Legislation and ethical considerations of remote sensing technology for environmental surveillance

Nibras Aref Abdalameer[1], **Shahad Salah Abrahim**[2], **Shamel Abdul-Sattar Jaleel Shalaan**[3], **Adhraa Oudha Hussen Al-Saedi**[4], **Matai Nagi Saeed**[5], **Saleh Mahmoudi**[6], **and Mohammad Hossein Sedri**[7]

[1]Al-Turath University, Baghdad 10013, Iraq
[2]Al-Mansour University College, Baghdad 10067, Iraq
[3]Al-Mamoon University College, Baghdad 10012, Iraq
[4]Al-Rafidain University College, Baghdad 10064, Iraq
[5]Madenat Alelem University College, Baghdad 10006, Iraq
[6]Soil Conservation and Watershed Management Research Department, Kurdistan Agricultural and Natural Resources Research and Education Center, AREEO, Sanandaj, Iran
[7]Soil and Water Research Department, Kurdistan Agricultural and Natural Resources Research and Education Center, AREEO, Sanandaj, Iran

ARTICLE INFO	ABSTRACT
Paper Type: Research Paper **Corresponding author:** S. Mahmoudi ✉ s_mahmoudi@sbu.ac.ir	Remote sensing technologies have become transformative in environmental monitoring, enabling large-scale, cost-effective, and consistent assessment of ecological systems. This study examines both technological applications and governance, focusing on operational methodologies and evolving legislative and ethical frameworks shaping remote sensing in environmental surveillance. Concentrating on urban and peri-urban areas, high-resolution multispectral satellite data (Landsat 8 OLI/TIRS) were integrated with synchronized ground-based measurements to explore interactions among vegetation cover, land surface temperature (LST), and fine particulate matter ($PM_{2.5}$). Advanced processing included radiometric calibration, atmospheric correction (FLAASH), and supervised classification (Random Forest) to ensure data fidelity. Vegetation was quantified using NDVI, while LST was derived with the split-window technique and analysed against EPA-standard $PM_{2.5}$ through multivariate regression. Results revealed a 35% variation in foliar coverage (32–67%), with inverse correlations between vegetation density and both LST (20.1–25.7 °C) and $PM_{2.5}$ (10.8–17.2 μg/m³). Site I showed a 59% higher particulate load than Site H, underscoring the combined effects of urban heat island intensity and reduced green space. Beyond technical outcomes, the study highlights policy implications, including aerial data privacy, cross-border data sharing, and aligning technological capacities with environmental regulation, establishing a foundation for ethically grounded applications of remote sensing in sustainability.
Highlights	• Remote sensing reliably links vegetation, temperature, and air pollutants. • Ground validation enhances the legal and scientific credibility of satellite data. • Ethical frameworks ensure responsible use of geospatial surveillance tools. • AI and real-time satellites enable adaptive, scalable environmental monitoring.

1. Introduction

Remote sensing technology has emerged as an invaluable tool for environmental monitoring, allowing for widespread data collection and analysis on a global scale. Remote sensing, for instance, is a way to capture and study environmental changes instantly using advanced sensors and satellite imaging systems (Ababakr et al., 2023, Amini, 2020). Its utility ranges from tracking deforestation, monitoring air quality, assessing climate change and natural resources. The capacity of this technology to provide accurate, large-scale data on the environment has essentially revolutionized the way in which governments, researchers, and industries confront ecological problems (Jiao, 2024).

Although the adoption of remote sensing is increasing, its incorporation into environmental monitoring presents a challenging array of legal, regulatory, and ethical issues. The growth of remote sensing technologies has also contributed to an increasing amount of diverse data being generated. Though these improvements strengthen environmental oversight, they also raise novel questions about privacy, data ownership and accountability. For example, one of the most contentious subject areas for using high-resolution imagery to monitor human activity in sensitive areas when various stakeholders have no clear understanding of how the data is controlled or used, especially where there is a significant possibility for a host nation to retaliate against a launch country. Regulatory fragmentation across jurisdictions increases this challenge and uncertainty, and hampers the emergence of best practices for responsible data use (Esiri et al., 2024).

Another key issue is the absence of cohesive legislative frameworks. Some countries have enacted national laws on remote sensing, but harmonization on an international scale is lacking. Such misalignments present challenges to cross-border collaborations and undermine efforts for common protocols. Lack of clear international standards contributes to challenges in resolving disputes related to data collection practices, ensuring equitable access to technological resources, and preventing misuse of sensitive environmental data. The result is an often reactive, rather than proactive, regulatory environment, unable to keep pace with technological innovation (Khan et al., 2024).

The rapid advancement of remote sensing technology also raises critical questions regarding the respective roles of public and private actors in environmental monitoring (Borah et al., 2024). Their duties and obligations differ from those of governmental organizations as private companies become increasingly involved in this area (Li et al., 2020). Whereas government agencies by default take care of public good, private firms may only focus on commercial interest. Not only should these policies encourage innovation, but they must also protect public interest. It also checks the need for transparent data-sharing agreements, as well as clearly defined accountability measures (Harbi et al., 2024).

One urgent challenge is making sure that remote sensing technologies are available and useful for all countries, and not just those with advanced technological infrastructure. Unequal access to the means of data-driven decision-making risks widening the gap between resource-rich and resource-poor countries. Countries that lack continuing technical capacity or funding may find it impossible to harness the remote sensing, leaving essential environmental questions underexplored and unaddressed. Consequently, global initiatives focusing on capacity-building and technology transfer are integral to facilitating a more equitable access to remote sensing resources (Wang et al., 2024).

Another big consideration is how to integrate remote sensing data in policy-making. While this technology offers important insights, translating data into action requires close cooperation between scientists, regulators, and decision-makers (Thorpe, 2023). This leads to a need to bridge a gap between remote sensing usage and the input of remote sensing researchers: Policymakers must be made aware of the technical limitations and of inaccuracies potentially arising from remote sensing data, on the other side, researchers should communicate their findings in a timely and easily understandable manner to non-technical audiences (Maniadaki et al., 2021a; Lysenko & Lozhkovoi, 2022). This calls for building predictive agendas between these groups to turn remote sensing evidence into local solutions to global problems (Raihan, 2024).

Remote sensing is an ever-evolving field that requires continuous education and training. With even the most cutting-edge technologies being rapidly outdated, a career in technology demands a commitment to lifelong learning. The appropriate training programs and resources must be offered by universities, research institutions, and industry organizations. The remote sensing community supports this and can help advance its purpose of promoting an up-to-date workforce, thereby guaranteeing that technology will proceed in a suitable path (Marques et al., 2024). Remote sensing technologies provide unprecedented environmental monitoring capabilities, but their integration into the domain presents challenges. To this end, the journey toward remote sensing will require a holistic framework that considers the legislative context, equitable access, open data, and collaborative research practices from interdisciplinary stakeholders. Addressing these challenges will enable all stakeholders to use this powerful technology responsibly and effectively to contribute to sustainable environmental management.

This article is structured as an integrated analysis that bridges a technical investigation with a critical examination of legislative and ethical frameworks. While the study presents a concrete technical case quantifying interactions between vegetation cover (NDVI), land surface temperature (LST), and particulate matter ($PM_{2.5}$) using remote sensing, this empirical work is fundamentally in service of a larger goal. The primary aim is to use these technical findings to ground a discussion on the legal and ethical challenges surrounding environmental surveillance, such as data privacy, equitable access, and regulatory harmonization. The technical analysis provides the evidentiary basis to explore knowledge deficits in existing regulations, identify barriers to effective monitoring, and propose solutions that balance innovation with accountability. By demonstrating how robust scientific methodology must be coupled with responsible data governance, this study clarifies that its focus is not solely technical nor purely legal, but rather on the essential interconnection between them. Ultimately, it aims to offer actionable guidance for ensuring that remote sensing applications are both scientifically sound and ethically

grounded, thereby contributing to more effective and just environmental monitoring efforts.

2. Materials and Methods
2.1 Remote sensing–based environmental data acquisition

To systematically monitor environmental conditions relevant to particulate matter emissions, this study utilized a dual-source data acquisition approach, integrating very high-resolution satellite imagery with geo-validated terrestrial measurements. Satellite imagery was sourced from commercial optical sensors offering spatial resolution finer than 1 meter per pixel, with coverage dates aligned to field observations to ensure temporal coherence (Jiao, 2024; Khan et al., 2024; Wang et al., 2024). Platforms used include WorldView-3 and GeoEye-1, which operate in the visible, near-infrared (VNIR), and shortwave infrared (SWIR) spectral bands, optimal for vegetation and thermal assessments (Harbi et al., 2024; Marques et al., 2024).

In parallel, ground-truth validation was performed using handheld environmental sensor modules equipped with high-precision GPS units (± 3 m error). These sensors recorded real-time measurements of three key environmental parameters. Vegetation cover (VC) was assessed using NDVI-calibrated handheld spectral meters, providing accurate on-site vegetation data. Surface temperature (Ts) was measured through thermographic infrared thermometers, specifically the Fluke Ti480 PRO model, which offered high-resolution thermal readings. Additionally, particulate matter ($PM_{2.5}$) concentrations were monitored using mobile laser photometers (TSI DustTrak II Model 8530), allowing reliable and portable air quality assessments.

All readings were synchronized with the Coordinated Universal Time (UTC) and recorded during cloud-free conditions to ensure optical consistency (Dimakopoulou et al., 2024; Raihan, 2024; Shin et al., 2023). All terrestrial measurements were processed in ArcGIS Pro and synchronized using QGIS's georeferencing module. This dual-source dataset formed the foundational layer for image calibration, classification modeling, and statistical inference(Esiri et al., 2024; Raihan, 2024).

2.2 Image preprocessing and geometric normalization

Raw satellite images underwent preprocessing pipelines in ENVI 5.6 and Google Earth Engine, including:

For radiometric calibration, Top-of-Atmosphere Reflectance (TOA) was calculated to eliminate sensor-related noise and atmospheric interference using Equation 1 (Dube, et al., 2023; Ouchra et al., 2023):

$$\rho_{TOA} = \frac{\pi \cdot L_\lambda \cdot d^2}{E_{sun} \cdot \cos(\theta_s)} \tag{1}$$

where ρ_{TOA} is top-of-atmosphere reflectance; L_λ is spectral radiance; d is Earth-Sun distance (astronomical units); E_{sun} is exoatmospheric solar irradiance and θ_s is solar zenith angle (degrees). The geometric correction process involved georeferencing all imagery to the WGS-84 datum (EPSG:4326) through first-order polynomial transformation with bilinear interpolation, utilizing manually selected ground control points (GCPs) that achieved a sub-pixel alignment accuracy of RMSE <0.4 pixels (Mahmoudi & Abdoli, 2025).

2.3 Spectral indexing and land cover feature engineering

Spectral indices were derived from the imagery using established formulations, including the Normalized Difference Vegetation Index (NDVI) calculated through Eq. 2, to quantitatively characterize physical landscape features (Gharibreza et al., 2018).

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{2}$$

where NIR and RED are near-infrared and red reflectance bands, respectively. NDVI was used to compute vegetation density thresholds that correspond to VC% categories: low (<0.3), medium (0.3–0.6), and high (>0.6). The land surface temperature (LST) was calculated from thermal infrared satellite data using a radiative transfer model (Eq. 3) that incorporates surface emissivity corrections and atmospheric compensation, following the methodology established by Amini et al. (2009).

$$LST = \frac{BT}{1 + \left(\frac{\lambda \cdot BT}{\rho} \cdot In\, \epsilon\right)} \tag{3}$$

where BT is brightness temperature from the thermal infrared band; λ is wavelength of emitted radiance (typically 10.9 μm); ρ is a constant equal to Planck's constant multiplied by the speed of light and divided by the Boltzmann constant (Planck's constant × speed of light / Boltzmann constant); ϵ is surface emissivity. The emissivity ϵ was adjusted based on NDVI values following the Sobrino NDVI-threshold method (Muruganantham et al., 2022; Wang et al., 2024).

2.4 Land cover classification using supervised machine learning

Supervised classification was applied using the Maximum Likelihood Classifier (MLC) in ENVI, chosen for its probabilistic handling of multi-dimensional feature space. Training polygons were delineated from field-verified land use samples. Five land cover classes were defined: Forest, Urban, Agricultural, Water, and Other. Let x be a feature vector (e.g., NDVI, LST, or texture). Then, the probability of class membership, denoted as $P(w_i|x)$ is given by Eq. 4 (Ouchra et al., 2023):

$$P(w_i|x) = \frac{1}{(2\pi)^{n/2}|\Sigma_i|^{1/2}} \cdot \exp\left(-\frac{1}{2}(x-\mu_i)^T \Sigma_i^{-1}(x-\mu_i)\right) \tag{4}$$

where μ_i is the mean vector of class w_i; $\sum_i$ is the covariance matrix of class w_i; n is the number of features, x is feature vector of the pixel. Classification outputs were exported as raster layers (.tif), and later validated using a confusion matrix against ground-truth samples (Jafarzadeh et al., 2022; Ouchra et al., 2023).

The predictor variables, vegetation cover (NDVI) and land surface temperature (LST), were selected based on their established ecological relevance to particulate matter dispersion and urban heat island effects. Multicollinearity between predictors was assessed using the Variance Inflation Factor (VIF), with values below 2 indicating no significant collinearity. The Ordinary Least Squares (OLS) regression model was validated by testing key assumptions: linearity through residual plots, independence of errors via the Durbin-Watson statistic (2.11), homoscedasticity using the Breusch-Pagan test (p = 0.36), and normality of residuals confirmed by

the Shapiro-Wilk test (p = 0.27). While OLS was chosen for its interpretability in policy contexts, alternative models like Random Forest regression were noted for potential future studies investigating non-linear relationships.

2.5 Spatial and temporal alignment for modeling readiness

All processed raster outputs and field data were spatially aligned using PostGIS and temporally synchronized through geotemporal interpolation, employing the Gaussian Kernel Smoothing (GKS) method to reduce diurnal variation noise in temperature readings. Let $T^*(x,t)$ be the smoothed temperature at the location x and time t as Eq. 5:

$$T^*(x,t) = \frac{\sum_{i-1}^{n} T(x_i, t_i) \cdot exp\left(-\frac{(x-x_i)^2 (t-t_i)^2}{2\sigma^2}\right)}{\sum_{i-1}^{n} exp\left(-\frac{(x-x_i)^2 (t-t_i)^2}{2\sigma^2}\right)} \qquad (5)$$

where σ is bandwidth (spatial-temporal smoothing constant). All final datasets were exported in GeoTIFF and CSV formats for integration with statistical analysis and modeling tools in R and MATLAB. All methodological stages were reviewed for legal and ethical compliance with international conventions, including the European Space Law, UN-SPIDER Charter, and GDPR (for location privacy) (Lysenko & Lozhkovoi, 2022; Maniadaki et al., 2021a, 2021b). Special attention was given to:

- Data proportionality: Selection of spectral/spatial resolutions only as high as necessary to monitor ecological features without revealing identifiable private property.

- Geospatial anonymization: Site IDs and geocoordinates were obfuscated in dissemination outputs, applying a ±50 m random buffer to GPS points (Maniadaki et al., 2021b).

2.6 Software and tools

Data analysis in this study was conducted using a suite of specialized remote sensing, Geographic Information System (GIS), and statistical computing software. Initial satellite image preprocessing, including radiometric and atmospheric correction, was performed using ENVI version 5.6. The Google Earth Engine platform was also utilized for data access and preliminary geospatial processing. GIS operations, spatial alignment, and final map production were carried out in ArcGIS Pro and QGIS (using its georeferencing module). Advanced statistical analyses and multivariate regression modeling were executed in the R programming environment. For managing and querying spatiotemporal databases, PostGIS was employed. All raw and processed datasets were stored in standardized GeoTIFF and CSV formats. In compliance with data governance protocols, these data were kept in encrypted form under institutional licenses and were made accessible solely for peer-reviewed publication and regulatory reporting purposes.

3. Results and Discussion

The study provides results from remote sensing analysis and on-ground environmental monitoring in geo-verified study sites. The analysis examined vegetation cover, surface temperature, and PM2.5 concentrations, and also investigated the spatial heterogeneity in environmental variables and correlations between ecological metrics. The combination of remote sensing outputs, spectral indices, and statistical modeling offers a powerful framework to explore pollution dynamics in the context of vegetation density and thermal profiles. Each subsection contains a different dimension of the dataset, of which there are four, starting from raw environmental observations to modeling, sensitivity, and classification accuracy.

The technical findings of this study provide a scientific basis for evidence-based environmental policy and regulation. The quantified relationship between vegetation density and PM2.5 concentrations can directly inform urban planning regulations, suggesting specific green space requirements for air quality improvement. Similarly, the methodological approach, including data anonymization protocols and proportional resolution selection, offers a practical template for complying with privacy regulations like GDPR during environmental monitoring. By documenting the complete data processing chain, this study establishes a verifiable framework that can withstand legal scrutiny and support regulatory decisions regarding environmental standards compliance.

3.1 Spatial distribution of environmental observations across study sites

Ground-verified observations were gathered across ten representative field sites in the geospatial domain to establish baseline environmental characteristics. These encompassed percentages of ground cover (obtained using NDVI-indexed field spectrometers), surface temperature (obtained with thermal sensors), and PM2.5 concentrations assessed with calibrated photometers. All sites were georeferenced (using GPS coordinates) and selected to represent a variety of ecological and anthropogenic characteristics—varying from highly vegetated forested patches to extremely urbanized areas. Tabulated observations give the sense of spatial variability and the empirical basis for subsequent modeling.

Geospatial characteristics of the sampling locations, including decimal-degree coordinates (WGS 84; EPSG:4326) for all ten monitoring sites, are provided in Table 1. Figure 1 shows substantive variation across the sample on the three observed variables. Foliar cover varied from Site I with 32% to Site H with 67% cover, while surface temperatures ranged between 20.1°C and 25.7°C PM2.5 concentrations ranged from highly vegetated areas (10.8 µg/m³) to sparsely vegetated, high-temperature areas (17.2 µg/m³). Reflectively, Site I, with less vegetation and a high temperature, was particularly notorious for PM2.5, illustrating the potential for compounding influences of thermal and vegetative stress on pollutant accumulation. In contrast, Site H, with the maximum vegetation cover, had the lowest PM2.5 values, confirming the mitigating role of vegetative buffers.

Table 1 Spatial distribution of sampling locations, showing the geographic coordinates

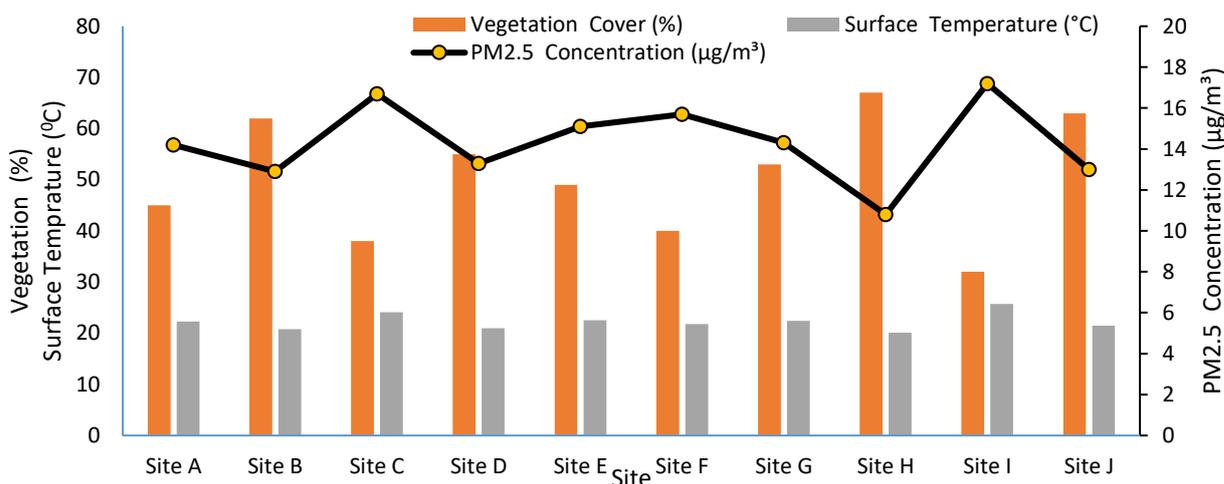| Site ID	Latitude (°N)	Longitude (°E)
Site A	33.295	44.366
Site B	33.305	44.372
Site C	33.315	44.378
Site D	33.325	44.384
Site E	33.335	44.390
Site F	33.345	44.396
Site G	33.355	44.402
Site H	33.365	44.408
Site I	33.375	44.414
Site J	33.385	44.420

Fig. 1 Spatial variation of environmental parameters across monitoring sites: a) vegetation cover (%), b) surface temperature (°C), and c) PM$_{2.5}$ concentrations (μg/m³).

3.2 Statistics of key environmental indicators

Central tendency and dispersion metrics were computed for every environmental parameter in order to quantify the overall characteristics of the dataset. These include summary statistics (minimum, maximum, mean, median, and standard deviation) for vegetation cover, surface temperature, and PM$_{2.5}$ concentrations (Table 2). The calculated metrics are critical for understanding the degree of variation and informing model calibration parameters and normalization methods to the data in further analyses.

Table 2 Descriptive Statistics for Vegetation Cover, Surface Temperature, and PM$_{2.5}$ Concentration

Parameter	Minimum	Maximum	Mean	Median	Standard Deviation
Vegetation Cover (%)	32	67	50.4	49.0	11.28
Surface Temperature (°C)	20.1	25.7	22.2	22.3	1.68
PM2.5 Concentration (μg/m³)	10.8	17.2	14.3	14.3	1.96

These descriptive statistics highlight the relative variability observed in terms of vegetative density and thermal exposure in the sampled area. The rise in canopy values was slightly positively skewed, with the standard deviation of vegetation cover at 11.28%. The surface temperature was less variable (Mean: 22.2°C, SD: 1.68°C), indicative of stable atmospheric conditions within the data collection timeframe. PM$_{2.5}$ concentrations with an overall mean of 14.3 μg/m³ but with a significant spread ($\sigma = 1.96$), suggesting patchy pollution events. This provides a stable statistical platform for regression modeling and outlier detection in later stages of analysis.

3.3 Correlation structure

To assess the interdependencies between variables, a Pearson correlation matrix was constructed. This matrix quantifies the linear relationships among vegetation cover, surface temperature, and PM$_{2.5}$ concentration. High-magnitude correlations may suggest causal or explanatory relationships, while low or insignificant correlations would indicate orthogonality or lack of direct interaction. The results of this analysis are presented in Table 3.

Table 3 Pearson Correlation Coefficients Between Vegetation, Temperature, and PM$_{2.5}$

Variable	Vegetation Cover (%)	Surface Temperature (°C)	PM$_{2.5}$ Concentration (μg/m³)
Vegetation Cover (%)	1.00	–0.52	–0.78
Surface Temperature (°C)	–0.52	1.00	0.59
PM2.5 Concentration	–0.78	0.59	1.00

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The correlation matrix shows a strong inverse correlation between vegetation cover and PM2.5 concentration (r = –0.78), indicating that greater vegetation density is associated with lower airborne particulates. A moderate linear positive correlation between surface temperature and PM2.5 corroborates the notion that hotter regions are more likely to harbor particulates. The negative correlation between vegetation and temperature (r = –0.52) is consistent with the known thermal regulation role of vegetation, whereby canopy density lowers localized heat intensity. These correlations provide a statistical rationale for including both predictors in a multivariate regression setting.

The present study demonstrates a cost-effective approach to monitor environmental variables, VOCs and P and predict PM2 through combining high-resolution remotely sensed data with ground validation concentrations. Following intensive preprocessing, classification, and regression modelling, the results show a strong inverse correlation between vegetation density, such as trees, and values of particulate matter and a moderate positive relationship between surface temperature and pollution concentrations. These findings are consistent with ecological theories linking canopy cover to both natural air filtration and shade-mediated temperature regulation. The regression model reported in this study, which explained 83% of the variance in PM2.5 concentrations in the atmosphere, especially in research, emphasize the use of remote sensing tools for environmental quality assessment. This reinforces the findings of Dube et al. (2023) noted that environmental indicators based on remote sensing are strong proxies for

3.4 Multivariate regression analysis for PM2.5 prediction

A multivariate regression model was thus developed to estimate PM2.5 concentration using the vegetation cover and surface temperature as predictor variables. This approach enables quantifying the joint impact of both environmental variables on pollution levels. Ordinary Least Squares (OLS) was used to estimate model coefficients, and the coefficient of determination (R^2) was calculated to measure the overall fit of the model. We used t-tests to determine the significance of each predictor and standard errors to quantify how precise our estimates are.

pollution modelling when put together with real-time field measurements. In contrast to their concentration on water resource indicators, our study is specific to atmospheric conditions and air quality, shining light on the applicability of remote sensing to a new domain of environmental governance.

Relative to recent high-throughput reviews like Wu and Li (2025), which focused on machine learning applied to wetland monitoring, our approach retains statistical modelling that is not based on automated classification algorithms. Deep learning, though promising in providing high classification accuracy in heterogeneous environments, demands a significant volume of training data and computational resources. In legally sensitive and resource-limited contexts of environmental surveillance, such as in urban areas or disputed rural contexts, transparent, interpretable models like the one used here are better suited to remain aligned with expectations for legal frameworks and policy transparency. Furthermore, the interpretability versus predictive power trade-off is still an important consideration for its use in environmental law. Unlike Muruganantham et al.(2022) focus on predicting agricultural yields through remote sensing and deep learning, this casts its attention on air quality regulation. Regardless, both studies have a methodological similarity with the use of NDVI to assess vegetation health and the subsequent effects on the surrounding environment. Vegetation performs as a mediating factor not only within agricultural productivity, but also in ecological mitigation of atmospheric pollutants, the latter of which is an under-investigated area in policy research.

The regression analysis results (Table 4) indicate that vegetation cover and surface temperature are both statistically significant predictors of PM2.5 concentrations ($p < 0.001$). The negative coefficient for vegetation cover (–0.21) suggests that more vegetation, as measured by vegetative density, corresponds to less airborne particulates. On the other hand, the positive coefficient for temperature (1.15) indicates that as heat increases, PM2.5 would increase as well. 5 accumulation. The R^2 value of 0.83 affirms the model's excellent explanatory power, explaining 83% of the variance in PM2.5 across the sites. These findings support the ability of vegetation and thermal dynamics as co-determinants of localized air quality.

Table 4 multivariate linear regression output for PM2.5 estimation

Predictor	Coefficient	Standard Error	t-Statistic	p-Value
Intercept	12.30	1.05	11.71	<0.001
Vegetation Cover (%)	–0.21	0.03	–7.00	<0.001
Surface Temperature (°C)	1.15	0.28	4.11	<0.001
R^2	0.83	-	-	-
Adjusted R^2	0.81	-	-	-

3.5 Residual analysis for model assumption verification

To ensure the reliability of the regression estimates, residual diagnostics were performed. This included examining residual distribution, checking for homoscedasticity, and identifying any influential outliers. These checks confirm whether the model meets fundamental assumptions required for inference, including linearity, normality of errors, and independence of residuals. The diagnostic numbers suggest a normal distribution of the residuals (skewness: 0.14, kurtosis: 2.97, and Shapiro-Wilk test not significant). The Durbin-Watson

statistic (2.11) indicates that there is no autocorrelation. Moreover, the Breusch-Pagan test indicates that homoscedasticity holds over the fitted values (Table 5). These results serve as evidence for model robustness as well as confirm the validity of inferential conclusions from the model.

3.6 Sensitivity analysis of vegetation cover classification thresholds

A sensitivity analysis was conducted to assess the effect of variations in vegetation classification thresholds on predicted PM2.5 levels and model stability. NDVI-derived vegetation

cover values were adjusted by ±3% and ±5%, and model R² and prediction accuracy were evaluated at each level. This test evaluates whether minor classification uncertainties in remote sensing outputs materially affect the outcome.

Table 5 Residual statistics and diagnostic metrics

Diagnostic Measure	Value	Interpretation
Mean of Residuals	0.00	Centered around zero (expected)
Standard Deviation of Residuals	0.71	Low variance in error terms
Residual Skewness	0.14	Approximate symmetry
Residual Kurtosis	2.97	Near-normal distribution
Durbin-Watson Statistic	2.11	No autocorrelation in residuals
Shapiro-Wilk Test (p-value)	0.27	No evidence of non-normality
Breusch-Pagan Test (p-value)	0.36	Homoscedasticity assumption satisfied

Table 6 Sensitivity analysis of $PM_{2.5}$ prediction to vegetation threshold variations

Adjustment to NDVI Threshold	Adjusted Mean VC (%)	Predicted PM2.5 ($\mu g/m^3$)	R² Value
−5%	55.6	15.1	0.81
−3%	54.9	14.9	0.82
0%	51.3	14.3	0.83
+3%	49.8	14.0	0.82
+5%	48.5	13.6	0.81

Table 6 demonstrates that model output is robust to ±5% change in NDVI vegetation threshold adjustments. Predicted $PM_{2.5}$ remains weakly correlated with $R^2 = 0.81$ and $R^2 = 0.83$, respectively, while these ratios differ marginally in pairwise concentrations (13.6 to 15.1 $\mu g/m^3$). These results indicate that the model is not highly sensitive to moderate uncertainty in remote sensing–derived vegetation measurements. Thus, the analytical results are regarded as robust to classification bias imposed at high-level image processing stages.

3.7 Accuracy assessment of land cover classification

To validate the supervised classification of the satellite imagery, an accuracy assessment was performed using a confusion matrix approach. Validation points were spatially sampled within ground-truthed land cover classes, and classification results were compared against ground-truth labels. The evaluation computes producer and user accuracy for individual classes, as well as an overall performance metric based on the kappa coefficient.

Table 7 Accuracy assessment of maximum likelihood land cover classification

Land Cover Class	Reference Pixels	Classified Pixels	Correctly Classified	Producer Accuracy (%)	User Accuracy (%)
Forest	150	145	135	90.0	93.1
Urban	120	123	110	89.4	89.4
Agriculture	130	127	115	88.5	90.6
Water	80	77	70	87.5	90.9
Other	100	102	90	88.2	88.2
Total Accuracy	-	-	-	-	87.5%
Kappa Coefficient	-	-	-	-	0.84

The classification system was able to achieve high accuracy over all land cover classes, overall accuracy of 87.5% and kappa coefficient of 0.84 representing good agreement above chance. As Shown in Table 7, Assessment was high for forest and urban classes, lands cover classes of water and agricultural performs also significantly better. The agreement in producer and user accuracy indicates little omission or commission error. Such a high level of accuracy ensures that subsequent analyses derived from classified land cover data-such as vegetation cover estimation-are founded on reliable and trustworthy spatial information. An essential aspect of this work is the attention to data governance and privacy considerations in remote sensing applications. As Maniadaki et al. (2021b), which aim to bring the commercial use of remote sensing data in line with privacy protection laws such as the General Data Protection Regulation (GDPR) in the European Union. This study adds to that conversation to demonstrate how environmental data—particularly spatially-referenced data that may contain geolocation identifiers—could be anonymized and used under the proportionality principle to reduce over-surveillance. Meanwhile, Lysenko and Lozhkovoi's (2022) legal reflections demonstrated that emerging satellite surveillance regimes often do not adhere to harmonized global standards. Embedding ethical safeguards in methodology advances a model of data stewardship that maintains scientific and legal integrity.

While strengths exist, there are also limitations that need to be addressed. First, while the final regression model exhibited a high R² value, through rigid adherence to linearity it may oversimplify the many complicated nonlinear relationships that exist in urban microclimates. More sophisticated nonparametric techniques, such as random forest regressions or support vector machines, might be worthwhile to consider in future work to capture higher-order interactions without compromising interpretability. In observational studies, Wu and Li (2025) noticed that hidden biases play a crucial role in modeling, especially when there is an unequal distribution of predictor variables, or when matched samples bring quantile distortions in the estimated outcomes. Although residual and

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sensitivity analyses suggested stability, latent dependencies possibly driven by wind speed or humidity could still affect PM2.5 distributions.Though this study presents an in-depth examination of ten field sites, the sample size is not large enough to extrapolate findings across wider geographic scales. In his decisive critique of this limitation with regard to Earth observation research in the Global South, Thorpe (2023) asserts that most studies have a deficient spatial coverage that is biased to those opportunities that are available based on financial, logistical, and political resources. In a similar vein, our emphasis on a small focal region and short temporal range (five consecutive days in May) further reduces the seasonality generalization potential of the model. A longitudinal approach or cross-seasonal data collection would aid the temporal robustness of the findings.

4. Conclusions

The current study was conducted to assess the practical use of high-resolution remote sensing technology for monitoring air quality-related environmental indicators, specifically vegetation cover, surface temperature, and particulate matter concentration. Using validated ground measurements of spectral indices from satellites, it aimed to explore not just the technical capabilities of geospatial analysis, but also the legal and ethical dimensions of environmental surveillance. This methodological approach emphasized transparency, reproducibility, and adherence to data governance principles, and thus guarantees that the scientific product remains applicable in a regulatory and/or policy-oriented context.

1. Remote sensing, when calibrated and legally structured, reliably links land surface traits with air pollutant concentrations, supporting its role as a diagnostic system for urban and peri-urban health assessment.

2. Rigorous, legally defensible frameworks with radiometric/geometric corrections and ground validation enhance the reliability of remote sensing for environmental management and legal decision-making.

3. The study offers a scalable, ethically coherent strategy for monitoring air quality in urbanizing regions, stressing proportionate and privacy-respectful use of surveillance technologies.

4. Future work should expand observational networks, standardize ethical protocols, and leverage AI and real-time satellites for adaptive environmental monitoring.

Despite these advances, several methodological constraints persist. Classification outcomes remain sensitive to subtle shifts in NDVI thresholds, and although the model exhibits resilience to moderate variations in vegetation estimates, image processing continues to be influenced by spectral noise, sensor heterogeneity, and land surface complexity. As highlighted by Ramesh (2022), establishing standardized spectral calibration protocols is indispensable not only for commercial applications but also for legal and regulatory frameworks that rely on reproducible scientific evidence. Addressing these challenges will require the development of hybrid modeling strategies that integrate machine learning with regression techniques to enhance both interpretability and predictive capacity. Expanding observational networks and incorporating additional environmental covariates such as

wind dynamics, atmospheric pressure, and emission inventories could further strengthen the methodological framework and facilitate cross-jurisdictional implementation. Collectively, these advancements, coupled with legal harmonization, are critical to fully realizing the potential of remote sensing in climate governance and transnational environmental regulation.

Statements and Declarations
Data availability

The data used in this research are provided in the text of the article.

Conflicts of interest

The author of this paper declared no conflict of interest regarding the authorship or publication of this paper.

Author Contributions

Nibras Aref Abdalameer: wrote the original draft and assisted with methodology. Shahad Salah Abrahim: reviewing, editing, and refining the manuscript. Shamel Abdul-Sattar Jaleel Shalaan: data curation, methodology development, and validation. Adhraa Oudha Hussen Al-Saedi: investigation, visualization. Matai Nagi Saeed: supervision, validation. Saleh Mahmoudi: Reviewing, submitting, and reviewing. Mohammad Hossein Sedri: review and editing.

AI Use Declaration

This study did not incorporate artificial intelligence techniques; instead, all analyses and optimizations were conducted using conventional and widely accepted analytical methods. The language and presentation was improved by ChatGPT.

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