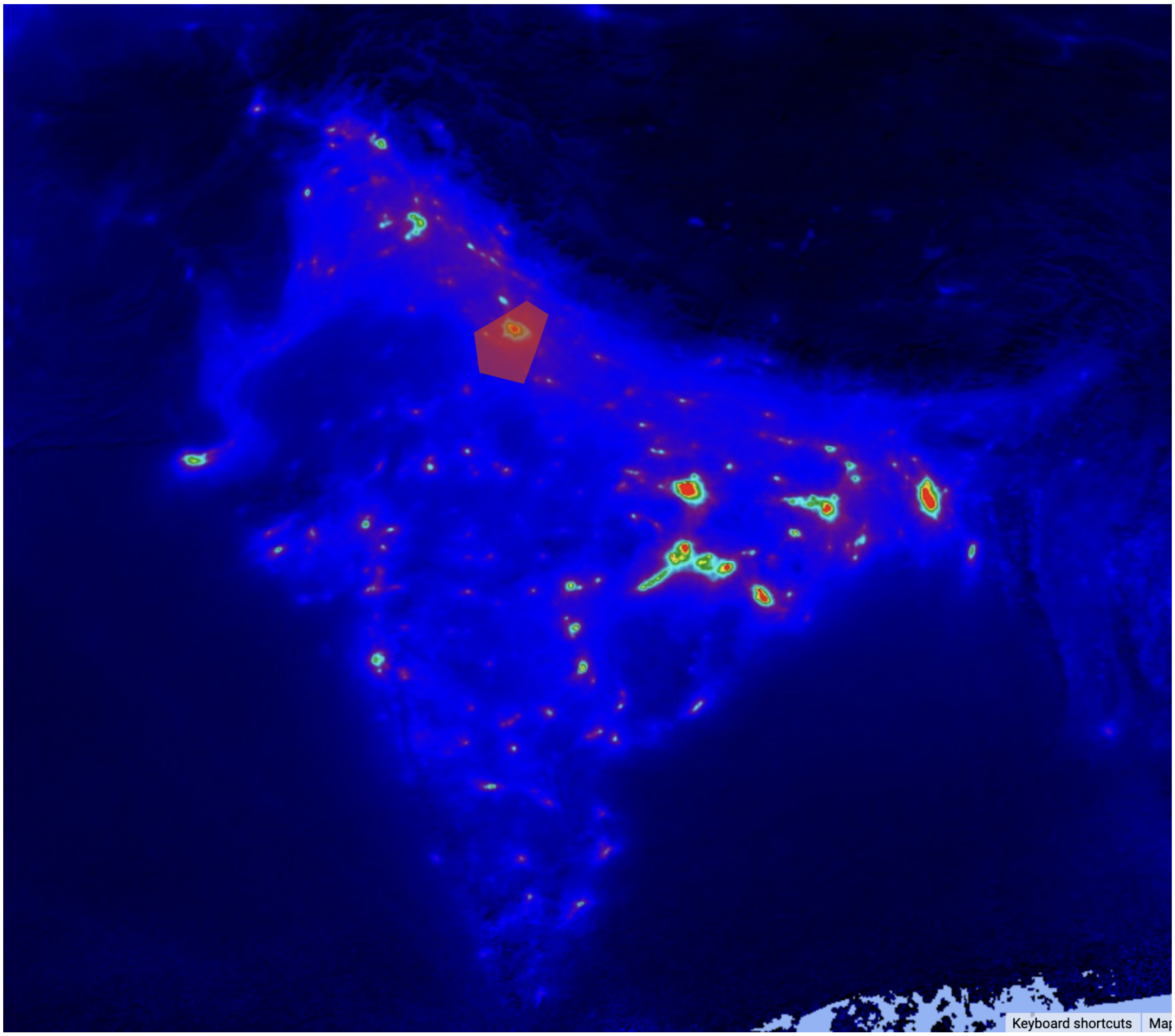
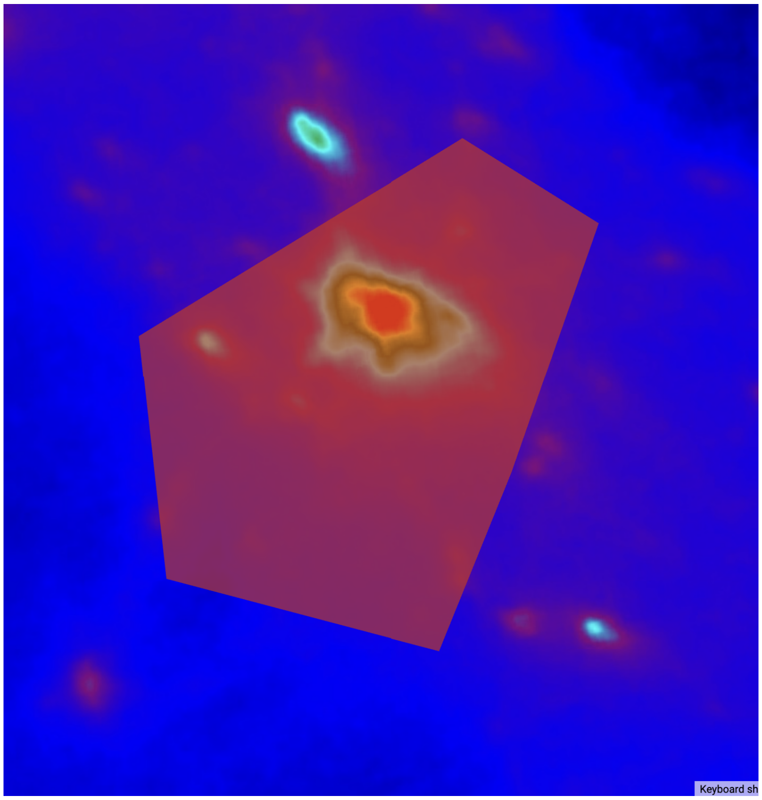
0.0000809093455269…
1/29

MAP FOR 2021 :

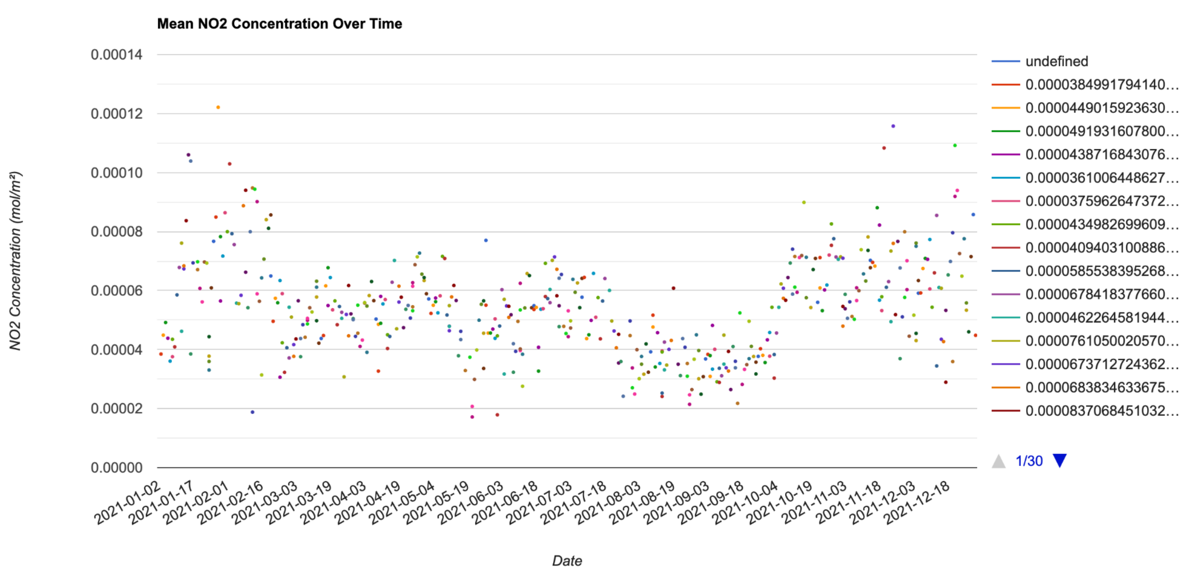
INDIA :



DELHI NCR :



GRAPH :



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