

Linking Temperature, NDVI, and Methane to Assess illegal dumpsites Impacts in Puebla, Mexico

Resumen

Evaluar el impacto ambiental de los tiraderos de Residuos Sólidos Municipales (RSM) no gestionados es crucial debido a sus efectos perjudiciales en el medio ambiente y en la salud pública. En la ciudad de Puebla, México, los tiraderos a cielo abierto representan un desafío significativo para la gestión urbana de los residuos. Este estudio tiene como objetivo evaluar el impacto ambiental de los RSM, centrándose en la contaminación y la degradación ambiental mediante técnicas de percepción remota. Utilizando herramientas como Google Earth y Google Maps Street View, se identificaron y cartografiaron las ubicaciones de los basureros en áreas problemáticas conocidas. La evaluación ambiental se enfocó en tres factores clave durante dos años (2021-2022): salud de la vegetación, temperatura superficial y emisiones de metano (CH_4), y añadió la proximidad a caminos y la topografía como factores contextuales. Los datos de temperatura superficial se obtuvieron a partir de imágenes del satélite Landsat 7, mientras que el verdor de la vegetación se midió mediante el índice espectral NDVI de imágenes de PlanetScope. Las emisiones de metano se cartografiaron a partir de datos del satélite Sentinel-5 (TROPOMI) procesados en Google Earth Engine. Mediante el análisis de componentes principales (PCA) de los mapas resultantes reveló tres patrones principales en ambos años: 1) Se observaron altas concentraciones de metano en los tiraderos, particularmente en áreas elevadas. 2) Existió una clara correlación entre los tiraderos en áreas de alta temperatura y el deterioro de la salud de la vegetación. 3) Cuanto más cerca estaba un tiradero de las carreteras, mayor era su tamaño. Estos hallazgos subrayan la necesidad de mejorar las prácticas de gestión de residuos para reducir el impacto ambiental y fomentar la sostenibilidad en la ciudad de Puebla. La combinación de técnicas de percepción remota y de análisis multivariado ofrece un enfoque robusto para monitorear y gestionar estos desafíos ambientales.

Palabras clave: Tiraderos, contaminación ambiental, gestión de residuos, monitoreo remoto, degradación del ecosistema.

Abstract

Assessing the environmental impact of illegal dumpsites is critical due to their harmful ecological and public health effects. In Puebla City, Mexico, illegal dumpsites pose a significant challenge to urban waste management. This study aims to evaluate the environmental impact of illegal dumpsites, focusing on pollution and environmental degradation through remote sensing techniques. Using tools like Google Earth and Google

Maps Street View, we identified and mapped illegal dumpsites locations based on known problem areas. The environmental assessment concentrated on three key factors over two years (2021–2022): vegetation health, surface temperature, and methane (CH₄) emissions, with road proximity and topography added as contextual factors. Surface temperature data were derived from Landsat 7 imagery, while vegetation health was measured using the NDVI index from PlanetScope imagery. Methane emissions were mapped using Sentinel-5 (TROPOMI) satellite data processed through Google Earth Engine. The resulting maps principal component analysis (PCA) revealed three major patterns across both years: 1) High methane concentrations were found in illegal dumpsites, particularly in elevated areas. 2) There was a clear correlation between illegal dumpsites in high-temperature areas and vegetation health decline. 3) The closer a waste site was to roadways, the larger its size tended to be. These findings underscore the need for improved waste management practices to reduce environmental damage and enhance sustainability in Puebla City. Combining remote sensing techniques and multivariate analysis offers a powerful approach for monitoring and managing these environmental challenges.

Keywords: Illegal dumpsites, environmental pollution, waste management, remote monitoring, ecosystem degradation.

1. Introduction

Illegal dumpsites cause unprecedented damage to terrestrial and marine ecosystems worldwide. The high demand for goods and services from both industry and the population leads to increased waste generation, far exceeding nature's capacity to assimilate and degrade it (Okwaro et al., 2026). Due to the high volume of illegal dumping sites, which include both organic and inorganic materials, it is challenging to implement an effective management strategy. It is estimated that a large proportion of municipal solid waste in low-income countries is still disposed of uncontrolled or open dumping sites, with rates exceeding 90%, compared to less than 5% in high-income countries (Kaza et al., 2018; UNEP, 2024).. This issue is compounded by the rapid increase in illegal dumpsites, which reached 2.01 billion tons in 2016 and is estimated to reach 170% of that level by 2050 (Kaza et al., 2018). This severely impacts environmental conditions and public health in affected regions, making the identification and assessment of their ecological impact a crucial issue. During the decomposition of solid waste, various harmful substances are released, including greenhouse gases, dioxins, and furans

(carcinogenic compounds), contributing to air, water, and soil pollution (Das and Chandrappa, 2012). These elements disproportionately affect vulnerable populations, especially when actions are not taken to identify areas with uncontrolled waste sites.

Remote sensing techniques have been widely employed to monitor the environmental conditions surrounding illegal dumpsites, as demonstrated by several studies that assess the broader environmental impact of poorly managed solid waste sites. For instance, Mahmood et al. (2022a) introduced geospatial indices as an alternative approach to assess the environmental impact of illegal dumpsites, focusing on satellite imagery to evaluate waste-related issues. Silvestri and Omri (2007) developed a remote sensing method to identify illegal dumpsites by analyzing the radiometric properties of surrounding vegetation. Furthermore, Arafat and Rafizul (2023) applied remote sensing tools to monitor the environmental degradation around the Rajbandh landfill in Khulna City, Bangladesh.

Several studies have specifically analyzed the impact of landfills on surrounding vegetation using satellite-based indices. Mahmood et al. (2022b) used satellite data to assess the bio-thermal effects in illegal dumpsites, focusing on their proximity to urban areas and the resulting environmental stress on vegetation. Similarly, Borrell et al. (2013) examined the territorial characteristics of illegal dumpsites in Andalucía, Spain, to identify the primary factors associated with environmental degradation, including effects on local vegetation. Land surface temperature (LST) has been another critical indicator in assessing the environmental impact of solid waste sites. Yan et al. (2014) analyzed multi-temporal Landsat satellite images to monitor LST at illegal dumpsites, providing insights into how waste decomposition affects local temperature variations.

Methane formation in open dumps and landfills primarily results from the anaerobic decomposition of organic waste (e.g., food waste, vegetation, and paper) under oxygen-limited conditions. In this environment, methanogenic microorganisms break down complex organic compounds, producing biogas composed mainly of methane (approximately 50–70%) and carbon dioxide (Bogner et al., 2007; Kjeldsen et al., 2002). This process is strongly controlled by environmental variables. Moisture content plays a key role by enhancing microbial activity, facilitating nutrient transport, and promoting the hydrolysis of organic matter, which in turn increases methane generation rates (Kjeldsen et al., 2002). Temperature is another critical factor, as it regulates microbial metabolism; methane production typically increases under

mesophilic ($\approx 20\text{--}40\text{ }^{\circ}\text{C}$) and thermophilic ($\approx 50\text{--}60\text{ }^{\circ}\text{C}$) conditions, while extreme temperatures inhibit biodegradation processes (Amini et al., 2012). Additionally, vegetation interacts indirectly with methane dynamics, as its presence often reflects favorable moisture and nutrient conditions. However, when landfill gas emissions are high, they can inhibit vegetation growth (Xiaoli et al., 2011) by altering root systems and physiological processes in the surrounding areas (Bian et al., 2016).. Together, these factors control the rate and magnitude of methane emissions, which constitute a significant contribution to global greenhouse gas emissions (Bogner et al., 2007). Bodah et al. (2022) utilized Sentinel-5P TROPOMI satellite data to study emissions of methane-related pollutants, such as NO_2 and CO , from landfills. Moreover, Wang et al. (2024) reported that methane emissions from landfills are globally underestimated, emphasizing the critical need for accurate satellite-based monitoring of these greenhouse gases. In Mexico, a large amount of illegal dumpsites are disposed of in uncontrolled sites (e.g. Israde-Alcántara et al., 2009; Nájera-Aguilar et al., 2012). Recent estimates indicate that Mexico generates over 120,000 tons of municipal solid waste per day, with a significant proportion still disposed of in uncontrolled or inadequately managed sites (SEMARNAT, 2020; SEMARNAT, 2023).. However, nearly half of these sites lack the basic infrastructure to contain pollution (SEMARNAT, 2020). This situation arises because the regulatory framework that sets out the criteria and standards for the proper management of final disposal sites is not enforced, as authorities lack the technical capacity to oversee compliance (Pérez, 2014). This issue is evident across all cities in the country, particularly in Puebla, where around 300 tons of waste from illegal dumpsites are disposed of daily at uncontrolled sites, including ravines, rivers, streets, and vacant lots (IMPLAN, 2019). This exacerbates environmental conditions in the region and impacts public health.

The overall aim of this study is to evaluate the impact of illegal dumpsites in Puebla, Mexico; using remote sensing and geographic information systems (GIS), to provide spatially implicit evidence that can inform remediation strategies and improve solid waste practices. Hence, we ask the following questions: 1) What is the spatial distribution and density of uncontrolled illegal dumpsites in the metropolitan area of Puebla? 2) How do environmental indicators such as vegetation health, land surface temperature (LST), and atmospheric methane (CH_4) concentrations vary in areas where potential illegal dumpsites are located compared to their surroundings? 3) Can multivariate analysis (i.e., principal component analysis) effectively distinguish environmental degradation patterns associated with illegal dumpsites?

We postulate the following overall hypothesis: illegal dumpsites in Puebla City result in measurable environmental degradation, as evidenced by reduced vegetation health, increased land surface temperatures, and elevated methane concentrations. Those impacts can be reliably detected, quantified, and spatially characterized using remote sensing and GIS assessment.

The relevance of this study is to provide a methodology applicable to other locations within Mexico or Latin America, as well as enhancing understanding of the ecological consequences of poor waste management. Also, this study supports the design of evidence-based remediation strategies and informs local policy, which can contribute to more sustainable urban environmental governance.

1.1 Study area

Puebla, the capital city of the state of Puebla in central Mexico, is situated within the Puebla-Tlaxcala Valley, bordered by the Malinche volcano to the northeast, the Popocatepetl and Iztaccíhuatl volcanoes to the northwest, and the Sierra del Tentzo to the south (Figure 1). Covering an area of 591 square kilometers, Puebla City has an estimated population of over 2.6 million, representing approximately 38% of the state's total population (INEGI, 2023). The city is intersected by various streams that feed into the Atoyac River, which flows from the northern part of the city to the south. The high population density and shifting lifestyles in Puebla have made waste management increasingly complex, leading to significant accumulation of illegal dumpsites SW in ravines, rivers, and vacant lots. This situation exacerbates environmental pollution and poses health risks to the population.

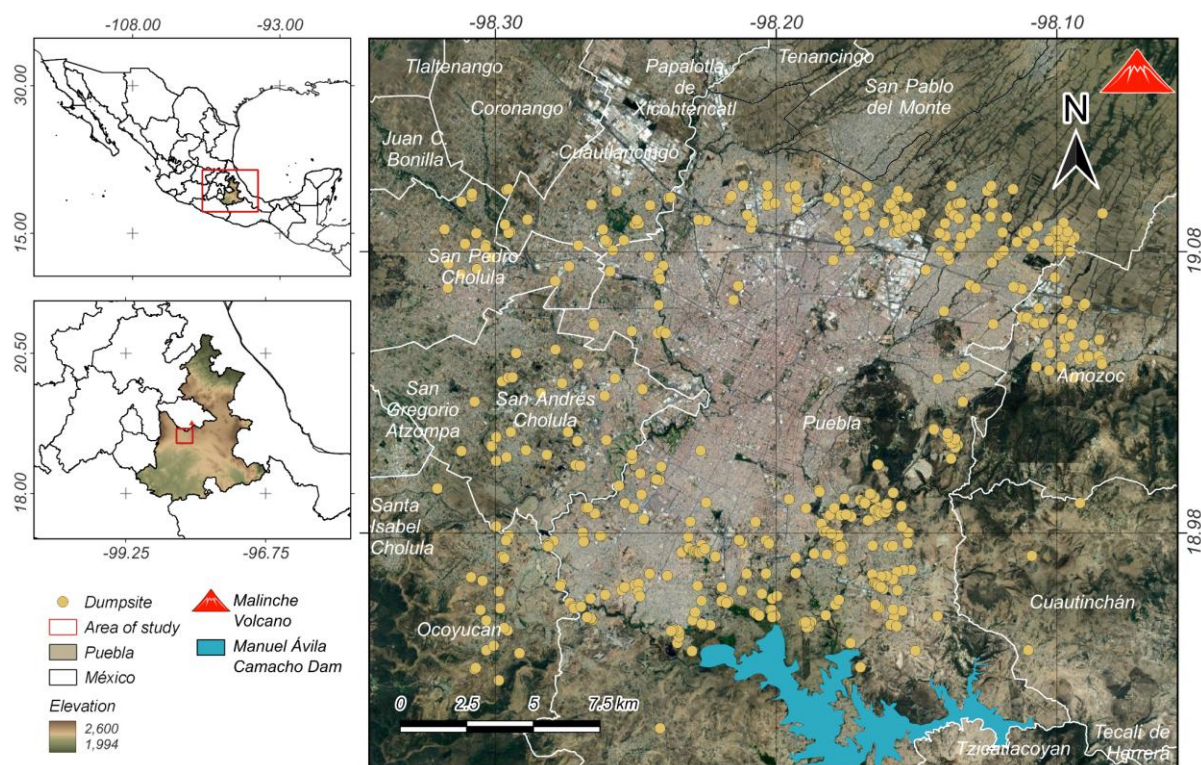


Figure 1: Location of the 502 illegal dumpsites identified in the municipality of Puebla and its metropolitan area through a visual search in Google Earth Pro.

2. Methodology

This study presents a structured methodology to evaluate the environmental impact of illegal dumpsites in Puebla City. Puebla has experienced rapid population growth, leading to high population density and complex waste management challenges. We organize a workflow based on three main tasks, followed by specific steps: 1) Mapping mismanaged illegal dumpsites, and the creation of a density map to represent their spatial distribution. 2) Selection of key environmental variables related to the impact of illegal dumpsites on the surrounding environment, such as vegetation health, surface temperature, and methane concentration. 3) Multivariate analysis to identify spatial correlation and patterns associated with illegal dumpsites. A rectangular region of interest (ROI) was defined to spatially encompass the entire Puebla metropolitan area and all identified illegal dumpsites. This extent was used to standardize methane extraction and spatial analysis across the study area. The following sections will outline the methods, tools, and techniques used for the illegal dumpsite inventory and the subsequent environmental analysis.

2.1 Inventory of solid waste sites

We conducted a systematic visual study using Google Earth Pro (images from 2019-2022), referencing known illegal dumpsites and their proximity to urban areas. We identified 502 illegal dumpsites, digitized their areas, and georeferenced them to the ITRF2008/UTM zone 14N coordinate system using QGIS. Figure 1 illustrates the spatial distribution of illegal dumpsites within the study area, while Figure 2 presents representative examples of their physical characteristics and appearance.

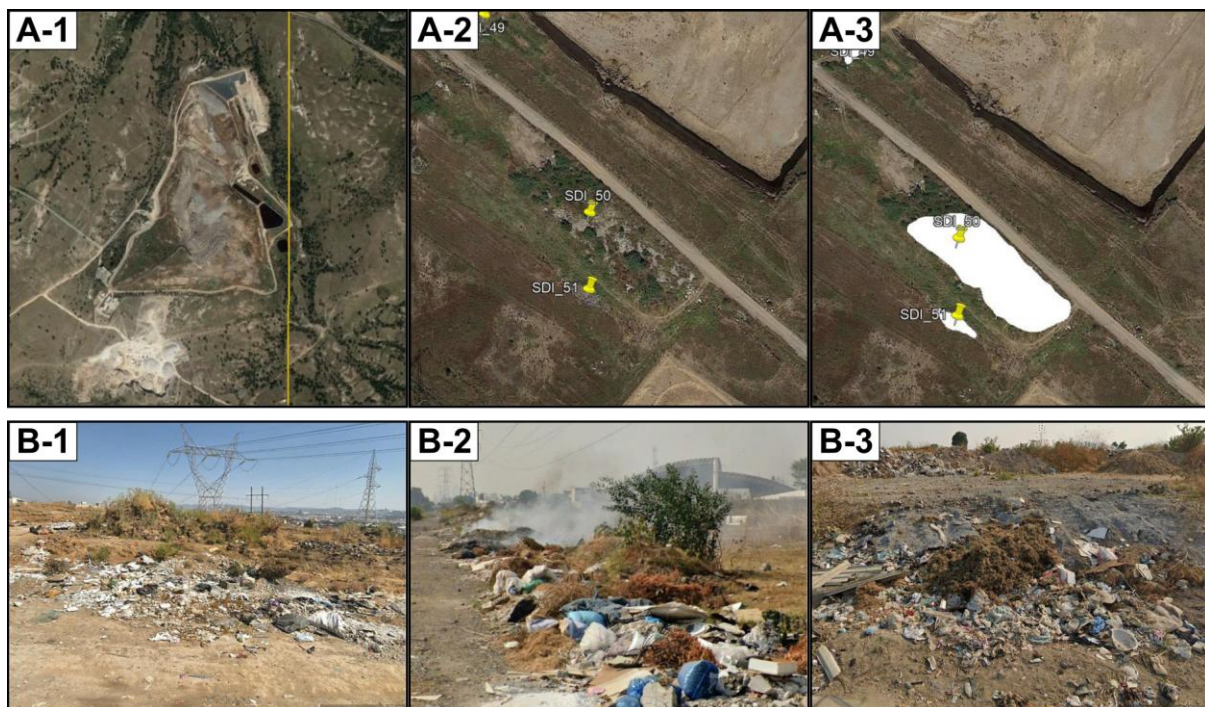


Figure 2. Representative examples of illegal dumpsites identified within the study area. (A-1) Large waste disposal site observed from satellite imagery. (A-2) Small and dispersed illegal dumpsites mapped within an urban-peripheral area. (A-3) Delineation of dumpsite areas used for spatial analysis. (B-1 to B-3) Ground-level photographs illustrating the physical characteristics, waste accumulation patterns, and environmental conditions of representative illegal dumpsites in Puebla City.

2.2 Data

In addition to the registry of illegal dumpsites, various geographic data were used to assess their environmental impact. This data includes maps of roadways and main highways, satellite imagery from the PlanetScope, Landsat 7, Global Wind Atlas (GWA), and Sentinel 5P

missions, and a digital elevation model retrieved from Earth Explorer. *Table 1* outlines the key characteristics of these datasets, their applications in the analysis, and their sources.

Table 1. Description of the Imagery Used for Processing Vegetation Health, Surface Temperature, Methane Concentration, wind speed and frequency and Topographic Data for Comparison.

Image	Band	Resolution	Date	Application	Source
Planet Scope	RGB	3 m	18/02/2021 20/02/2022	Vegetation Greenness	Planet
Landsat 7	Thermal Infrared (TIR)	60 m; 30m	20/02/2021 23/02/2022	Surface Soil Temperature; Soil Moisture	Earth Explorer
Sentinel 5p	Shortwav e Infrared (SWIR)	1113.2 m	02/2021; 02/2022	Methane Concentration	Google Earth Engine
Global Atlas	Wind	250 m		Wind speed and frequency	Global Wind Atlas
Digital elevation model		30 m		Topographic Features	Earth Explorer

2.3 Image Pre-processing

The data pre-processing aimed to correct errors and minimize atmospheric interference in Landsat 7 and PlanetScope images. Radiometric calibration was applied to adjust pixel values for sensor inaccuracies, followed by atmospheric correction to remove distortions caused by atmospheric conditions.

2.4 Inventory and Density Map

To map illegal dumpsites, a segmentation of the area of interest was established to facilitate the control of the reviewed zones. Each cell of this grid was manually examined using Google Earth and Google Maps Street View to identify solid waste sites. Additionally, images of known illegal dumpsites were used as guides for visualization and identification. A total of 502 sites were located, and their areas were calculated. Furthermore, the proximity of these sites to roadways was notorious. Once the sites were identified, a density map of these locations was created using the heatmap tool in the QGIS geoprocessing toolbox. The density map was based on the methodology of Rizzatti et al. (2020), which generated a distance matrix to compute the mean and standard deviation of the distances between the sites. This allowed the definition of the influence radius to calculate the density of SW in the city.

2.5 Vegetation Greenness

A spectral index was calculated from PlanetScope images to assess vegetation greenness. The Normalized Difference Vegetation Index (NDVI), the most widely used index for vegetation assessment, uses spectral bands in the red and infrared wavelengths to distinguish between healthy and stressed vegetation, producing values that range from -1 to 1 (S. Huang et al., 2020). Values close to zero indicate the absence of vegetation, while values near 1 indicate lush, vibrant greenery. The NDVI is calculated using the following equation 5:

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad \text{Eq 5}$$

NIR represents the reflectance in the near-infrared band, and *RED* represents the reflectance in the red band. This index provides a quantitative measure of vegetation greenness, enabling monitoring of vegetation vitality and density over time and across different geographic areas.

2.6 Land Surface Temperature (LST)

LST was calculated using Landsat 7 imagery, following the methodology established by Sobrino et al. (2004). This approach incorporates thermal band data and the Normalized Difference Vegetation Index (NDVI) to accurately estimate surface temperatures. The spectral radiance is converted to brightness temperature using the following equation 6:

$$T_b = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda + 1}\right)} \quad \text{Eq. 6}$$

Donde T_b Land Surface Temperature (in Kelvin), L_λ is the Spectral radiance of the thermal band (in $\text{W/m}^2/\text{sr}/\mu\text{m}$). K_1 And K_2 are the calibration constants specific to the Landsat sensor's thermal band (666.09 and 1282.71, respectively). NDVI values are first classified into three land-cover categories to derive surface emissivity, as shown in Table 2.

Table 2. Categorization of NDVI values used for the land surface temperature methodology.

Class	NDVI
Vegetation	> 0.5
Mixed	$0.2 - 0.5$
Bare soil	< 0.2

After classifying the NDVI values, the percentage of vegetation P_v is calculated for each pixel in the mixed category. This is done using the following equation (7):

$$P_v = \left(\frac{NDVI - NDVI_s}{NDVI_v - NDVI_s} \right)^2 \quad \text{Eq. 7}$$

Where $NDVI_v$ represents the NDVI threshold for fully vegetated areas (typically > 0.5) and $NDVI_s$ represents the NDVI threshold for bare soil (typically < 0.2). After classifying NDVI values into vegetation, bare soil, and mixed categories, emissivity values are assigned to these land cover types. Typically, standard emissivity values are used for fully vegetated and bare soil areas, as well as for mixed land cover, and a weighted equation is applied to calculate the emissivity.

For fully vegetated areas, emissivity is set to 0.99; for bare soil, emissivity is set to 0.97. For mixed areas, where the land cover is a combination of vegetation and bare soil, the following equation is used to calculate emissivity

$$\epsilon = 0.004P_v + 0.986 \quad \text{Eq. 8}$$

Donde ϵ is the emissivity of the mixed land cover and P_v is the percentage of vegetation calculated from NDVI. The constants 0.004, and 0.986 adjust the influence of vegetation on the emissivity value.

Lastly, the surface temperature (T_s) is calculated using the following equation:

$$T_s = \frac{T_b}{1 + \frac{\lambda T_b}{\rho} \cdot \ln(\epsilon)} - 273.15 \quad \text{Eq. 9}$$

Where T_b is the brightness temperature (in Kelvin), λ is the wavelength of the emitted radiance (in micrometers, typically for Landsat 7, around 10.4–12.5 μm for thermal bands), ρ is Wien's displacement constant ($1.438 \times 10^{-2} \text{ mK}$), ϵ is the surface emissivity, which corrects for the efficiency of the surface in emitting radiation. The constant 273.15 is used to convert the temperature from Kelvin to Celsius.

2.7 Soil Moisture Mapping

The Temperature Vegetation Dryness Index (TVDI) estimates soil moisture conditions by parameterizing the relationship between land surface temperature (LST) and the Normalized Difference Vegetation Index (NDVI) (Sandholt et al., 2002). The LST–NDVI feature space typically forms a triangular distribution, where the upper (dry edge) and lower (wet edge) boundaries represent limiting soil moisture conditions associated with evapotranspiration processes (Amani et al., 2016, Zhao et al. (2020)). TVDI values range from 0 to 1, with values near 0 indicating high soil moisture and those near 1 indicating extremely dry conditions.

The Temperature Vegetation Dryness Index (TVDI) is computed as a function of land surface temperature (LST) normalized between the minimum and maximum temperature values corresponding to a given NDVI::

$$TVDI = \frac{LST - LST_{min}}{LST_{max} - LST_{min}} \quad \text{Eq. 10}$$

Where LST represents the land surface temperature at each pixel, while LST_{min} y LST_{max} corresponds to the minimum and maximum temperature values associated with a given NDVI. These limits are defined by the wet and dry edges of the LST–NDVI feature space and are estimated as linear functions of NDVI

$$LST_{min} = a_1 + b_1 \cdot NDVI \quad \text{Eq. 10}$$

$$LST_{max} = a_2 + b_2 \cdot NDVI \quad \text{Eq. 11}$$

Where a_1 , a_2 are the intercepts and b_1 , b_2 are the slopes of the wet and dry edge models, respectively, obtained through ordinary least squares regression.

2.8 Methane concentration map

The troposphere's methane (CH_4) concentration was estimated using data from the Sentinel-5P satellite, specifically the Tropospheric Monitoring Instrument (TROPOMI), following methodologies already known and calibrated in global and regional works (e.g., Hu et al., 2018; Scheneising et al., 2019; Lorente et al., 2021; Plant et al., 2022). According to Richa-Singh (2023), TROPOMI detects methane by measuring characteristic absorption features in the infrared region of the electromagnetic spectrum. The sensor records the intensity of solar radiation reflected from the Earth's surface and atmosphere, where methane molecules absorb specific wavelengths of light. These absorption signatures are processed through atmospheric correction and retrieval algorithms to estimate atmospheric methane concentrations spatially.

The analysis was conducted on the Google Earth Engine (GEE) platform. Data were obtained from the Sentinel-5P image collection, which provides column-averaged methane volume mixing ratios. A temporal filter was applied from January 1, 2021, to December 31, 2022, to compute the average methane concentration for the study area during this period. A rectangular region of interest was defined, and the CH_4 data were filtered to include only the observations within this area. Pixels were further filtered based on data quality, selecting only those with a

quality assurance value greater than 0.5 to ensure measurements reliability. A temporal average of the filtered images was then calculated to create a representative map of methane concentration for 2021 and 2022. Finally, the mean methane concentration was visualized using a color palette, with values ranging from 1750 to 1900 parts per million to highlight variations, and the resulting map was exported as a GeoTIFF image for further analysis and interpretation.

2.9 Wind speed and frequency

The speed and frequency of the wind were obtained from the Global Wind Atlas (GWA) dataset, which provides estimates of average wind speed over the entire land surface at a spatial resolution of 250 m. The methodology used in GWA to reduce the spatial resolution of the wind is based on linearized flow models and high-resolution topographic data applied to databases and high-resolution wind maps (Davis et al., 2023). To download the data, 12 wind sampling points were spatially distributed across the study area to provide representative coverage and achieve a balanced spatial representation of local wind conditions. Information on average wind directions and frequencies was obtained in csv format. In addition, average wind speeds at a height of 100 m for the study area were obtained as a TIFF file.

2.11 Multivariate data analysis

PCA is a multivariate data analysis technique that aims to reduce the dimensionality of a correlated dataset while preserving as much variance as possible. The procedure involves computing the covariance matrix of the original variables, followed by extracting the eigenvalues and eigenvectors. The eigenvectors, which represent the directions of maximum variance in the data, are then ordered by their corresponding eigenvalues. This allows the identification of principal components and linear combinations of the original variables. By projecting the data onto these principal components, researchers can effectively identify patterns, relationships, and underlying structures within the dataset, facilitating a clearer understanding of the data's inherent characteristics. Data processing using the PCA technique was performed with the help of R software and its graphical interface Rstudio.

3. Results and discussion

This section presents the findings from the analysis of vegetation health, surface temperature, methane concentration, and the influence of topography and roadways in the study area.

Additionally, the cartography of illegal dumpsites was developed to serve as a comparative factor against all the analyzed variables. The results highlight the complex interactions among these factors and their implications for environmental monitoring and management. By integrating remote sensing data with multivariate analysis techniques, we aim to uncover patterns and relationships that enhance our understanding of the spatial and temporal dynamics affecting vegetation health and land surface temperature. The insights gained from this analysis are critical for informing mitigation strategies and improving land-use planning in response to environmental changes.

3.1 MSWD Density Map

The density map (Figure 3) illustrates the areas with the highest concentrations of illegal sites in Puebla, highlighted in red in the northeastern and southern regions. The city's southern part notably contains more illegal dumpsites. A total of 502 sites were identified, exhibiting significant variation in size. The median area of these sites is 154 m², with 75% covering less than 400 m². Most illegal dumpsites exceed 1,000 m², with the largest reaching 5,047.06 m². The identified solid waste sites also exhibit specific characteristics concerning their distance from major roadways and highways in the city. The median distance from these sites to the nearest roadways is 29 m, with 75% located within 54.4 m of a roadway. Several sites are more than 250 m away from roadways, with the maximum distance recorded at 2,221.4 m.

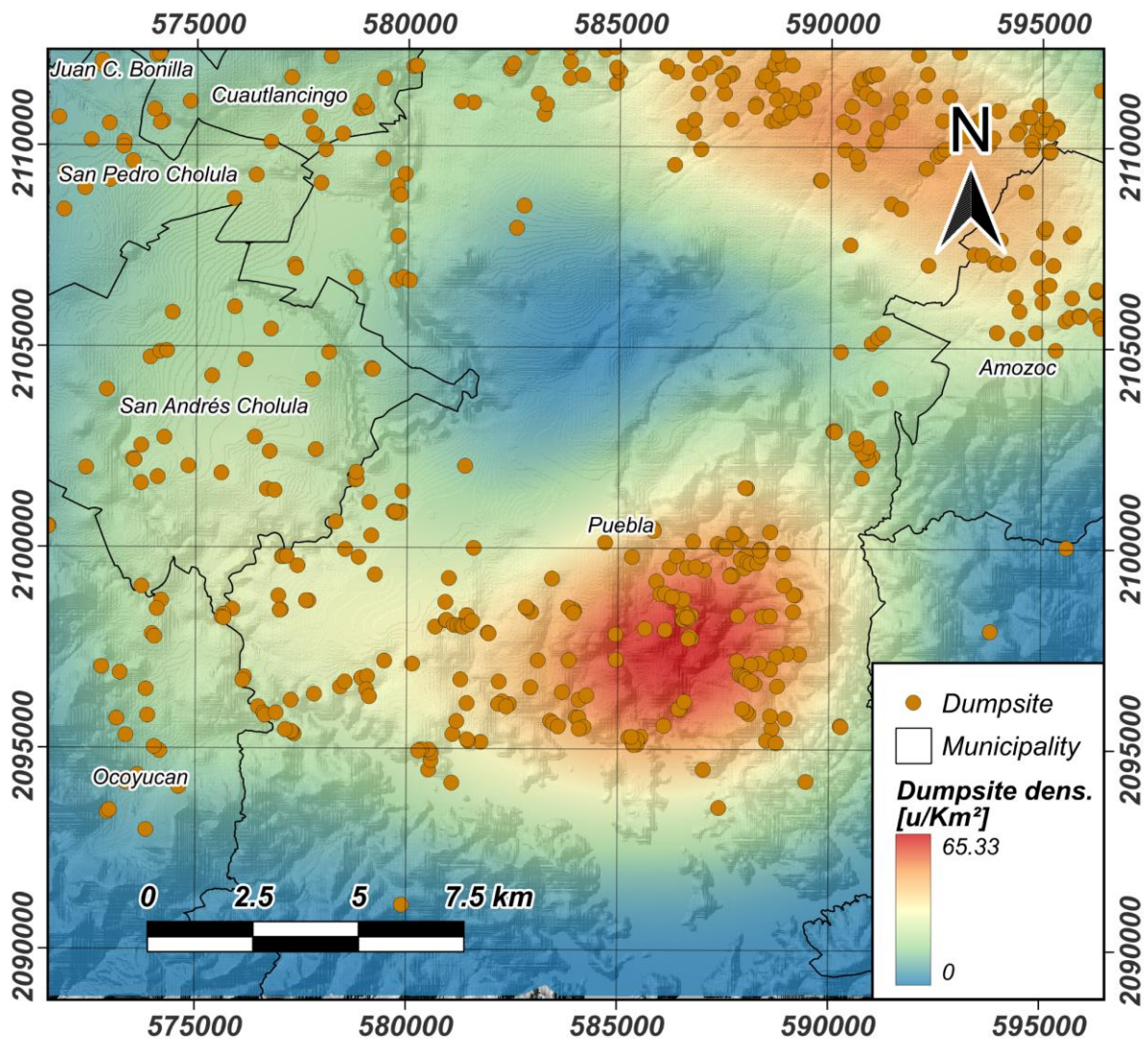


Figure 3. Density map of poorly managed SW sites identified through remote sensing.

3.2 Vegetation Greenness

The assessment of vegetation health in the study area for 2021 and 2022, as indicated by the NDVI (Figure 4), reveals three prominent peaks at 0, 0.4, and 0.85 (Figure 3, C1 and C2). The first peak indicates the presence of water bodies in the region. The second peak reflects moderately healthy vegetation interspersed with bare soils typical of urban environments. The final peak signifies agricultural lands and the presence of aquatic lilies. The average NDVI values for these years were 0.46 and 0.50, indicating a slight improvement in vegetation health in 2022. The boards C1 and C2 (Figure 4) show the identified peaks for 2021 and 2022, while board D (Figure 4) shows box plots summarizing NDVI statistics for each site in both years. It can be seen that for 2021, most sites have stressed and moderately healthy vegetation, with

values ranging from 0.41 to 0.53, and that, for 2022, the overall condition of the vegetation improves compared to the previous year. However, despite the overall improvement, vegetation health remains affected.

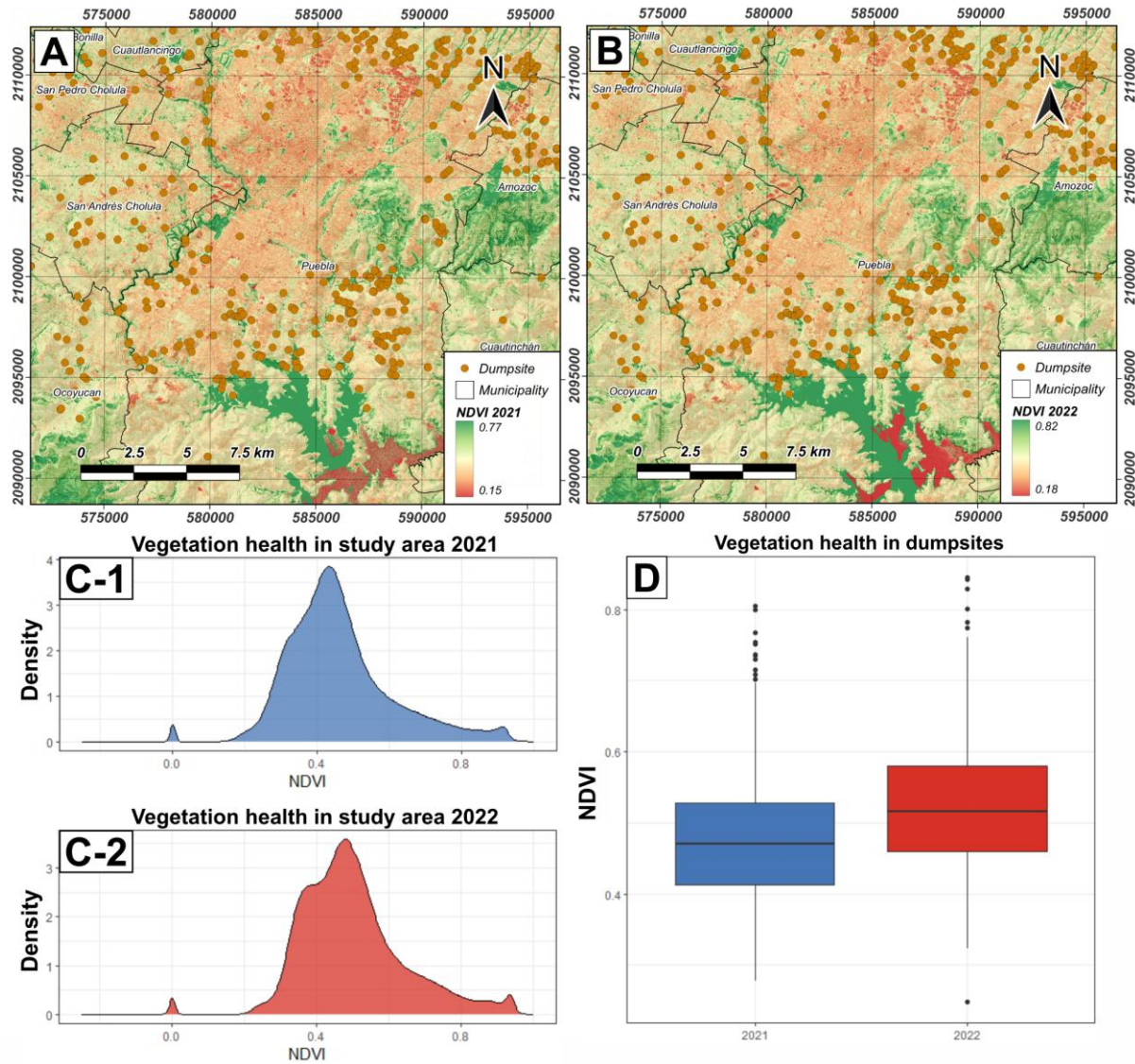


Figure 4: NDVI Analysis of Vegetation Health in the Study Area for 2021 and 2022. Panels A and B show NDVI maps, while Panels C1 and C2 illustrate the corresponding peak values. Panel D presents box plots summarizing NDVI statistics across sites for both years.

The average vegetation health in the sites identified with SW shows slight variation between the two years. However, in 2021, the impact on vegetation health was more pronounced.

In 2022, although the minimum NDVI decreased from 0.28 to 0.25, overall vegetation improved. In addition, the first quartile limit increased from 0.41 in 2021 to 0.46 in 2022, suggesting a slight improvement in vegetation health at SW sites, although some areas remain affected.

The outliers observed in both years indicate healthy vegetation within the MSWD sites (Figure 4-D), with a general improvement in 2022. Healthy vegetation is linked to improved overall conditions in the study area, primarily due to increased rainfall. Nevertheless, the reduction in the minimum NDVI values at the SW sites indicates ongoing issues with vegetation health. This suggests that climatic factors, which have positively influenced overall vegetation conditions, may be masking the deterioration experienced by most SW sites. Therefore, despite the overall improvement, SW continues to negatively impact vegetation health in the area.

3.3 LST

The analysis of surface soil temperature in the study area for 2021 and 2022 reveals significant trends, as shown in Figure 4. The surface temperature maps for 2021 and 2022 are shown in panels A and B of Figure 5, respectively. Specifically, the average temperature at illegal sites in 2021 was 21.14 °C, exceeding the regional average. The recorded surface temperatures show peak averages of approximately 20.5 °C in 2021 and 24.05 °C in 2022, indicating a general increase in temperature from one year to the following (Figure 5 C1 and C2). The third-quartile temperature in 2021 was 22.37 °C, with a maximum recorded temperature of 27.60 °C. These results indicate that at least 25% of the monitored sites exhibited surface temperatures above the regional average, likely due to high soil reflectance resulting from vegetation degradation and the thermal output of ongoing organic matter decomposition. (Figure 5D; Mahmood et al., 2016).

In 2022, surface soil temperatures rose at the SW sites, mirroring a similar trend across the entire study area (Figure 5B). The average temperature at these sites was 23.99 °C, which remains below the overall 2022 average. The third quartile ranged from 25.31 to 30.83 °C (Figure 5D). These trends are supported by the density histograms in Figure 5C1 and 5C2, which depict the temperature distributions for 2021 and 2022, respectively. The box plots in Figure 5D summarize the temperature results by site for both years, illustrating the variability and central tendency of the data. Overall, the data indicates that while temperatures have increased, the influence of illegal dumpsites remains critical to the area's thermal dynamics.

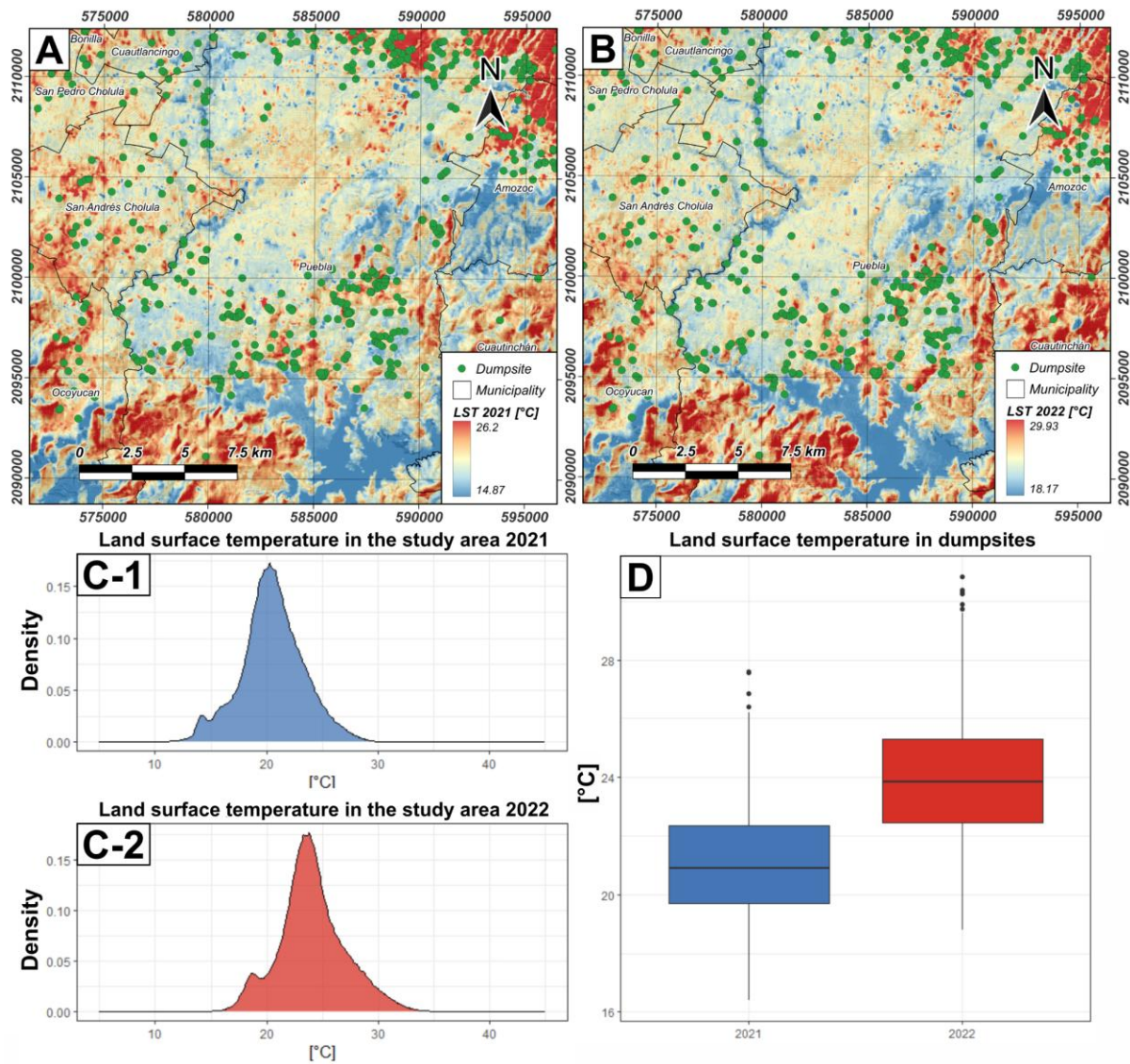


Figure 5: Surface Temperature Analysis in the Study Area for 2021 (A) and 2022 (B). C1 and C2 present the corresponding density histograms for each year. D provides box plots summarizing temperature statistics across sites for both years.

3.4 Soil Moisture Mapping

The LST–NDVI feature space for February 2021 and 2022 is shown in Figure 6. Linear relationships defining the wet edge and dry edge were derived for each period using ordinary least squares regression (Table 3).

In 2021, the wet edge is described by the equation $LST = 8.975 + 7.793 \cdot NDVI$ (Table 3), exhibiting a positive slope, indicating an increase in land surface temperature across vegetation cover under maximum evapotranspiration conditions. This positive trend may be influenced by the presence of unmasked water pixels within the study area. The dry edge is defined by LST

$= 32.614 - 16.312 \cdot \text{NDVI}$, where the negative slope reflects a decrease in maximum surface temperature with increasing vegetation cover under minimal evapotranspiration conditions. This upper boundary represents the limit beyond which soil moisture is insufficient to sustain continuous evaporative flux.

In 2022, the wet edge is represented by $\text{LST} = 10.400 + 9.204 \cdot \text{NDVI}$ (Table 3), with a positive slope indicating that surface temperature increases with higher NDVI values under wet conditions. The dry edge is defined by $\text{LST} = 39.776 - 22.646 \cdot \text{NDVI}$, with a negative slope consistent with the 2021 pattern, indicating a reduction in maximum surface temperature as vegetation cover increases. Figure 6B illustrates the spatial distribution of the LST–NDVI feature space and the corresponding wet and dry edge equations for Puebla City for both periods (A: 2021; B: 2022).

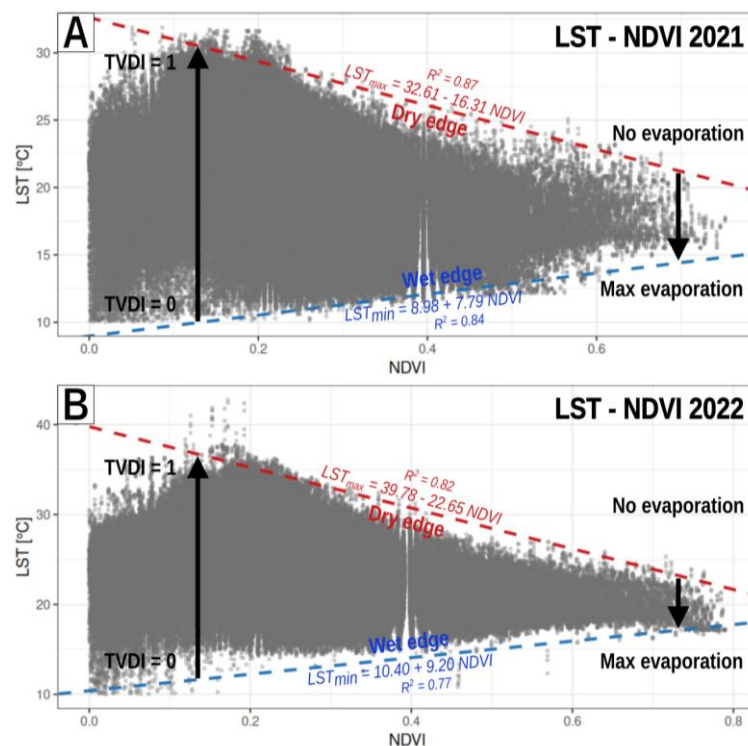


Figure 6. LST–NDVI Feature Space and Derived Dry and Wet Edge Relationships for Puebla City. A) 2021; B) 2022.

Table 3. Linear equations of the dry and wet edges derived from the LST–NDVI feature space, including their coefficients of determination (R^2) for February 2021 and 2022.

Year	Dry edge	Wet edge
2021	$\text{LST}_{\text{max}} = 32.61 - 16.31 \cdot \text{NDVI}$ $R^2 = 0.87$	$\text{LST}_{\text{min}} = 8.98 + 7.79 \cdot \text{NDVI}$ $R^2 = 0.84$
2022	$\text{LST}_{\text{max}} = 39.78 - 22.65 \cdot \text{NDVI}$ $R^2 = 0.82$	$\text{LST}_{\text{min}} = 10.40 + 9.20 \cdot \text{NDVI}$ $R^2 = 0.77$

2021	32.614 – 16.312 (NVDI) $R^2 = 0.867$	8.975 + 7.793 (NVDI) $R^2 = 0.843$
2022	39.776 – 22.646 (NVDI) $R^2 = 0.819$	10.40 + 9.204 (NVDI) $R^2 = 0.766$

The results indicate that the southwestern, eastern, and north-central areas (aquamarine colors) exhibit the highest soil moisture, whereas a large portion of the study area is characterized by high dryness. In 2021, the TVDI shows a mean value of 0.54 with a standard deviation of 0.13, indicating moderate variability around the mean. The corresponding histogram (Figure 7C-1) displays an approximately normal distribution, with a higher concentration of values above 0.5. In 2022, a slight decrease in the mean TVDI (0.52) is observed, along with a standard deviation of 0.12, suggesting a similar level of dispersion but a general shift toward lower values. This pattern is reflected in the histogram (Figure 7C-2), where a reduction in values above 0.5 can be observed.

TVDI values at sites with solid waste indicate relatively higher soil moisture conditions in 2022 compared to 2021. In 2021, most waste sites exhibit TVDI values above the median (0.55), whereas in 2022, the median decreases to approximately 0.51, and the third quartile falls below the median observed in 2021, suggesting an overall shift toward wetter conditions.

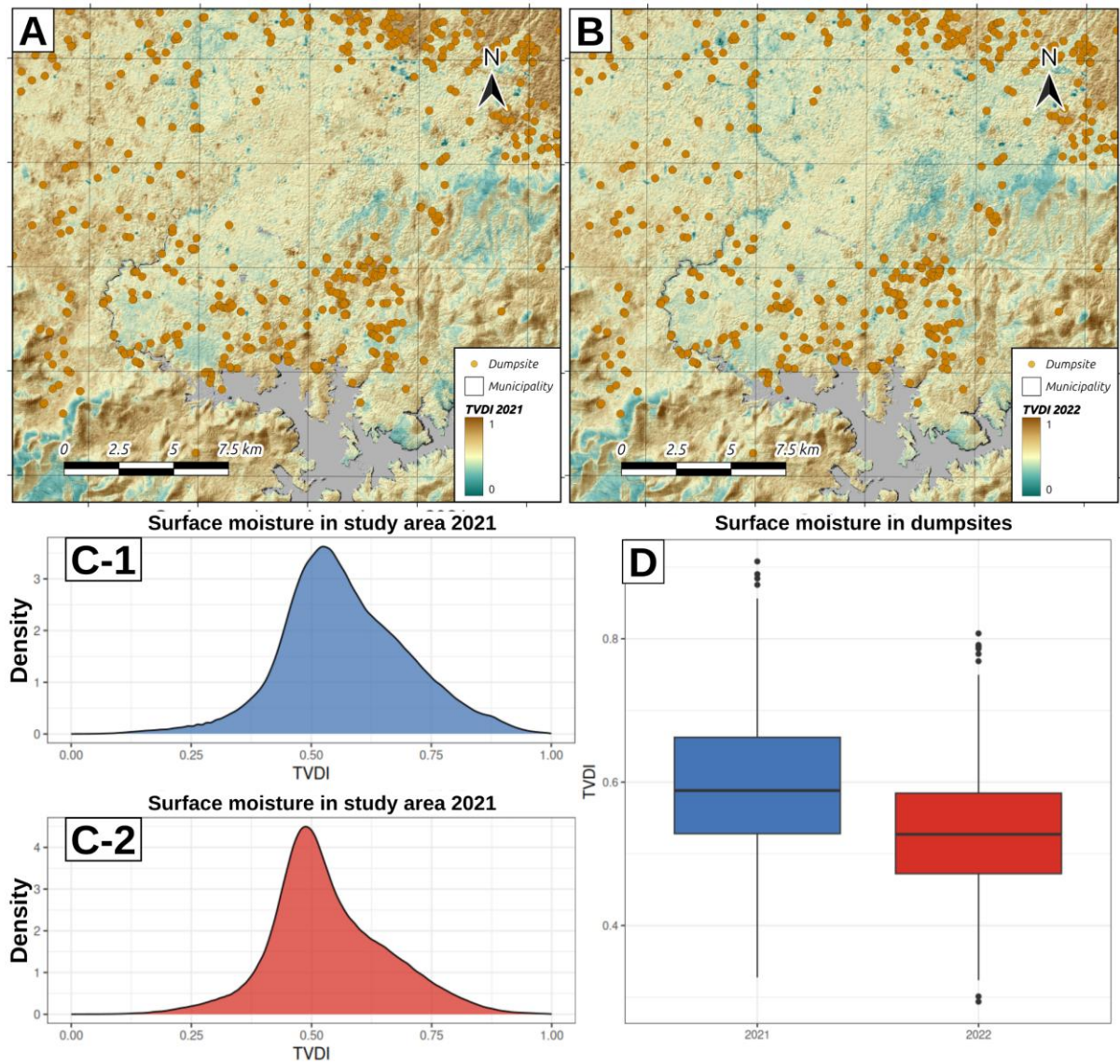


Figure 7: Soil moisture analysis for the study area in 2021 and 2022. (A–B) Spatial distribution maps of TVDI-derived soil moisture conditions for each period. (C1–C2) Corresponding density histograms. (D) Box plots summarizing soil moisture statistics across solid waste sites for both years.

3.5 Methane concentration map

Methane concentration data were recorded in 2021 and 2022, showing notable differences between the two years. The results of methane concentration measurements in Puebla are summarized in Figure 8. The highest levels of methane gas are found in the northeastern and western parts of the city, with elevated concentrations also detected in the central area (Figure 8A and B). Conversely, the lowest concentrations are primarily located in the southern region.

Moderate methane levels are dispersed throughout the city, with lower levels observed in the central-northern area; however, this distribution does not match the concentration patterns observed in the northeast and south. Density plots indicate that the distribution of methane concentrations exhibited several peaks, reflecting significant variability in the data. In 2021, most values clustered around the mean of 1889 ppb, with high dispersion and a variance of 229 (Figure 8C1). In contrast, the 2022 methane concentration had a mean of 1884 ppb, with reduced dispersion compared to 2021, as indicated by a much lower variance of 30 (Figure 8C2). Similar variability in methane fluxes has been reported in other illegal dumpsites due to fluctuating biological activity and waste age (Zhang et al., 2023 reported 750 parts per billion (ppb) to approximately 1850 ppb in 2017; Wang et al., 2024 reported values around 678 ppb, generally in the USA).

For sites with illegal dumpsites, methane measurements in 2021 showed greater dispersion, with an interquartile range of 35 and a maximum of 1914 ppb (Figure 8D). This could be associated with irregular methane releases from the illegal sites decomposition. In 2022, the dispersion of measurements decreased, with minimum and maximum levels of 1875 and 1900 ppb, respectively, reflecting lower variability than in 2021 (Figure 8D).

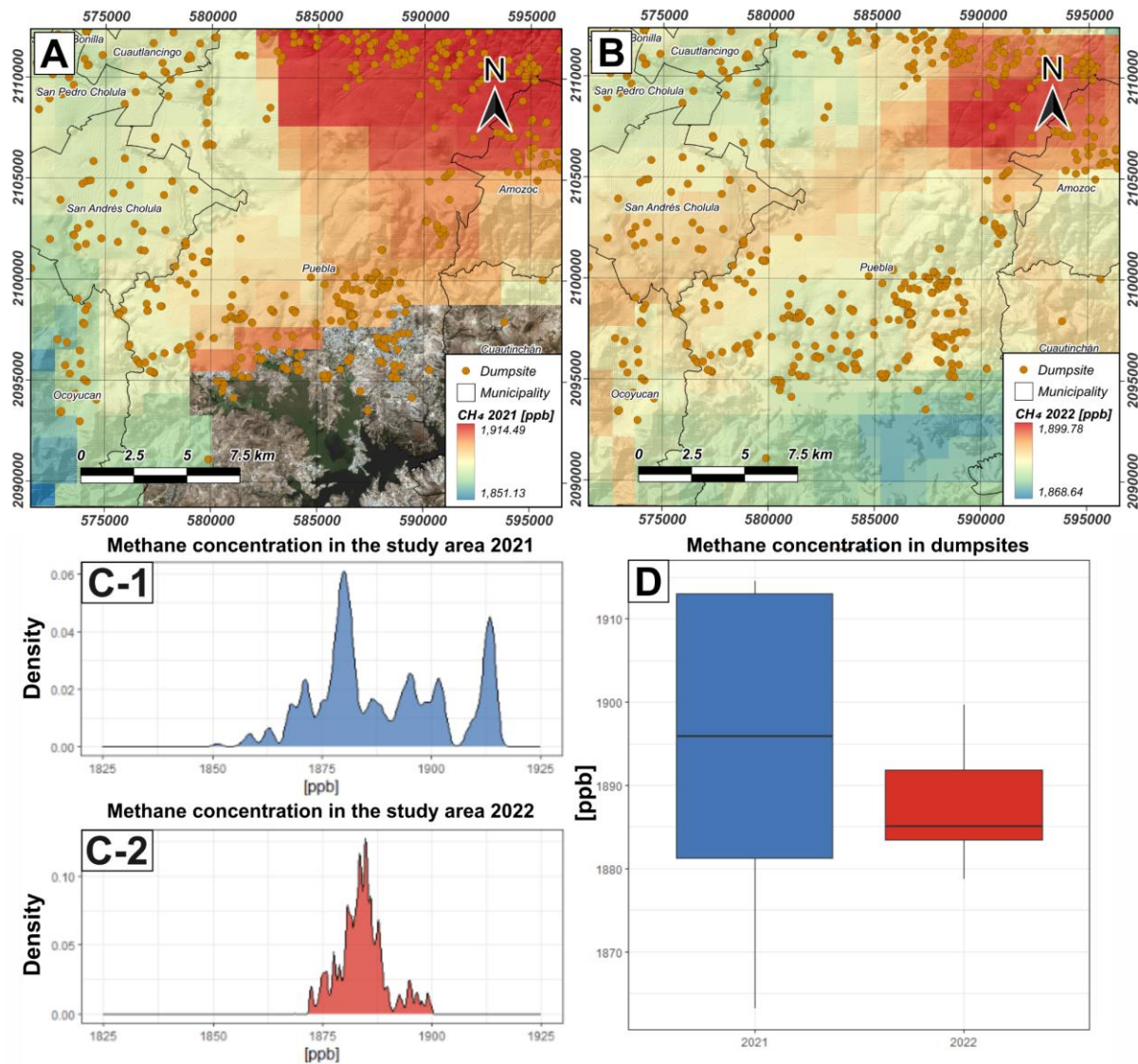


Figure 8: Methane Concentration Mapping in Puebla for 2021 and 2022. Panels A and B display concentration maps, while Panels C1 and C2 illustrate yearly density distributions. Panel D presents box plots summarizing methane concentration statistics across sites for both years.

3.6 Distribution of wind speeds and directions

The average wind speed and frequency in the study area indicate two spatial patterns. The first pattern is observed in the northeast, located on the southern slope of the Malinche volcano, where the highest methane measurements are recorded. This zone has the lowest average wind speeds in the area, ranging from 2.83 m/s to 3.34 m/s, corresponding to points 2, 5, 6, and 7 (Figures 9 and 10).

In these points, the wind exhibits a more or less regular frequency for various directions, however, there is a slightly greater predominance towards the southeast and south (Figure 10), and a lower frequency towards the southwest (Figure 10). The second pattern observed in the study area is mainly found in the southern and western parts of the city, located above the municipality of San Andrés Cholula and the Manuel Ávila Camacho dam (Figure 9). In this area, average wind speeds of 3.53 m/s to 5.19 m/s are recorded at points 1, 3, 4, 8, 9, 11, and 12 (Figures 9 and 10). The main wind directions in this area are toward the southwest and, to a lesser extent, toward the north and east (Figure 10).

The correlation between the lower speeds and methane accumulation in the northeast part of the city may be due to the topography of the area. Where the elevation of La Malinche volcano acts as a barrier, creating stagnant conditions that reduce the dispersion of polluting gases. In addition, lower speeds and the lack of a predominant flow direction may be causing gas recirculation in the northeast, due to the faster winds around it and its predisposition toward the southwest.

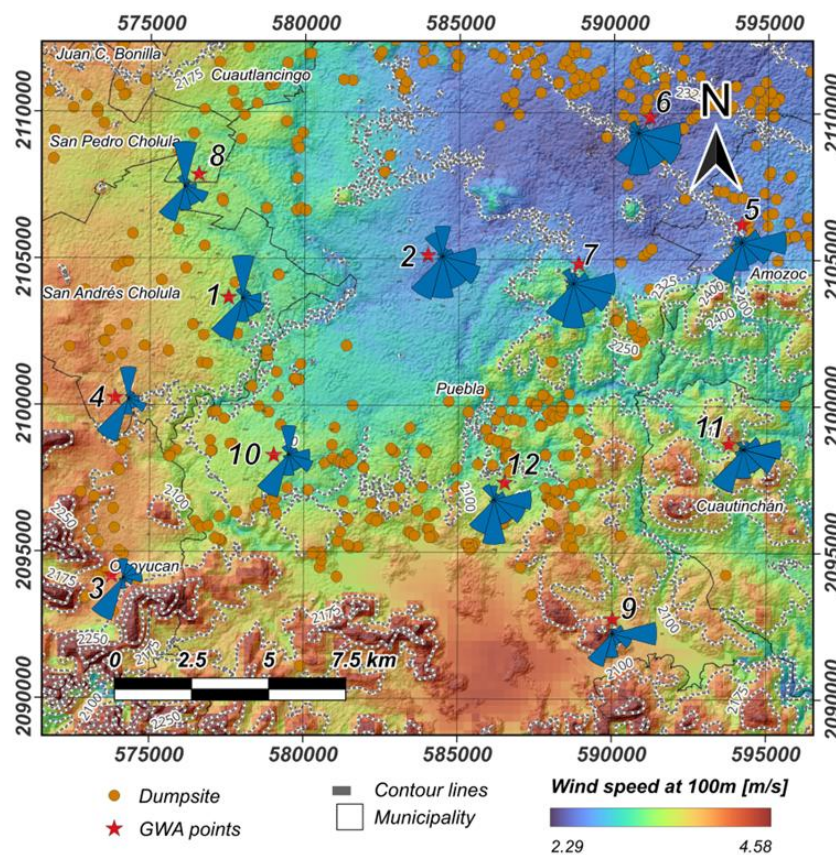


Figure 9. Map of the average wind speed in the Puebla-Tlaxcala metropolitan area. Average wind speed per site: 1) 3.53 m/s; 2) 2.83 m/s; 3) 5.19 m/s; 4) 4.81 m/s; 5) 3.34 m/s; 6) 3.14 m/s; 7) 3.13 m/s; 8) 4.37 m/s; 9) 4.78 m/s; 10) 3.45 m/s; 11) 4.47 m/s; 12) 4.31 m/s.

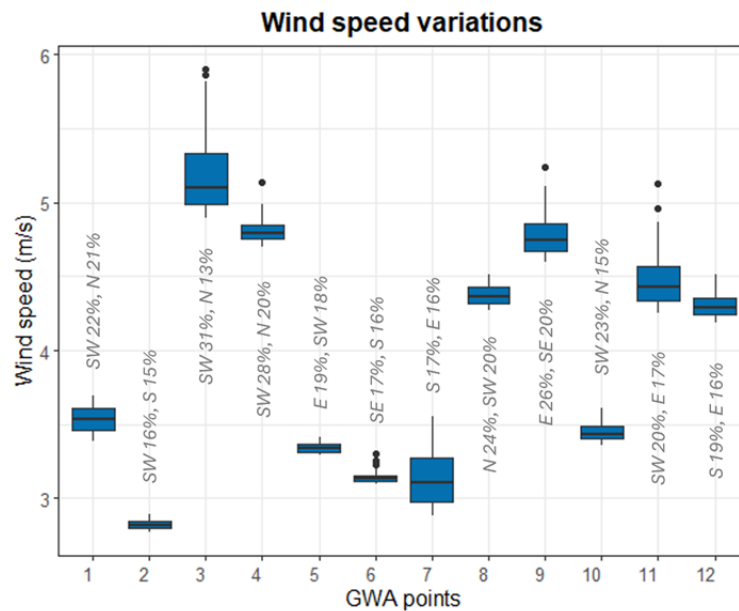


Figure 10: Wind speed and prevailing wind directions at sampling points in the study area. Prevailing directions and frequencies at recorded points: N – North; S – South; E – East; SW – Southwest; SE – Southeast.

3.7 PCA

The principal component analysis (PCA) was applied to a dataset composed of seven variables: area, elevation, NDVI, LST, TVDI, CH₄, and distance to roadways for 2021 and 2022. In 2021, the first two principal components (PC1 and PC2) explained approximately 50% of the total variance (Table 4). When the third component (PC3) was included, the cumulative explained variance increased to 65% (Table 4). The correlations between the principal components and the original variables indicate the following patterns. The first component showed strong correlations with LST, TVDI, and distance to roadways (Table 4), indicating a relationship associated with water stress conditions. The second component was correlated with CH₄, elevation, and TVDI (Table 4), suggesting a relationship between altitude and methane concentration. The third component was mainly associated with NDVI; however, a negative relationship was also observed within the first two components (Table 4), indicating an inverse relationship between LST and TVDI.

The PCA results for 2022 show that the first two principal components (PC1 and PC2) explained 58% of the total variance (Table 4). When the third component (PC3) was included, the cumulative explained variance increased to 73% (Table 4). The correlations between the principal components and the original variables were similar to those observed in 2021. The

first component was mainly associated with LST, TVDI, and distance to roadways (Table 4). The second component showed a correlation between CH₄ and elevation (Table 4). The third component was primarily related to NDVI and the area of the solid waste sites (Table 4).

Table 4: PCA results for 2021 and 2022 with three principal components.

	2021			2022		
Variables	PC1	PC2	PC3	PC1	PC2	PC3
Area	0.48	-0.21	0.24	0.38	-0.09	0.59
Elevation	-0.24	0.63	0.17	-0.18	0.91	0.10
NDVI	-0.28	-0.13	0.92	-0.34	-0.06	0.70
LST	0.79	0.45	-0.09	0.92	0.26	-0.14
TVDI	0.58	0.62	0.27	0.91	0.22	-0.02
CH ₄	-0.40	0.71	-0.02	-0.16	0.91	0.14
Dist. Roads	0.61	-0.34	0.15	0.49	-0.21	0.41
Std. Deviation	1.36	1.29	1.02	1.49	1.35	1.02
Variance %	0.27	0.24	0.15	0.32	0.26	0.15
Cumulative variance	0.27	0.50	0.65	0.32	0.58	0.73

During the analysis, three main groups were identified with the following characteristics. In 2021, Group 1 (red) was characterized by high LST and TVDI values, as well as relatively high CH₄ concentrations and elevation (Figure 11A). Group 2 (green) showed high NDVI values associated with low LST and TVDI conditions (Figure 11A). Group 3 (blue) presented very low CH₄ concentrations and average elevation values (Figure 11A). In 2022, the previously identified groups maintained similar general characteristics. Group 1 (red) remained associated

with high LST and TVDI values (Figure 11B). Group 2 (green) continued to exhibit the highest NDVI values and lower water stress conditions (Figure 11B). In contrast, Group 3 (blue) showed a substantial change, exhibiting the highest methane concentrations and elevation values (Figure 11B).

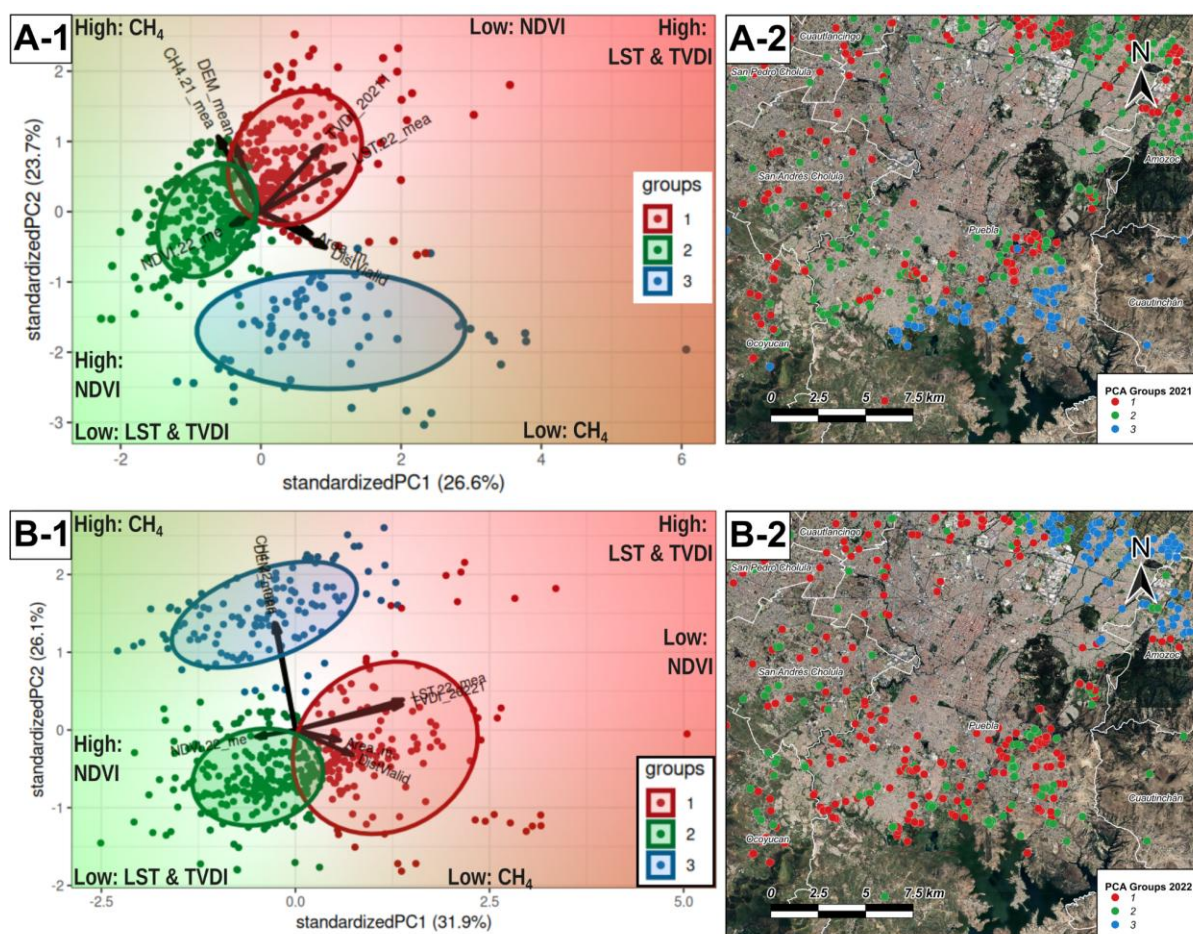


Figure 11: Principal Component Analysis of Environmental Variables Influencing Illegal Dumpsites SW Sites in Puebla. A) 2021, B) 2022.

3.8 Integrated Analysis of Methane and Environmental Variables

Atmospheric methane concentrations observed in Puebla City (mean values of approximately 1,884–1,900 ppb) are consistent with the urban background concentrations commonly reported for large metropolitan areas. Previous studies using TROPOMI data have shown that methane

concentrations in urban environments are strongly influenced by local anthropogenic sources, atmospheric mixing conditions, and meteorological variability (Plant et al., 2022).

The PCA results suggest that methane concentrations in the Puebla metropolitan area are not strongly controlled by local environmental conditions surrounding illegal dumpsites, such as vegetation cover or soil moisture. Groups characterized by contrasting NDVI, LST, and TVDI conditions showed similar methane concentrations in both analyzed years, indicating that the presence of vegetation or favorable moisture conditions for organic matter decomposition does not directly correspond to higher atmospheric methane levels. Furthermore, areas with the highest concentration of illegal dumpsites did not show a substantial increase in methane concentrations relative to the local background average.

Instead, methane variability appears to be more closely associated with topographic conditions. In 2021, higher methane concentrations were associated with elevated areas and moderate water stress, whereas in 2022, methane concentrations were concentrated within a cluster characterized by higher elevations. These results suggest that atmospheric circulation, topographic configuration, and local wind dynamics may influence methane transport and accumulation patterns in the study area. Previous studies using TROPOMI have demonstrated that methane concentrations detected in urban environments are strongly affected by atmospheric stability, boundary layer dynamics, wind circulation, and sensor detection thresholds, which can obscure direct relationships between small emission sources and detected atmospheric methane concentrations (Plant et al., 2022; Jacob et al., 2022).

The inverse relationship observed between NDVI and both LST and TVDI suggests that vegetation cover may partially mitigate thermal stress, whereas areas lacking vegetation are more susceptible to higher surface temperatures and lower soil moisture. Although methane concentrations did not show a strong relationship with vegetation conditions, NDVI values revealed measurable differences among several illegal dumpsites, suggesting that these sites still produce localized environmental impacts. These impacts likely depend on factors such as waste deposition conditions, residence time, deposit age, and site persistence. It is possible that Group 1, characterized by lower NDVI values, corresponds to older dumpsites where vegetation degradation has occurred over longer periods. However, climatic variability may also influence vegetation conditions in the study area. February 2022 recorded higher precipitation (12.6 mm) than February 2021 (7.2 mm), which may have enhanced vegetation greenness independently of waste-related effects. Therefore, longer temporal analyses are necessary to better distinguish the environmental impacts associated with illegal dumpsites from broader climatic influences.

These results also highlight an important limitation of TROPOMI for detecting emissions from small and dispersed illegal dumpsites. Previous studies have shown that TROPOMI is more effective for identifying large and concentrated methane sources, such as sanitary landfills, industrial facilities, livestock emissions, and oil and gas infrastructure, than diffuse urban waste sites (Jacob et al., 2022; Lauvaux et al., 2022; Irakulis-Loitxate et al., 2021). Additionally, although the area of each dumpsite was mapped, it was not possible to estimate waste volume, which may also influence methane production potential.

Finally, the PCA revealed a relationship between dumpsite area and distance to roadways, indicating that larger illegal dumpsites tend to be located farther from urban roads. This pattern suggests that areas with lower accessibility, reduced human presence, or limited surveillance may facilitate the accumulation and persistence of larger volumes of waste. Unlike large sanitary landfills, illegal dumpsites are generally smaller, spatially dispersed, and characterized by variable waste accumulation times and compositions, which can limit the detectability of methane anomalies at the spatial resolution of Sentinel-5P. Nevertheless, the environmental conditions associated with these sites, including elevated surface temperatures, reduced vegetation cover, and lower soil moisture conditions, may still indicate localized environmental degradation linked to waste accumulation processes (Richa-Singh, 2023).

4. Conclusions

This study successfully analyzed the interactions between environmental variables and illegal dumpsites in Puebla using advanced remote sensing techniques. The findings demonstrate that vegetation health, as indicated by NDVI, and surface temperature are distributed in ways controlled by the conditions at these illegal dumpsites. Notably, the analysis revealed that sites with higher elevations tend to have greater methane concentrations, suggesting a direct correlation that warrants further investigation.

The Principal Component Analysis (PCA) provided valuable insights into the underlying patterns among various environmental factors. In 2021, two principal components captured 66% of the variance, primarily explaining correlations between methane levels, elevation, and distance to roads and vegetation health and land surface temperature. The PCA for 2022 indicated similar trends, with three components explaining 73% of the data variance, underscoring the persistent relationships among these variables over time.

From a geophysical standpoint, this study contributes to environmental geophysics by demonstrating how satellite-based measurements, such as land surface temperature, spectral vegetation indices, and atmospheric methane concentration, can be used to detect and characterize surface processes associated with anthropogenic waste accumulation. The integration of thermal infrared data (Landsat 7), high-resolution reflectance imagery (PlanetScope), and gas emissions monitoring (Sentinel-5P TROPOMI) supports the geoscientific assessment of energy exchange dynamics, surface degradation, and pollution dispersion in urbanized environments. This framework strengthens the application of geophysics to urban sustainability and risk management in Latin America.

Ultimately, this research contributes to a greater understanding of the complex dynamics in urban areas with poorly managed waste. The insights gained can guide future studies and inform stakeholders in developing sustainable dumpsites practices that mitigate environmental impacts and improve public health in Puebla City and other similar urban regions.

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