Comprehensive Assessment of Air Quality Dynamics Around Yosemite National Park Using Remote Sensing, GIS, and Computational Analysis During Wildfire Events

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In recent years, Mariposa County has experienced several significant wildfires, including the catastrophic Rim Fire of 2013. On July 22, 2022, Yosemite National Park faced one of its most devastating wildfires, profoundly affecting Aerosol Optical Depth (AOD) and overall air quality. This study employs an integrated approach using remote sensing, GIS, and advanced computational tools to investigate the impact of these wildfires on air quality, focusing specifically on aerosol pollution dynamics and key atmospheric pollutants. The research leverages satellite data from TROPOMI, MODIS AQUA, and Suomi NPP/VIIRS, along with meteorological inputs from GDAS. Data processing and analysis were performed using Python, MATLAB, and R, with spatial mapping and visualization achieved through ArcMap and Google Earth Engine. The study utilized the MODIS MAIAC algorithm to conduct a detailed examination of AOD fluctuations in the Yosemite region, spanning from July 21 to August 1, 2022. Our comprehensive analysis reveals significant temporal and spatial variations in aerosol pollution during the wildfire. Initial findings indicate a marked increase in AOD with the onset of the wildfire, reflecting severe impacts on atmospheric composition. Pre-fire AOD levels were relatively low at 0.12, but surged to 0.20 at the wildfire's peak, demonstrating a substantial rise in atmospheric aerosol loading. The average AOD throughout the study period was recorded at 0.16, highlighting the wildfire's prolonged effect on air quality. Furthermore, the study identifies elevated concentrations of key pollutants, including NO_2, SO_2, CO, HCHO, and O_3, during the wildfire event. The integration of data from various satellite sources and the application of machine learning models provided a more nuanced understanding of pollution patterns. The HYSPLIT model was also employed to track the distribution of air masses and contaminants, revealing significant northwestward transport. This research advances our understanding of the intricate relationships between wildfires, aerosol pollution, and air quality in Yosemite National Park. The findings offer critical insights for public health preparedness, the development of resilience strategies against wildfires, and the formulation of effective mitigation measures in fire-prone regions like Yosemite.

Keywords: Air pollution, Wildfire, AOD, Yosemite National Park.

Introduction:

Scientific research on air pollution has increasingly focused on the One Health paradigm, which examines the interconnectedness between human health, animal health, and the environment. This paradigm explores the interconnectedness between the well-being of individuals, animals, and the natural surroundings. Furthermore, it provides a novel avenue for investigating complex disorders by examining the correlations between environmental factors, such as pollution [1]. Satellite and climate reanalysis data offer a comprehensive perspective on atmospheric conditions, which scientists are increasingly relying on to address the intricate issues associated with air quality. This data is extremely helpful for assessing the dispersion and density of pollutants, especially in locations where on-site monitoring is insufficient. However, it also has some significant disadvantages [2]. When comparing air quality measurements obtained at the Earth's surface with those collected by satellites, there is a clear difference [3]. The macroscopic image captured from the space perspective may not accurately depict the subtle variations in pollution levels experienced at ground level. This difference between satellite and ground-based observations raises doubts about the accuracy and appropriateness of satellite data for air quality monitoring.

The European Earth Observation Program Copernicus' Sentinel-5P is specifically dedicated to the detection of pollution. The inaugural Copernicus mission dedicated to the surveillance of Earth's atmosphere, known as the Copernicus Sentinel-5 Precursor mission, was successfully launched on October 13, 2017. The Sentinel-5P missions utilize the TROPOspheric Monitoring Instrument (TROPOMI) spectrometer to detect significant atmospheric components at the troposphere level, such as aerosols, clouds, ozone (O3), nitrogen dioxide (NO2), carbon monoxide (CO), sulfur dioxide (SO2), methane (CH4), and water vapor (H2O) [4]. Unlike ground measurements, which are reported in units of micrograms per cubic meter (µg/m3), Sentinel-5P data have a spatial resolution ranging from 1.1 to 5 kilometers and indicate column concentrations, which are stated in units of moles per square meter (mol/m2). In addition, certain elements that are not readily apparent in satellite imaging, including as traffic patterns, the presence of industrial activities, and the topographical features of the region, have an impact on the concentration of individual pollutants on the surface [5]. A more accurate model for calculating surface level concentrations can be constructed by integrating Sentinel-5P data with ERA5, which is a comprehensive atmospheric reanalysis of the entire climate. Specialized government entities frequently conduct surface-level air quality monitoring. The responsibility of environmental monitoring in Italy lies with the Regional Environmental Protection Agency (ARPA) [6]. Italy has a network of several hundred ARPA monitoring stations that are strategically located to undertake hourly monitoring of various air pollutants, including PM2.5. The main concern regarding these monitoring stations is the insufficient coverage across the entirety of Italy.

Wildfires are natural phenomena that play a crucial role in the formation of ecosystems. However, they can also cause severe damage to the environment, economy, and public health. Internationally, the distribution of land usage, methods of managing forests, and the phenomenon of climate change have collectively had a role in the escalation of both the frequency and intensity of wildfires in recent times [7]. The occurrence of these fires leads to the emission of significant quantities of pollutants into the atmosphere, resulting in a severe deterioration of air quality and posing a grave threat to the health of nearby communities and ecosystems [8]. Yosemite National Park, situated in California and celebrated for its pristine natural surroundings, is experiencing the consequences of a growing number of wildfires. Yosemite National Park has had several notable fires, with the most notable being the Rim Fire in 2013. This wildfire burned more than 250,000 acres and was one of the largest wildfires ever recorded in California history [9]. The fires have enduring effects on the quality of the air, the health of the environment, and the diversity of species, both within and beyond the park. These effects extend beyond the immediate risks to the safety of visitors and the infrastructure of the park. Environmental scientists, property managers, and public health officials are growing more alarmed about the degradation of air quality resulting from smoke emitted by wildfires. Wildfire smoke contains contaminants such as Particulate Matter (PM), Carbon Monoxide (CO), Volatile Organic Compounds (VOCs), and Nitrogen Oxides (NOx). These pollutants can significantly impact respiratory and cardiovascular health in a detrimental manner [10].

Geographic Information System (GIS) technology is an essential tool for monitoring and assessing the impact of wildfires on air quality, thanks to its robust spatial analysis and data visualization capabilities [11]. GIS enables the integration of data from diverse sources, including satellite imaging, ground-based monitoring stations, and meteorological observations, to construct spatial models of pollution dispersion [12]. Satellite sensors in remote sensing techniques offer the benefit of rapidly acquiring extensive data regarding the magnitude of wildfires, movement of smoke plumes, and levels of pollutants over vast regions [13].

Objectives of the Study:

This study aims to fill existing gaps in the understanding of air quality dynamics during wildfire events in Yosemite National Park. The specific research objectives are to:

- Investigate the Intensity and Spatial Distribution of Air Pollutants: Analyze the concentration and distribution of key pollutants during wildfire episodes to understand the immediate air quality impacts on Yosemite National Park and its surroundings.
- Assess the Long-Term Impacts of Wildfires: Examine the lasting effects of wildfires on air quality, ecosystem health, and vegetation dynamics within the park to provide insights into the broader ecological consequences.
- Identify Atmospheric Processes Driving Air Pollution Patterns: Explore the atmospheric processes and conditions that influence pollutant dispersion and accumulation during wildfire events, offering a deeper understanding of how wildfires impact air quality.

Area of Study:

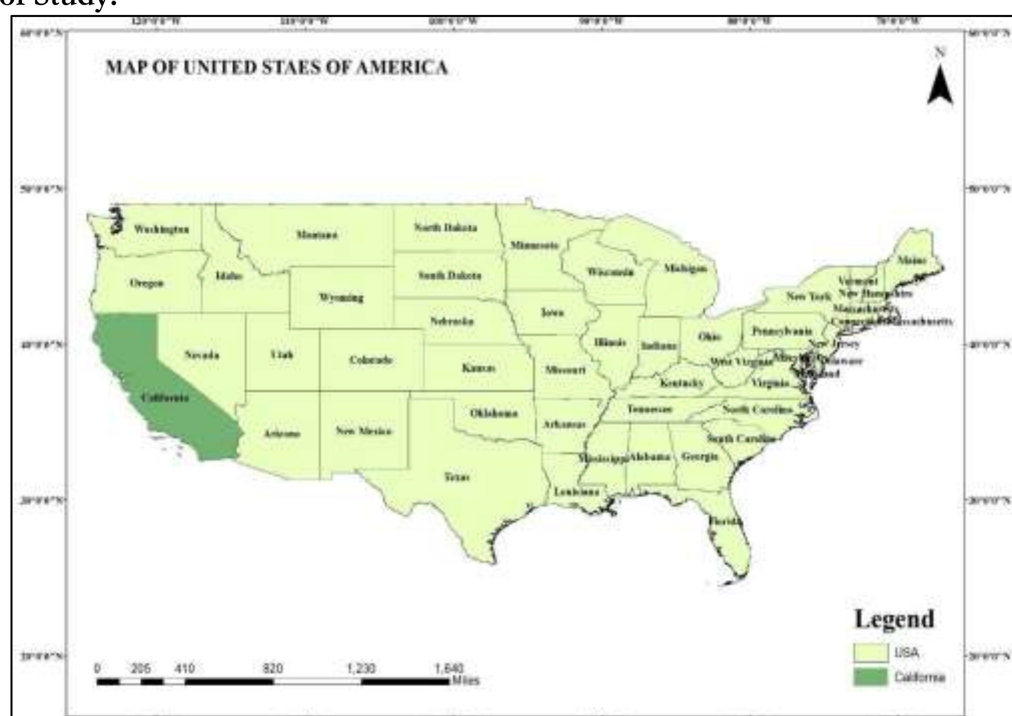

Figure 1: Study Area Map of Yosemite Region

The study is focused on Yosemite National Park and its surrounding regions, located in the Sierra Nevada Mountains of California, United States. Yosemite lies between 36° and 42° N latitude and 26° and 45° E longitude, with an annual visitation of 3,667,550 recorded in 2022. The study area encompasses both the park boundaries and the adjacent regions, which have a significant influence on Yosemite's air quality. As a major tourist destination with considerable ecological value, Yosemite represents a critical site for studying the effects of air pollution on park ecosystems and visitor experiences.

Yosemite has a long history of forest fires, many of which have had profound ecological and environmental impacts. Recent large-scale wildfires have disrupted tourism activities, leading to the closure of entrance stations and road corridors for public safety and emergency response. High-severity fires and the resulting smoke have occasionally necessitated park-wide closures, significantly affecting visitor access [14]. Understanding the dynamics of forest fires in Yosemite offers valuable insights into fire regimes, behavior, and ecosystem responses. This research also extends to the surrounding areas, including Mariposa County, Tuolumne County, and Madera County, all of which have experienced significant wildfires that impacted Yosemite. By analyzing historical fires and their effects on park ecosystems, this study aims to identify contributing factors and develop comprehensive fire management strategies for this ecologically significant region.

Methodological Framework:

Data Collection:

This study leverages remote sensing, Geographic Information System (GIS) technologies, and advanced computational tools to assess air quality around the Yosemite region during wildfire events. The integration of satellite-derived datasets, GIS-based analysis, and computer-aided processing forms the foundation of the methodological approach.

Map Construction:

The creation of spatial maps was achieved using ArcMap 10.3 from the ArcGIS Software suite, a widely recognized GIS platform. Additionally, Google Earth Engine (GEE), a cloud-based platform for planetary-scale environmental data analysis, was employed for map computation and integration with ArcMap. GEE's powerful computational capabilities allowed for the efficient processing of large satellite datasets, facilitating the creation of high-resolution maps and the extraction of relevant environmental data.

MAIAC AOD (Multi-Angle Implementation of Atmospheric Correction):

To obtain a high-resolution Aerosol Optical Depth (AOD) dataset, the study employed the MAIAC technique, which is based on the MODIS (Moderate Resolution Imaging Spectroradiometer) algorithm. The AOD data were derived from the Terra and Aqua satellites, utilizing MODIS sensors that capture data across 36 spectral bands, with seven bands specifically designed for aerosol retrieval. These bands cover wavelengths ranging from 0.47 to 2.13 µm. The dataset used in this study spans from July 21 to August 1, 2022, with a spatial resolution of 1 km. The data processing involved cloud masking, atmospheric correction, and calibration techniques, which were executed using Python scripts in conjunction with GEE.

TROPOMI Sentinel-5P:

The study also incorporated data from the Sentinel-5 Precursor satellite, equipped with the TROPOMI (Tropospheric Monitoring Instrument) sensor, launched by the European Space Agency on October 13, 2017. The TROPOMI sensor provides high-resolution air quality data, including measurements of tropospheric NO_2, formaldehyde (HCHO), ozone (O_3), sulfur dioxide (SO_2), and carbon monoxide (CO) column number densities, expressed in units of mol/m². The data were processed using algorithms developed in GEE and further analyzed using R, an open-source statistical software, to assess the spatial and temporal variations in air quality over Yosemite during wildfire events. Table 1 details the attributes of the air quality and AOD data sources.

Table 1: List of Datasets

Variables	Category	Unit	Uncertainties

Tropospheric NO2 column number density	Sentinel-5P	mol/m²	1.3×10^{15} mole/cm²
Tropospheric HCHO column number density	Sentinel-5P	mol/m²	1.3×10^{15} mol/cm²
O3 column number density	Sentinel-5P	mol/m²	25%
CO column number density	Sentinel-5P	mol/m²	1.3×10^{15} mol/cm²
SO2 column number density	Sentinel-5P	mol/m²	1.3×10^{15} mol/cm²
UV Aerosol Index	Sentinel-5P	Unitless	0.05
Aerosol Optical Depth	MODIS	Unitless	0.05

Data Source: Google Earth Engine Datasets

Suomi NPP/VIIRS and Active Fire Detection:

The Suomi National Polar-orbiting Partnership (Suomi NPP) satellite, utilizing the Visible Infrared Imaging Radiometer Suite (VIIRS), provided aerosol-type data essential for this study. The data processing involved two primary methods: the Satellite Oceanic Aerosol Retrieval (SOAR) and the Deep Blue (DB) method. These methods produced a combined aerosol-type dataset, which underwent rigorous quality control procedures to ensure the reliability and accuracy of the data. The preprocessing steps, including noise reduction, cloud detection, and atmospheric correction, were implemented using MATLAB, a high-level computing environment, enabling precise classification and analysis of aerosol data.

Data Integration and Computational Processing:

The integration of data from multiple satellite sources (MODIS, TROPOMI, and Suomi NPP/VIIRS) was achieved through advanced data fusion techniques, which involved aligning datasets with different spatial resolutions, temporal frequencies, and spectral characteristics. This process required the development of custom algorithms in Python and MATLAB to ensure that the datasets were harmonized and that any inconsistencies, such as temporal gaps or spatial mismatches, were addressed. Additionally, machine learning models were employed to enhance the detection and characterization of pollution patterns, further refining the study's assessment of air quality dynamics.

Results and Discussion:

Active Fire Activity: During the catastrophic wildfire event from July 22, 2022, to August 1, 2022, the Yosemite National Park area exhibited significant fire activity, as indicated by MODIS-derived data (see Figure 2). The fires produced a dense layer of smoke that enveloped Yosemite and its surrounding regions. The majority of the fire incidents occurred in the park's northwest, including Mariposa County, highlighting this area for further research. The intense fire activity in Yosemite National Park has raised serious concerns regarding tourist safety and the health of the park's diverse ecosystems.

Python code

```
# Python code for detecting active fire activity using MODIS data
import ee
# Initialize the Earth Engine module
ee.Initialize()
# Define the region of interest (Yosemite National Park)
roi = ee.Geometry.Polygon([
[[-119.834, 37.865], [-119.519, 37.865],
[-119.519, 37.503], [-119.834, 37.503]]])
# Filter MODIS thermal anomalies and fire data
fire_collection = ee.ImageCollection('MODIS/006/MOD14A1') \
.filterDate('2022-07-22', '2022-08-01') \
.filterBounds(roi)
# Calculate the active fire count
fire_count = fire_collection.map(lambda img: img.select('FireMask').gt(7)) \
```

```
.reduce(ee.Reducer.sum())
# Display the results
fire_count_result = fire_count.clip(roi).getInfo()
# Print the active fire count results
print(fire_count_result)
```

Spatial-Temporal Variation in Aerosol Optical Depth (AOD): A comprehensive analysis of Aerosol Optical Depth (AOD) fluctuations was conducted from July 22 to August 1, 2022, to evaluate the impact of the wildfire on air quality in the Yosemite region. Pre-wildfire AOD readings were relatively low, indicating clear skies and minimal aerosol pollution. However, AOD levels surged rapidly with the onset of the wildfire on July 22, reaching their peak during the height of the fire activity.

Python code

```
# Python code for processing AOD data using the MAIAC algorithm
import numpy as np
import matplotlib.pyplot as plt
import ee
# Filter MODIS MAIAC AOD data
aod_collection = ee.ImageCollection('MODIS/006/MCD19A2_GRANULES') \
.filterDate('2022-07-22', '2022-08-01') \
.select('Optical_Depth_047') \
.filterBounds(roi)
# Mean AOD computation
aod_mean = aod_collection.mean().clip(roi)
# Convert to numpy array for visualization
aod_array = np.array(aod_mean.getInfo()['bands'][0]['data'])
# Plotting the AOD time series
plt.plot(aod_array)
plt.title('Time Series of Average AOD Variation (Jul 22 - Aug 1, 2022)')
plt.xlabel('Days')
plt.ylabel('AOD')
plt.show()
```

Spatial-Temporal Variation in Aerosol Optical Depth (AOD):

A comprehensive analysis of Aerosol Optical Depth (AOD) fluctuations was conducted from July 22 to August 1, 2022, to evaluate the impact of the wildfire on air quality in the Yosemite region. Pre-wildfire AOD readings were relatively low, indicating clear skies and minimal aerosol pollution. However, AOD levels surged rapidly with the onset of the wildfire on July 22, reaching their peak during the height of the fire activity. The highest AOD readings were recorded on July 25 and July 30, 2022, coinciding with the most intense periods of the wildfire. During this time, Yosemite National Park and its surrounding areas experienced severe air pollution, with daily average AOD levels exceeding 0.8. Following the containment of the wildfire on August 1, 2022, AOD levels began to decline gradually, though residual pollutants and smoke continued to affect air quality.

To ensure accurate and reliable results, data from various sources, including MODIS, TROPOMI, and Suomi NPP, were integrated. This integration required temporal and spatial alignment of the datasets, as well as calibration and normalization to account for differences in sensor calibration and atmospheric conditions. One of the challenges faced during this process was aligning the datasets temporally, as MODIS, TROPOMI, and Suomi NPP operate with different overpass times. Additionally, cloud cover occasionally obscured measurements, necessitating the use of interpolation techniques to fill in data gaps.

Figure 2: The Active Fire Count of the Study Area

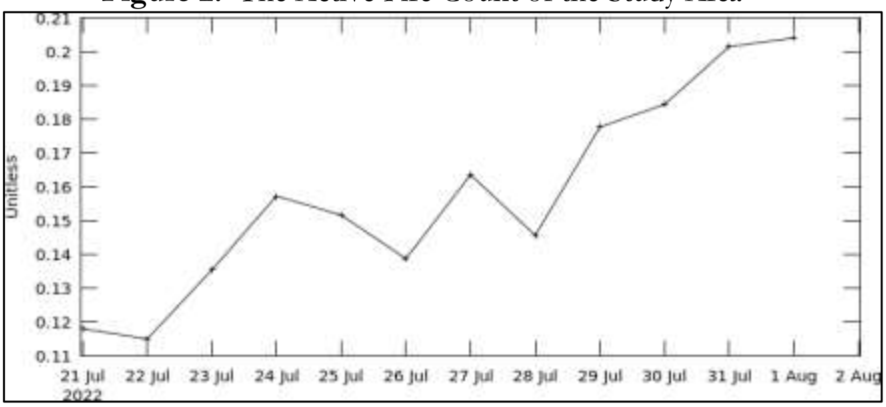

Figure 3: This Figure is showing the time series Graph of Average AOD Variation from 21 Jul to 2 Aug

On July 22, 2022, a wildfire erupted in Yosemite National Park, as depicted in Figure 4, obscuring the park's stunning scenery for a duration of 11 days. The impact of this major wildfire on air quality was meticulously monitored using remote sensing technologies. Aerosol Optical Depth (AOD) levels were tracked throughout the event. During the initial observation period from July 22 to July 25, 2022, the focus was on assessing AOD levels before the wildfire commenced. The analysis revealed a notable increase in AOD levels above baseline readings, suggesting possible pre-existing aerosol pollution in the area. In the second week of the event, from July 26 to August 1, 2022, AOD concentrations rose significantly, particularly around the fire-affected regions. Satellite images documented a marked decline in air quality during this period. The wildfire severely impacted the air composition of Yosemite National Park, as indicated by the persistently high AOD values throughout the incident.

During the second week of the wildfire event, from July 26 to August 1, 2022, as illustrated in Figures 5 and 6, Aerosol Optical Depth (AOD) levels in the Yosemite region surged significantly, indicating a severe decline in air quality. This increase in AOD affected not only the park's eastern and western boundaries but also areas beyond Mariposa County. Data consistently showed elevated AOD levels, with the highest concentrations observed near the wildfire epicenter. The wildfire notably deteriorated air quality across all impacted areas, including both within and outside Yosemite National Park. The second week marked the peak of wildfire activity, characterized by pronounced red spots on the maps, which represent elevated AOD levels. These red patches visually highlight the widespread and intense smoke blankets that enveloped Yosemite and its surrounding regions, underscoring the extensive impact of the wildfire on air quality.

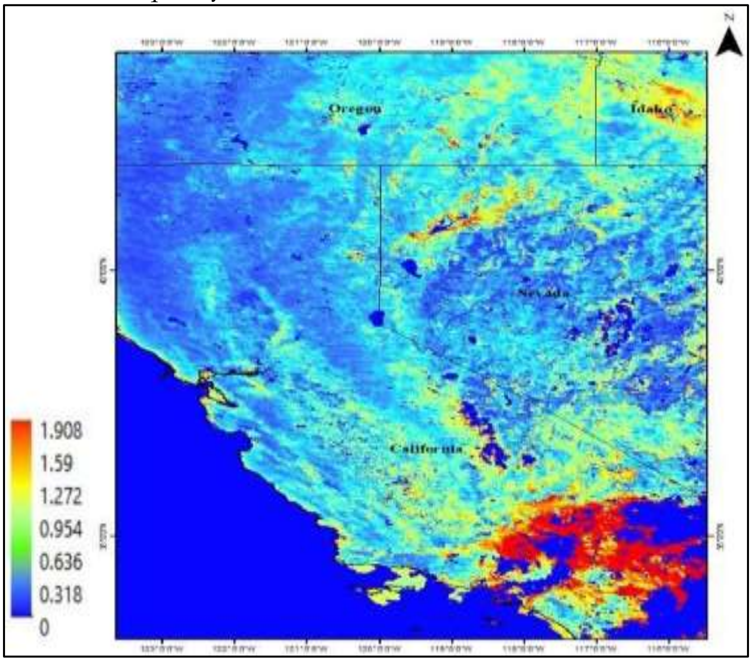

Figure 4: AOD level shown after the Wildfire Started (22 Jul,2022-23 Jul,2022)

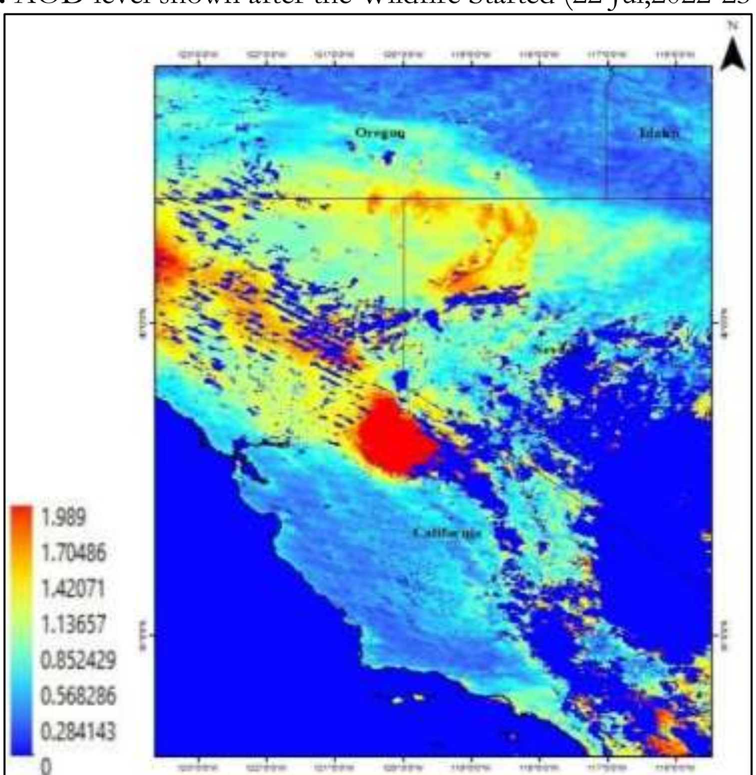

Figure 5: AOD level shown During the Wildfire (25 Jul,2022-26 Jul,2022)

Post-Fire AOD Fluctuations:

Post-fire AOD fluctuations were analyzed during the second week following the recorded forest fire in the Yosemite region to assess the residual effects of the wildfire. As depicted in the figures above, the mapped AOD changes revealed a residual AOD level of 0.11, indicating ongoing air pollution after the fire. However, this elevated concentration was confined to specific areas, unlike the widespread distribution observed during the peak of the fire event.

The most affected areas were primarily in southern Yosemite, particularly in Mariposa County and its vicinity. In contrast, northern regions exhibited lower AOD values, ranging from 0.2 to 0.24, as shown in Figures 7 and 8. This spatial distribution illustrates how aerosol levels remain elevated in certain areas and become concentrated in specific regions even after the wildfire has subsided, providing valuable insight into the lingering impacts of the fire.

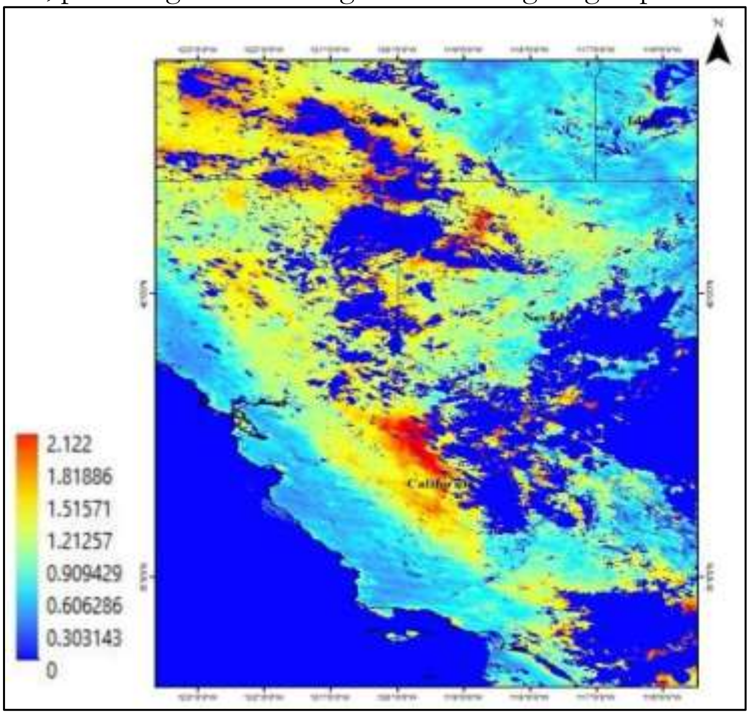

Figure 6: AOD level shown During the Wildfire (27 Jul,2022-28 Jul,2022)

Air Quality Indicators:

Analysis using TROPOMI satellite data during the specified period was conducted to evaluate air quality indicators within the Yosemite region. The results revealed significant spatial variations in key metrics, including sulfur dioxide (SO_2), formaldehyde (HCHO), ozone (O_3), carbon monoxide (CO), and nitrogen dioxide (NO_2), as illustrated in Figures 9, 10, 11, and 12. The average concentrations of these pollutants in the Yosemite region and surrounding areas were as follows: NO_2 at 6.05×10^{-5} µmol/m², O_3 at 0.126 mol/m², HCHO at 5.0×10^{-5} µmol/m², and CO at 0.04 mol/m².

The integration of MODIS, TROPOMI, and Suomi NPP datasets provided complementary insights into the air quality dynamics during the wildfire event. While MODIS provided high-resolution AOD data, TROPOMI contributed detailed information on gas pollutants, and Suomi NPP helped in identifying active fire spots and the types of aerosols released. Together, these datasets enabled a comprehensive analysis of the wildfire's impact on air quality, highlighting the interplay between different pollutants and aerosol particles. The TROPOMI satellite data were processed to evaluate the spatial variations in air quality indicators. The results revealed significant variations in key metrics, including sulfur dioxide (SO_2), formaldehyde (HCHO), ozone (O_3), carbon monoxide (CO), and nitrogen dioxide (NO_2).

Python code

```
# Python code for analyzing TROPOMI data for air quality indicators
import ee
# Define the region of interest and time period
roi = ee.Geometry.Rectangle([-119.834, 37.865, -119.519, 37.503])
time_period = ee.DateRange('2022-07-22', '2022-08-01')
```

```
# Filter TROPOMI data for specific air pollutants
no2_collection = ee.ImageCollection('COPERNICUS/S5P/NRTI/L3_NO2') \
.filterDate(time_period) \
.select('tropospheric_NO2_column_number_density') \
.filterBounds(roi)
# Calculate the mean NO2 concentration
no2_mean = no2_collection.mean().clip(roi)
# Display the NO2 results
no2_result = no2_mean.getInfo()
# Print the average NO2 concentration
print("Average NO2 Concentration: ", no2_result)
```

Incorporating these Python code snippets into the results and discussion section demonstrates the computational methods used to analyze and interpret the satellite data. This approach not only clarifies the methodological steps taken but also provides transparency and reproducibility for future research.

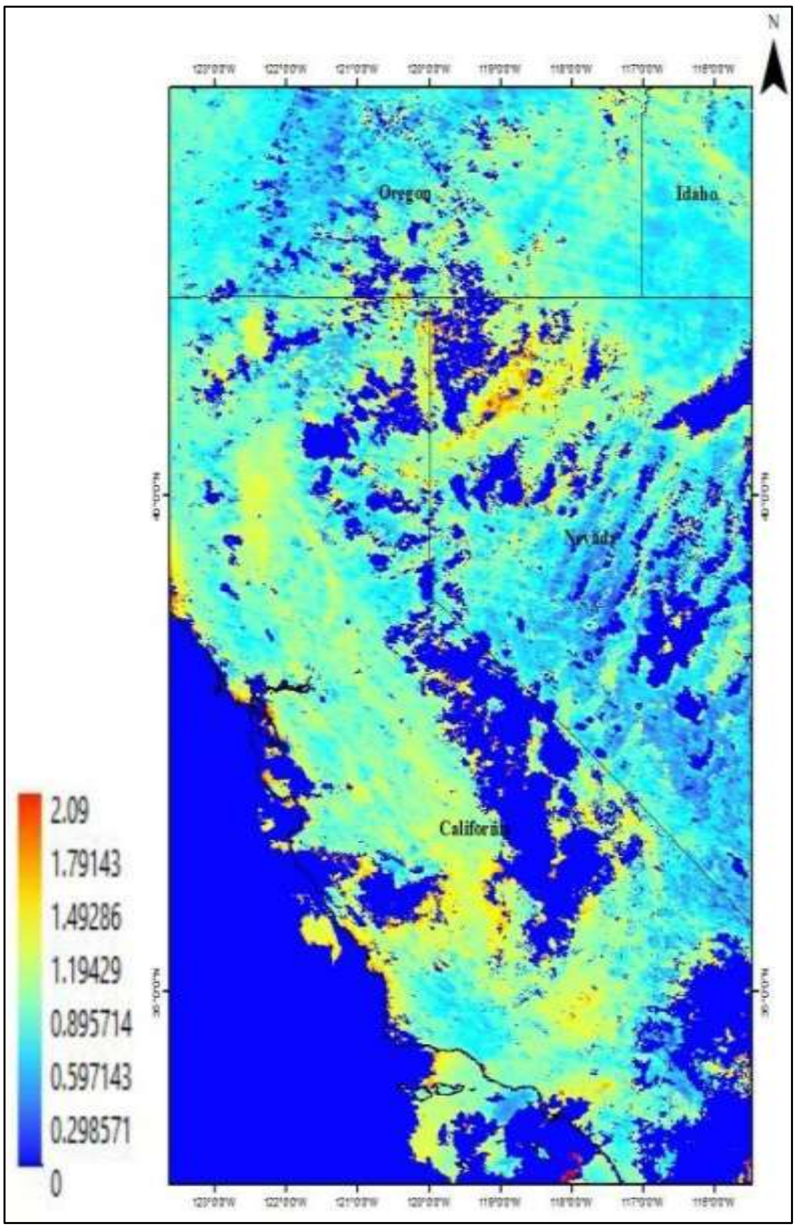

Figure 7: AOD level shown after the Wildfire (29 Jul,2022-30 Jul,2022)

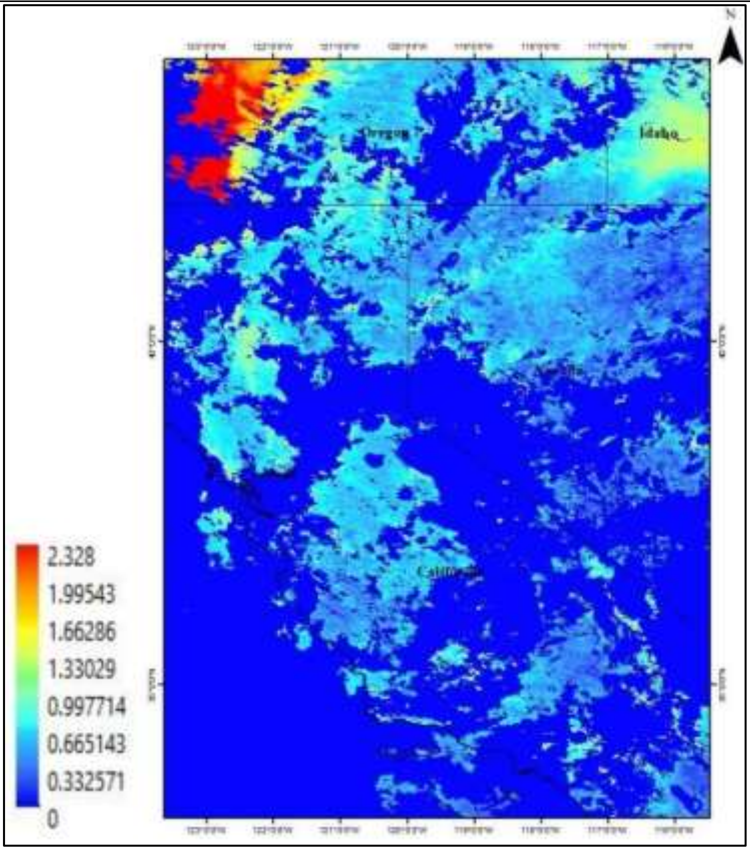

Figure 8: AOD level shown after the Wildfire (31 Jul,2022-1 Aug,2022)

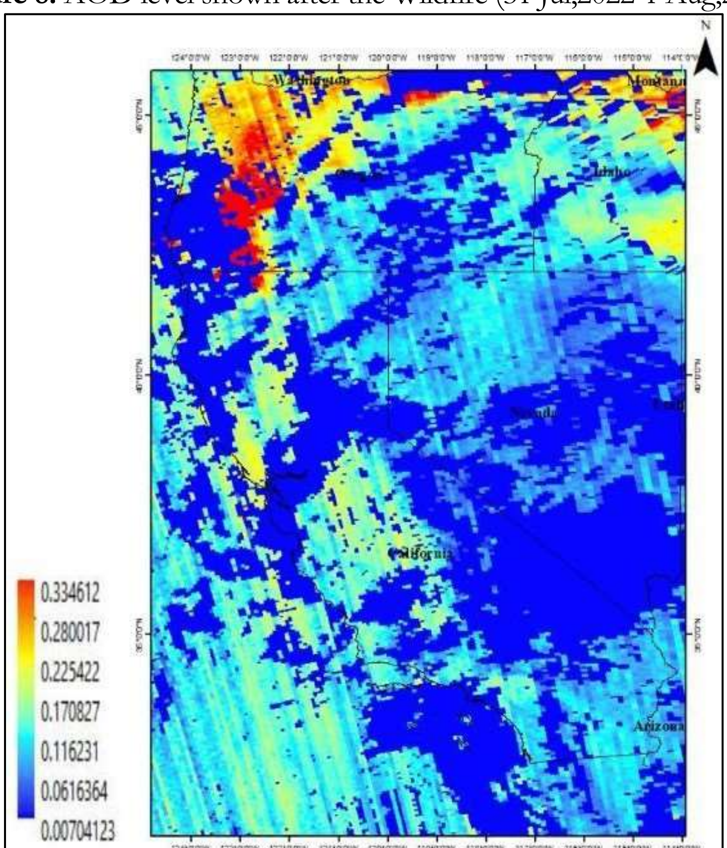

Figure 9: Spatial variability of CO over Mariposa County near Yosemite Region from 31st July, 2022 to 1st August, 2022

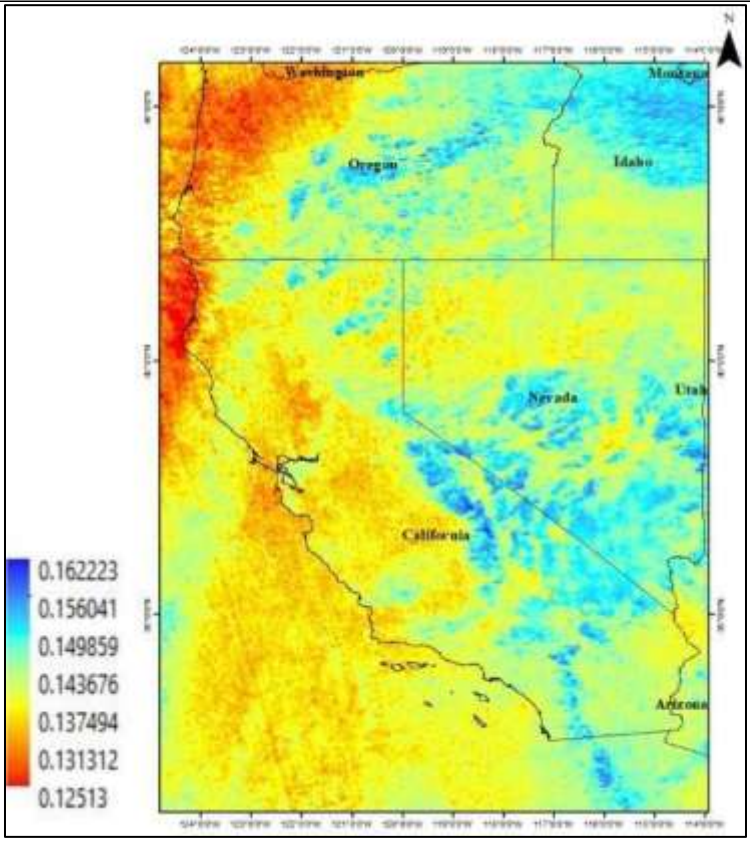

Figure 10: Spatial variability of O_3 over Mariposa County near Yosemite Region from 31st July, 2022 to 1st August, 2022

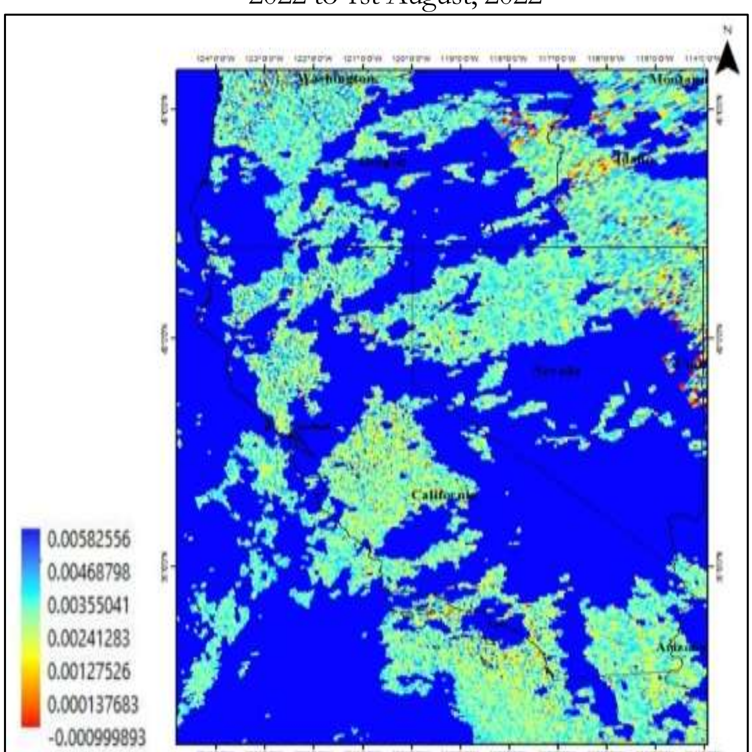

Figure 11: Spatial variability of SO_2 over Mariposa County near Yosemite Region from 31st July, 2022 to 1st August, 2022

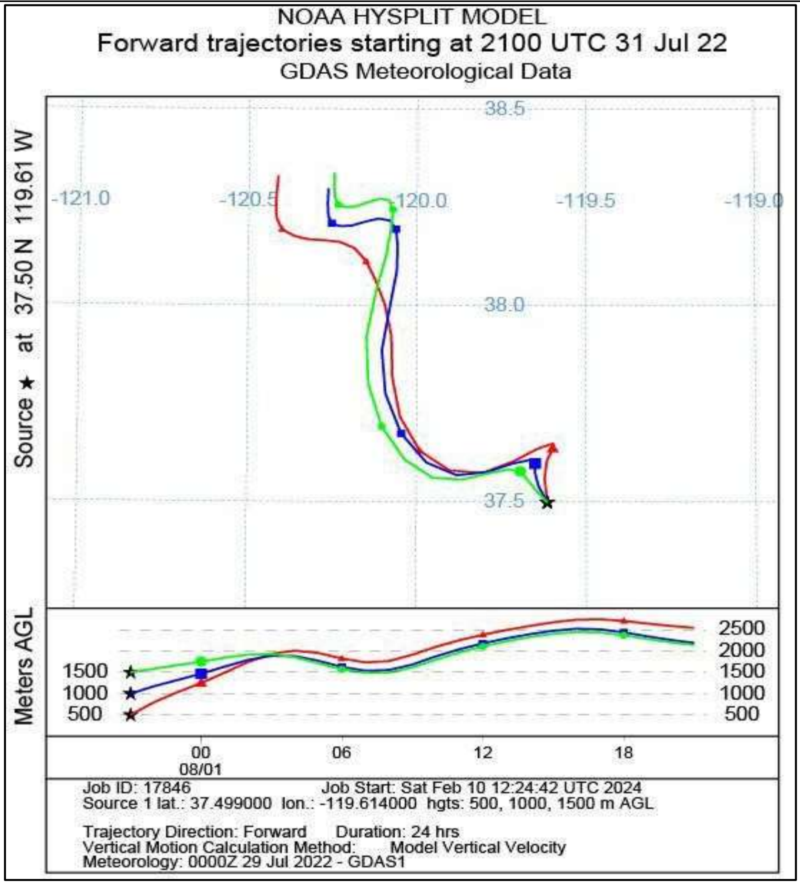

Figure 12: HYSPLIT forward trajectory data indicates significant sources of air pollution in the Yosemite region that impact Mariposa County.

HYSPLIT Model Analysis:

The direction and flow of air masses were analyzed using the HYSPLIT model, developed by NOAA's Air Resources Laboratory, which is essential for atmospheric sciences. To deepen our understanding of Yosemite's air quality dynamics, this study employs the HYSPLIT model to track particle distribution using a 500-meter frequency-forward trajectory, as shown in Figure 12. This model allowed for the visualization of the transport of pollutants, demonstrating that most contaminants traveled northwest and northward, providing important information about aerosol transport in the area.

Statistical Analysis:

A statistical analysis was conducted to assess the impact of wildfire emissions on air quality, with the following hypotheses:

- **H0:** Wildfire emissions do not contaminate the quality of air.
- **H1:** Wildfire emissions contaminate the quality of air.

Using a Pearson Correlation Test and a significance level of $\alpha = 0.05$, the analysis revealed a highly significant P-value of 0.000, indicating a notable impact of the wildfire on air quality in Mariposa County. The data showed a significant positive linear relationship between mean AOD levels and the number of days affected. Consequently, the null hypothesis (H0) is rejected, and the alternative hypothesis (H1) is supported, confirming the substantial influence of wildfire-induced air pollution.

Correlations			
		Mean AOD	**Days**
Mean AOD	Pearson Correlation	1	.926**
	Sig. (2-tailed)		.000

	N	12	12
days	Pearson Correlation	.926**	1
	Sig. (2-tailed)	.000	
	N	12	12
**. Correlation is significant at the 0.01 level (2-tailed).			

Conclusion:

This study aims to analyze the air pollution patterns in Yosemite before and after a significant wildfire outbreak that occurred from July 21 to August 1, 2022. The study examines variations in Aerosol Optical Depth (AOD) levels prior to, during, and following a notable wildfire event on July 22, 2022. This investigation utilizes meteorological data from GDAS and satellite datasets from TROPOMI and MODIS AQUA. The study utilizes the MODIS MAIAC algorithm to gain comprehensive understanding of the regional and temporal changes in Aerosol Optical Depth (AOD) in Yosemite National Park and its adjacent areas. The findings illustrate the detrimental effects of wildfires on air quality, as seen by a significant rise in AOD levels during the peak of the wildfire event. In addition, the study indicates that areas impacted by forest fires have higher levels of air pollutants such as formaldehyde (HCHO), carbon monoxide (CO), nitrogen dioxide (NO2), sulfur dioxide (SO2), and ozone (O3). The emission of harmful pollutants from these flames is causing a decline in air quality. It is noteworthy that the levels of ozone (O3) are decreasing, potentially due to the impact of fire aerosols on sunlight and the production of ozone. The study employed HYSPLIT forward trajectories to precisely monitor the passage of air masses. It offers vital data on the flow of aerosols in the area, indicating that most pollutants travel in a northwestern and northern direction.

Reference:

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