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Assessing Vegetation Health Impacts of Air Pollution Using Medium-Resolution Satellite Data: A Case Study of Pasir Gudang, Malaysia

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Abstract – Air pollution has become a common phenomenon nowadays, and people are unaware that polluted air can affect the health of vegetation. As we know, vegetation plays a crucial role in producing oxygen in the air, which helps reduce air pollution. This study was conducted in response to air pollution incidents at the Kim-Kim River in Pasir Gudang, Johor, Malaysia, in March 2019. The illegal chemical dumping that produced chemical gas in the Kim-Kim River impacted the affected areas and vegetation health. Thus, using the medium-resolution remote sensing method, the researchers were able to detect the impact of air pollution on the health of vegetation growth. Four of the vegetation indices from medium resolution multispectral bands were extracted, namely the Normalised Difference Vegetation Index (NDVI), Normalised Difference Water Index (NDWI), Soil Adjusted Vegetation Index (SAVI) and Atmospherically Resistant Vegetation Index (ARVI). As a result, vegetation indices from Sentinel-2 and Landsat-8, respectively, successfully demonstrate the correlation trend between vegetation health and air pollution, generating trends in vegetation health affected by air pollution.

Keywords *– Air Pollution, Vegetation, Health Impacts, Medium-Resolution Satellite, Pasir Gudang*

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1.0 Introduction

Air pollution is caused by industrialisation and urbanisation, introducing harmful pollutants that affect both human health and vegetation (Shi et al., 2020; Turner et al., 2020). Industrial hazardous chemicals, such as benzo[a]pyrene (PAHs), dioxins and sulfur compounds (SO3, H2SO4), pose a significant risk, especially to vulnerable populations (Ismail & Rasdi, 2020). Air pollution also contaminates precipitation, impacting soil and water ecosystems (Manisalidis et al., 2020). Additionally, prolonged exposure to polluted air can alter plant physiological processes, resulting in reduced growth rates and decreased overall resilience of vegetation.

A notable example case was the illegal disposal of chemical waste into the Kim-Kim River, Pasir Gudang, Johor, on March 7, 2019, which affected over 20,108 students and caused 4,000 individuals to seek medical attention (Yiswaree et al., 2019). The event led to the closure of 475 schools and was linked to seven distinct toxic gases, including methyl mercaptan, benzene, xylene, hydrogen chloride, acrylonitrile, and acrolein (Ismail et al., 2020). The combination of industrial emissions and rising temperatures contributed to the urban heat island effect, further damaging the health of vegetation.

This study aims to assess vegetation health trends in Pasir Gudang before, during, and after the pollution event using medium-resolution remote sensing data. By analysing vegetation indices, including the Normalised Difference Vegetation Index (NDVI), Normalised Difference Water Index (NDWI), Soil Adjusted Vegetation Index (SAVI), and Atmospherically Resistant Vegetation Index (ARVI), through multispectral analysis based on vegetation from the visible spectrum (0.45 – 0.51 m) and the near-infrared spectrum (0.75 – 1.2 m), this study seeks to understand the impact of air pollution on vegetation health.

This approach enables a comprehensive evaluation of how air pollution impacts vegetation health and recovery, providing more accurate insights into the environmental consequences through the use of remote sensing techniques.

This research investigates the correlation between vegetation health and the occurrence of air pollution, utilising remote sensing techniques for comprehensive analysis. To achieve this, the study is divided into two main objectives:

i. To determine the trend of vegetation health over the Pasir Gudang area using vegetation indices, and

ii. To analyse the trend of vegetation indices before, during and after air pollution occurrences.

2.0 Methodology

This research follows four phases: data acquisition, pre-processing, processing, and data analysis. Figure 1 shows the research methodology used in this study.

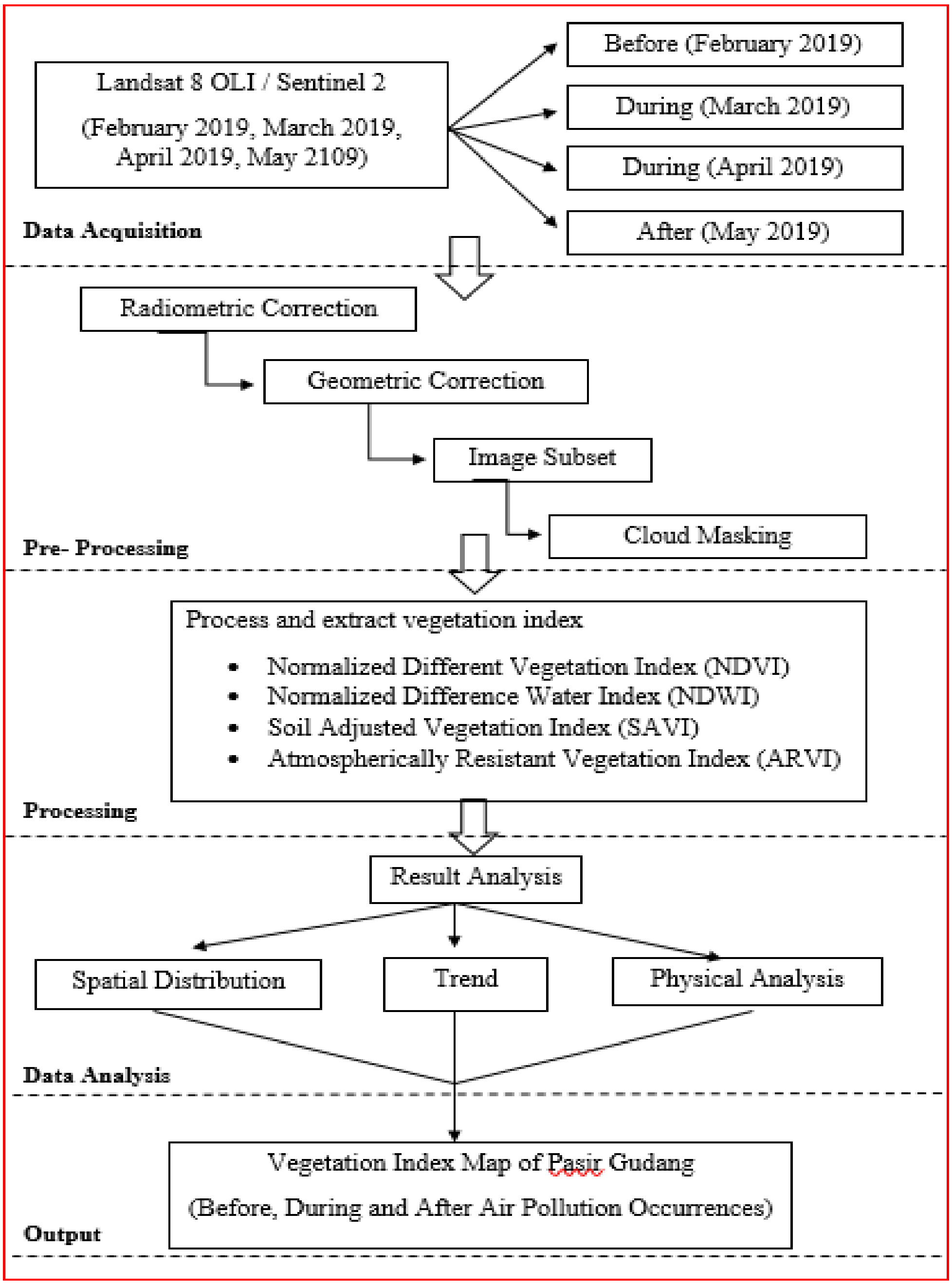

Figure 1. Research methodology flowchart

2.1 Study Area

The study area is located in Pasir Gudang, Johor, at approximately 1.502778°N, 103.935556°E (Figure 2). Pasir Gudang is an industrial town situated in Mukim Planting, Johor Bahru District, spanning 359.57 km² and with a population of 46,571. Significant industries include transportation, shipbuilding, logistics, and petrochemicals.

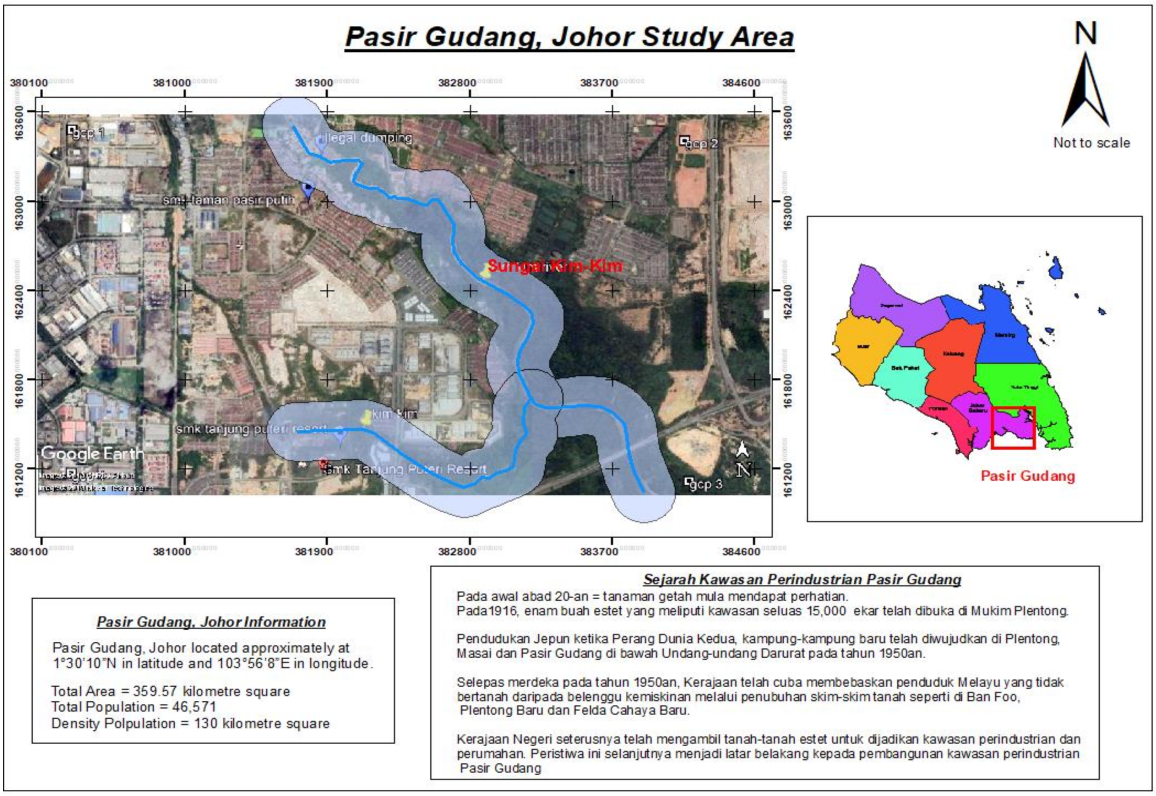

Figure 2. Location of the study area

This area was selected due to the 2019 Kim-Kim River pollution incident. The 15 km-long rivers, located at 1.464548°N, 103.939289°E, flow into the Johor Strait. The illegal disposal of marine oil waste in the river released hazardous gases, including methane and benzene (Ismail et al., 2020). By March 19, 2019, approximately 1,500 metric tonnes of contaminated water and 900 tonnes of hazardous waste had been removed from a 1.5 km stretch of the affected river (Yiswaree et al., 2019).

The incident led to severe health concerns, affecting thousands of residents and students who suffered from respiratory issues and nausea. Due to its significant environmental impact, this event serves as a critical case study for analysing the effects of air pollution on vegetation.

2.2 Data Acquisition

To analyse vegetation health, this study utilised satellite imagery from Landsat 8 OLI and Sentinel-2A. These satellites provide multispectral data essential for assessing vegetation conditions over time. Four acquisition dates were selected—February (before pollution), March and April (during pollution), and May 2019 (after pollution)—to capture vegetation changes before, during, and after the pollution event. The integration of Sentinel-2A and Landsat 8 OLI medium-resolution satellite data ensured comprehensive coverage, allowing for cross-verification of vegetation health trends in the event of data gaps or quality inconsistencies in either source. The specifications of Landsat 8 OLI and Sentinel-2A are detailed in Tables 1, respectively.

Table 1. Specification of Landsat 8 OLI and Sentinel-2A data

Specification	**Landsat 8 OLI**		**Sentinel- 2A**
Acquisition Date	Before	During	After
	February 2019	March & April 2019	May 2019
Spectral Bands	Band 9 Cirrus (1.36 – 1.38 µm) 30m		Band 12 – SWIR (2.190µm) 20m
Coordinate System	WGS 1984		UTM 48N
Source	U.S Geological Survey (USGS)		

Source: Landsat Science (https://landsat.gsfc.nasa.gov/satellites/landsat-8/) and Satellite Imaging Corporation (https://www.satimagingcorp.com/satellite-sensors/other-satellite-sensors/sentinel-2a/)

2.3 Data Pre-processing

In the pre-processing phase, several steps were taken to enhance image accuracy, including radiometric correction, geometric correction, image subset, and cloud masking. Radiometric correction adjusted for sensor irregularities and atmospheric noise to ensure accurate reflectance values. Geometric correction corrected distortions and aligned the images with real-world coordinates. Image subset refined the study area by extracting relevant portions of the dataset. Lastly, cloud masking identified and removed cloud cover to minimise interference in the analysis.

2.4 Data Processing

The data processing phase focuses on extracting vegetation indices from satellite images to assess vegetation greenness. The four indices used are NDVI, NDWI, SAVI, and ARVI.

2.4.1 Normalised Difference Vegetation Index (NDVI)

NDVI was used to determine the correlation between vegetation and air pollution during the contamination event. This index helps identify stress levels in vegetation exposed to pollutants.

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \qquad \text{(Eq. 1.0)}$$

2.4.2 Normalised Difference Water Index (NDWI)

NDWI evaluates moisture levels in vegetation, indicating water stress from pollution exposure.

$$NDWI = \frac{(NIR - SWIR)}{(NIR + SWIR)} \qquad \text{(Eq. 2.0)}$$

2.4.3 Soil Adjusted Vegetation Index (SAVI)

SAVI minimises soil brightness effects to improve vegetation analysis in polluted areas.

$$SAVI = (1+L) \times \frac{(NIR - RED)}{(NIR + RED + L)} \qquad \text{(Eq. 3.0)}$$

2.4.4 Atmospherically Resistant Vegetation Index (ARVI)

ARVI reduces atmospheric interference for accurate vegetation assessment in polluted areas.

$$ARVI = \frac{(NIR - (2 \times RED - BLUE))}{(NIR + (2 \times RED - BLUE))} \qquad \text{(Eq. 4.0)}$$

2.5 Data Analysis

Data analysis was conducted to extract useful information for assessing vegetation trends before, during, and after air pollution. NDVI, NDWI, SAVI, and ARVI values were analysed, with 100 random points selected in the study area and statistically tested to evaluate the impact of illegal air pollution.

3.0 Results and Discussion

In this section, we present the results of data processing and analysis. Pre-processing and vegetation index calculations were conducted using image processing software to enhance data accuracy (Didan & Barreto, 2023). The formulas for these indices were integrated using raster calculators, facilitating precise computations for vegetation analysis (Wang & Zhang, 2023). Additionally, statistical analyses were performed to evaluate vegetation changes, with results summarised in Table 4. Understanding the impact of environmental factors on vegetation health is crucial, as studies have shown that vegetation patterns and spatial organisation are influenced by changing environmental conditions and human activities (Didan & Barreto, 2023; Wang & Zhang, 2023).

3.1 Pre-Processing Data

In the pre-processing phase, satellite images undergo several corrections to ensure accurate vegetation analysis. Atmospheric correction is applied to remove atmospheric effects, converting digital number (DN) values into surface reflectance, which is essential for quantitative analysis of satellite remote sensing images (Yang et al., 2021). Geometric correction is also performed to align images with real-world coordinates, reducing distortions caused by sensor movement and Earth's curvature (Li & Xia, 2021). The corrected reflectance values, typically ranging from 0 to 1, indicate that images have undergone necessary pre-processing steps before vegetation index calculations.

3.2 Quantitative Analysis of Vegetation Index

This study analysed NDVI, NDWI, SAVI, and ARVI to assess vegetation changes before, during, and after the pollution event at the Kim-Kim River in Pasir Gudang, Johor. NDVI is widely used to quantify vegetation greenness and detect plant stress (USGS, 2023), while NDWI estimates water content in vegetation to identify moisture stress (Farmonaut, 2024). SAVI adjusts for soil brightness effects in areas with sparse vegetation (NASA Earthdata, 2024), and ARVI reduces atmospheric interference for more reliable vegetation monitoring (Auravant, 2023). These indices were compared across different periods to quantify vegetation degradation and recovery. The spatial distribution of these indices is illustrated in Figure 3(a)–(d), showing vegetation variations over time.

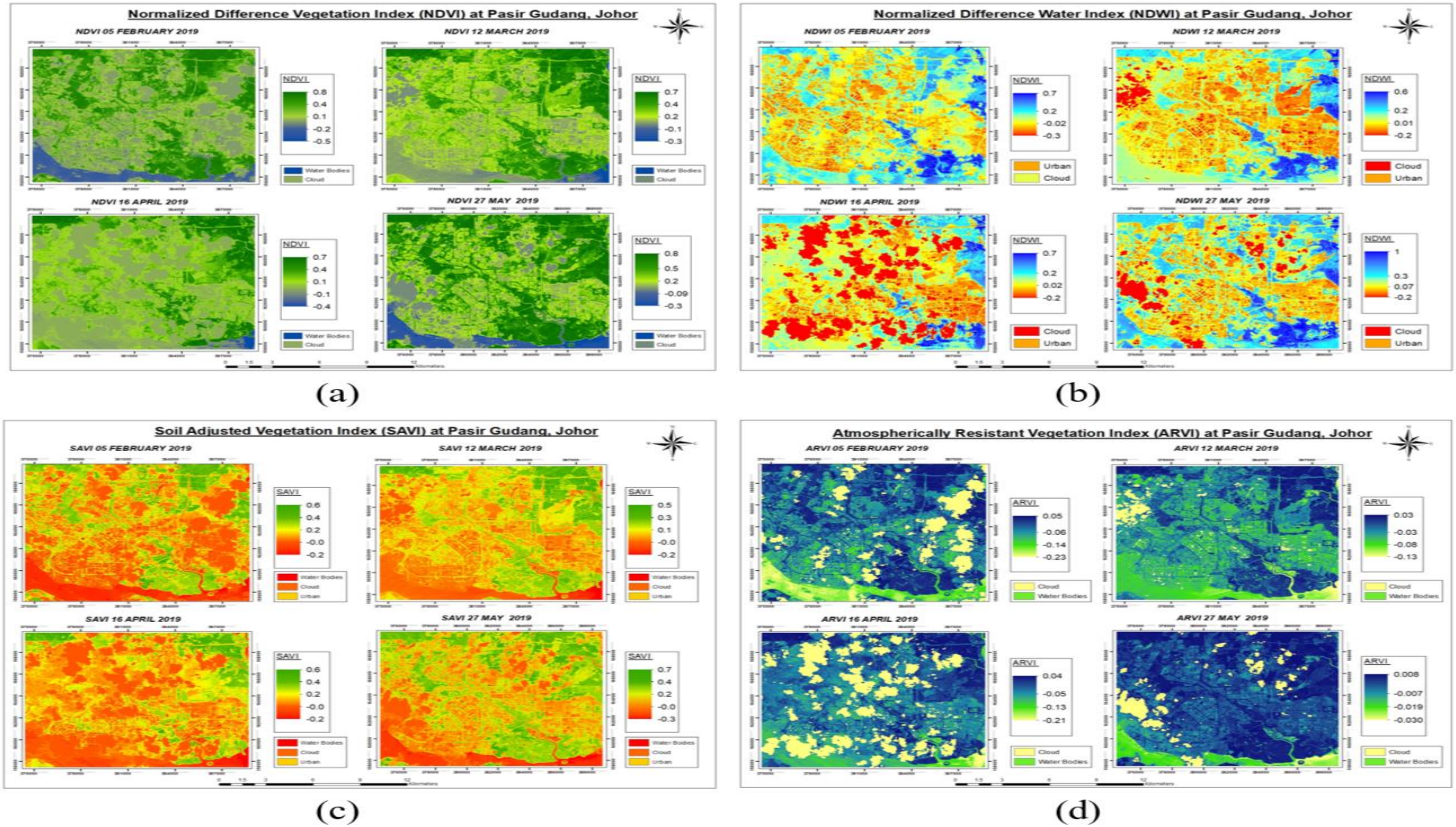

Figure 3. Spatial distribution of (a) NDVI, (b) NDWI, (c) SAVI, and (d) ARVI before (February 2019), during (March - April 2019), and after (May 2019) the pollution event.

3.2.1 Normalised Difference Vegetation Index (NDVI)

Figure 3(a) illustrates NDVI values before, during, and after the pollution incident. NDVI ranged between -1 and +1, with higher values indicating healthier vegetation. NDVI declined on 12 March and 16 April 2019, followed by a recovery on 27 May 2019. This suggests a temporary negative impact on vegetation health, with signs of regrowth post-event. The lowest NDVI recorded was 0.464 on March 12, while the highest recovery value reached 0.664 on May 27, 2019.

3.2.2 Normalised Difference Water Index (NDWI)

Figure 3(b) presents the NDWI variations, indicating water content in vegetation. A decrease in NDWI values during the pollution period suggests moisture stress, potentially due to airborne contaminants affecting plant physiology. NDWI values were lowest on 12 March 2019 at 0.206 but showed an increasing trend after 27 May 2019, reaching 0.359, indicating recovery. This highlights the temporary impact of air pollution on plant water retention.

3.2.3 Soil Adjusted Vegetation Index (SAVI)

Figure 3(c) highlights changes in SAVI values, which account for soil brightness effects. The SAVI index displayed a similar declining trend as NDVI, confirming vegetation stress during the pollution period. Lower SAVI values in March and April 2019 suggest that pollution exposure may have contributed to soil degradation, ultimately affecting plant health. The lowest SAVI value was recorded at 0.294 on March 12, with a significant increase to 0.435 on May 27, 2019.

3.2.4 Atmospherically Resistant Vegetation Index (ARVI)

Figure 3(d) represents ARVI values, which correct for atmospheric effects on vegetation indices. The ARVI trend mirrored the NDVI pattern, with a sharp decline during periods of pollution and a gradual recovery after May 2019. This indicates that pollution-induced atmospheric disturbances also contributed to vegetation stress. The lowest ARVI value recorded was -0.011 in March and April, with a recovery to 0.001 by May.

The decline in NDVI, NDWI, SAVI, and ARVI during the pollution event was followed by a gradual recovery. Table 3 presents the descriptive statistics for these vegetation indices, providing a numerical summary of their variations across different time periods.

Table 3. Descriptive Statistics for Vegetation Indices (NDVI, NDWI, SAVI, ARVI).

Date	NDVI (Mean ± SD)	NDWI (Mean ± SD)	SAVI (Mean ± SD)	ARVI (Mean ± SD)	N
5 Feb 2019	0.583 ± 0.131	0.270 ± 0.168	0.338 ± 0.104	-0.006 ± 0.022	100
12 Mar 2019	0.464 ± 0.103	0.206 ± 0.152	0.294 ± 0.082	-0.011 ± 0.014	100
16 Apr 2019	0.467 ± 0.117	0.233 ± 0.141	0.283 ± 0.084	-0.011 ± 0.017	100
27 May 2019	0.664 ± 0.138	0.359 ± 0.159	0.435 ± 0.111	0.001 ± 0.013	100

Table 3 presents the descriptive statistics for NDVI, NDWI, SAVI, and ARVI across the study period. The mean and standard deviation (SD) for each index were calculated based on 100 sampled points within the study area. The results indicate a significant decrease in NDVI and SAVI on 12 March and 16 April 2019, followed by an increase on 27 May 2019, reflecting vegetation recovery. Similarly, NDWI highlights moisture stress caused by air pollution, while ARVI reveals atmospheric disturbances affecting vegetation health. Figure 4 further illustrates these trends visually, showing the changes before, during, and after the pollution incident.

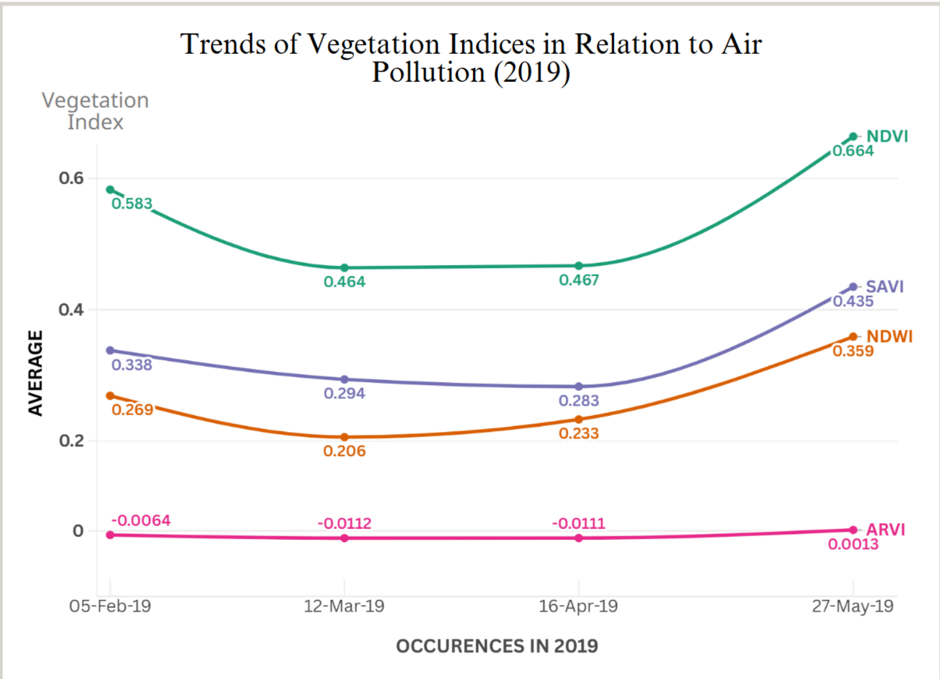

Figure 4. Trend of Vegetation Indices before, during, and after the pollution event

Figure 4 shows a decline in NDVI and SAVI during the pollution event (from 0.583 to 0.464 for NDVI), reflecting vegetation stress. NDWI also decreased, indicating moisture stress, while ARVI dropped due to atmospheric disturbances. By May 2019, the indices, except for NDWI, had recovered, with NDVI rising to 0.664, indicating regrowth of vegetation. This suggests air pollution negatively impacted vegetation health, but that recovery began after the event.

3.3 Correlation Analysis

The correlation analysis was conducted to evaluate the relationship between NDVI, NDWI, SAVI, and ARVI over different time periods. This analysis helps determine the extent to which air pollution events influenced vegetation indices. Table 4 presents the correlation coefficients (r) between indices, showing a strong positive relationship between NDVI and SAVI ($r = 0.92$, February-May), indicating that vegetation greenness and soil brightness were similarly affected by pollution. NDVI and NDWI had a moderate correlation ($r = 0.80$, February-May), while ARVI showed the lowest correlation values, reflecting its sensitivity to atmospheric disturbances.

3.3.1 T-Test

A t-test was conducted to evaluate the significance of changes in the vegetation index before, during, and after the pollution incident. For clarity, NDVIb refers to NDVI in February (before), NDVId in March–April (during), and NDVIa in May (after). The strongest correlation was found between NDVIb and NDVIa ($r = 0.92$), indicating substantial recovery in vegetation health after the pollution event. A similarly high correlation was observed between NDVId and NDVIa ($r = 0.89$), suggesting that regrowth had already commenced during the affected period. Meanwhile, NDVIb and NDVId showed a slightly lower correlation ($r = 0.87$), reflecting vegetation stress during the incident.

For NDWI, the correlation between NDWIb and NDWIa was moderate ($r = 0.80$), consistent with moisture-related stress during pollution. SAVI also showed a strong relationship between before and after periods ($r = 0.89$), while ARVI had the weakest correlation values overall, highlighting its sensitivity to atmospheric disturbances.

The F-test results further support these findings, showing significant variation across time for all indices. Table 4 summarises the correlations and their statistical significance.

Table 4. Correlation Analysis with Statistical Significance

Variables	Correlation (r)	t-test (p-value)	F-test (p-value)

NDVIb – NDVIa	0.92	0.003 ($p < 0.05$)	0.015 ($p < 0.05$)
NDVId – NDVIa	0.89	0.008 ($p < 0.05$)	0.021 ($p < 0.05$)
NDVIb – NDVId	0.87	0.012 ($p < 0.05$)	0.028 ($p < 0.05$)
NDWIb – NDWIa	0.80	0.026 ($p < 0.05$)	0.034 ($p < 0.05$)
NDWId – NDWIa	0.79	0.031 ($p < 0.05$)	0.040 ($p < 0.05$)
NDWIb – NDWId	0.75	0.038 ($p < 0.05$)	0.045 ($p < 0.05$)
SAVIb – SAVIa	0.89	0.009 ($p < 0.05$)	0.022 ($p < 0.05$)
SAVId – SAVIa	0.81	0.020 ($p < 0.05$)	0.032 ($p < 0.05$)
SAVIb – SAVId	0.79	0.029 ($p < 0.05$)	0.038 ($p < 0.05$)
ARVIb – ARVId	0.75	0.035 ($p < 0.05$)	0.041 ($p < 0.05$)
ARVId – ARVIa	0.74	0.039 ($p < 0.05$)	0.044 ($p < 0.05$)

From this study, Table 4 summarises the correlation analysis and statistical significance between the vegetation indices (NDVI, NDWI, SAVI, and ARVI) during the pollution event. The high correlation between NDVIb (before) and NDVIa (after) at 0.92 suggests significant vegetation recovery post-pollution, while the correlation between NDVId (during) and NDVIa indicates regrowth even during the event. The NDWI correlation (0.80) indicates moderate moisture stress, while SAVI exhibits a strong recovery, with a correlation of 0.89. However, ARVI displays the weakest correlation (0.74), suggesting that atmospheric interference affected its reliability in tracking vegetation health. Overall, the table highlights the varying impacts of pollution on vegetation health and the reliability of different vegetation indices.

3.4 Qualitative Analysis

Previous studies support the findings of this research by highlighting the effects of air pollution on vegetation. Ryabuhina et al. (2019) analysed transboundary air pollution in the Orenburg region, showing that industrial emissions, particularly from gas and chemical industries, release pollutants such as nitrogen oxides that persist in the atmosphere for days. These pollutants contribute to stress and degradation in vegetation.

The illegal chemical dumping in the Kim-Kim River further confirms that improper chemical waste disposal can lead to air pollution, negatively affecting vegetation. This aligns with the quantitative results, where NDVI, NDWI, SAVI, and ARVI values decreased during the pollution event, indicating stress on plant health.

Additionally, air pollution has a significant impact on the metabolism and growth of vegetation. Ryabuhina et al. (2019) found that dust and gas emissions lead to calcium salt accumulation in wood, premature ageing, and reduced growth in woody plants. These effects demonstrate how pollution alters vegetation health at both physiological and morphological levels.

In line with these findings, Huang et al. (2021) highlighted the challenges of interpreting NDVI data in polluted environments. They discussed how NDVI can saturate in areas with dense vegetation, which may limit its ability to detect subtle vegetation stress in areas affected by air pollution. This understanding is crucial for our study, where vegetation health is impacted by pollution, and the limitations of NDVI must be considered when analysing the data.

4.0 Conclusion

Vegetation plays a crucial role in atmospheric purification and pollutant reduction (Ferrini et al., 2020). Through photosynthesis and respiration, plants exchange gases with the atmosphere (Semenov et al., 2022). Meanwhile, contaminants can penetrate vegetation via root absorption and leaf stomata, thereby impacting plant health (Gavrilescu, 2021). This study utilised Sentinel-2 and Landsat 8 satellite imagery to analyse NDVI, NDWI, SAVI, and ARVI, demonstrating that air pollution significantly affected vegetation health at the Kim-Kim River. The quantitative results confirm a decline in vegetation indices during the pollution event, highlighting the impact of air contamination. Ultimately, this research reinforces that multispectral remote sensing can effectively detect air pollution by analysing vegetation index variations. This study highlights the importance of vegetation indices in monitoring pollution. The observed fluctuations in NDVI, NDWI, SAVI, and ARVI values indicate that vegetation stress can serve as an early warning system for air quality degradation. Future research could integrate higher-resolution satellite data and machine learning techniques to enhance pollution detection accuracy. These findings emphasise the need for stricter environmental regulations to prevent similar incidents and protect vegetation from further degradation.

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Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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