ILLEGAL OIL MINING DETECTION THROUGH REMOTE SENSING IN MUSI BANYUASIN REGENCY, SOUTH SUMATRA, INDONESIA

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Abstract. Illegal oil mining activities present significant environmental, economic, and regulatory challenges, particularly in resource-abundant regions that are difficult to monitor such as Musi Banyuasin Regency in South Sumatra. Using high-resolution UAV (drone) imagery, this study identified and georeferenced 2,664 illegal shallow oil wells from orthomosaic products derived from DJI Phantom 4 Pro flights. Spatial autocorrelation analysis yielded a Moran's I value of 0.652075, indicating statistically significant clustering, with concentrations in sub-districts including Lawang Wetan, Batang Hari Leko, and Tungkal Jaya. The methodological workflow combined drone-based remote sensing, visual interpretation, and spatial statistics to detect and evaluate the spatial distribution of illegal wells. Ground validation was conducted through direct field surveys, which verified the presence of the wells and provided supporting photographic documentation and GPS coordinates. The dataset was also compared with official records of legal oil wells to ensure accuracy and distinction between legal and illegal infrastructure. The findings demonstrate that unmanned aerial vehicle-based spatial analysis offers a reliable and scalable solution for monitoring unregulated extraction activities. This approach supports data-driven enforcement, enhances environmental oversight, and informs the development of more effective regulatory policies in regions impacted by informal oil production.

Keywords: *illegal oil mining, remote sensing, DJI Phantom 4, spatial analysis, Musi Banyuasin*

1 INTRODUCTION

Illegal oil mining refers to the practice of drilling oil wells without the necessary permission from the authorities (Lioty, 2017). This has led to environmental degradation, loss of revenue for the government, and safety hazards for the individuals involved in these activities (Adu et al., 2017; Alvizuri-Tintay et al., 2022; Amankwah, R., & Anim-Sackey, C., 2021). In Musi Banyuasin, illegal oil mining have been a long-standing issue, with many unregulated operations causing environmental damage and posing safety risks to nearby communities. The lack of oversight and enforcement has allowed these wells to proliferate, leading to concerns about their impact on the local ecosystem and public health (Marpaung et al., 2023).

The presence of these illegal oil wells has also led to conflicts between local authorities and the operators, as efforts to shut down these operations have been met with resistance (Crawford & Botchwey, 2018). As a result, finding a sustainable solution to address this issue has become a pressing concern for the region (Fingas & Brown, 2017). The environmental and safety hazards posed by these illegal oil wells cannot be ignored, as they have the potential to cause long-term damage to the ecosystem and harm to nearby communities (Douglas, 2018; Dube et al, 2023). It is crucial for authorities to prioritize the detection and shutdown of these operations in order to protect both the environment and public health (Putri, 2023).

The government, both at the central and regional levels, is synergizing efforts to tackle illegal oil mining. In addition to law enforcement, another effort is to enhance monitoring and supervision of oil drilling activities, both through aerial monitoring technology and through regular field audits (Prihatmaja et al., 2021). Information regarding the distribution and analysis of the potential spread of illegal oil mining is necessary because it can enhance the understanding of the factors influencing the occurrence of illegal oil mining, including the potential locations and types of natural resources targeted by these illegal activities (Palacios et al., 2023). Determining areas that are potentially affected by illegal oil mining activities can enhance the ability to predict and establish more effective preventive measures, thereby improving the long-term effectiveness of natural resource management, especially in optimizing the legal and sustainable use of oil resources.

Remote sensing techniques, such as aerial mapping, combined with GIS analysis, offer powerful tools for identifying unauthorized wells and monitoring activities (Sassani et al., 2025). Aerial mapping can be used for detecting illegal oil mining by utilizing various remote sensing techniques such as passive observation of the land surface, infrared sensors, and radar technology. Various techniques such as passive observation using cameras in the visible and infrared spectra, optical techniques, and the use of radar can be employed for this purpose (Fingas & Brown, 2017; Gkountakos et al., 2025). Aerial surveillance can provide real-time monitoring to validate the detection of illegal oil activities (El-Magd et al., 2020). The use of aerial imagery, particularly SAR and SLAR methods, along with RGB cameras, offers high-resolution data acquisition for accurate detection and localization of illegal oil wells (Gkountakos et al., 2025).

The primary objective of this study is to develop and implement an integrated geospatial approach for detecting and mapping illegal shallow oil wells in Musi Banyuasin Regency, South Sumatra, by combining high-resolution drone imagery, Geographic Information System (GIS) analysis, and field validation. This research seeks to identify spatial distribution patterns, assess clustering tendencies through spatial autocorrelation metrics, and generate accurate, georeferenced datasets that can be cross-verified with existing legal well records. By doing so, the study aims to provide actionable insights that support monitoring, enforcement, and policy-making efforts to mitigate environmental risks and enhance sustainable resource management in the region.

2 MATERIALS AND METHODOLOGY

2.1 Study Area

Musi Banyuasin Regency is located in South Sumatra Province and spans an area of 14,265.96 km², accounting for approximately 15% of the total area of South Sumatra Province. The regency lies between 1.3° and 4.0° South Latitude and 103.0° to 104.75° East Longitude. It is bordered by Jambi Province to the north, Penukal Abab Lematang Ilir Regency to the south, Musi Rawas Regency to the west, and Banyuasin Regency to the east.

Musi Banyuasin hosts extensive oil and gas infrastructure, both legal and illegal. In recent years, the area has witnessed a rise in unauthorized artisanal oil mining activities, particularly in sub-districts such as Batang Hari Leko, Babat Toman, and Keluang. These activities often involve unsafe and unregulated extraction practices, leading to serious environmental degradation, including oil spills, soil contamination, and deforestation.

Figure 2-1 shows the study area. This study area was selected due to its strategic relevance to the research objective, which is the detection and spatial mapping of illegal oil mining activities using aerial data. The combination of persistent oil exploitation, availability of historical and field-verified illegal mining sites provides a suitable environment for testing remote sensing-based detection approaches.

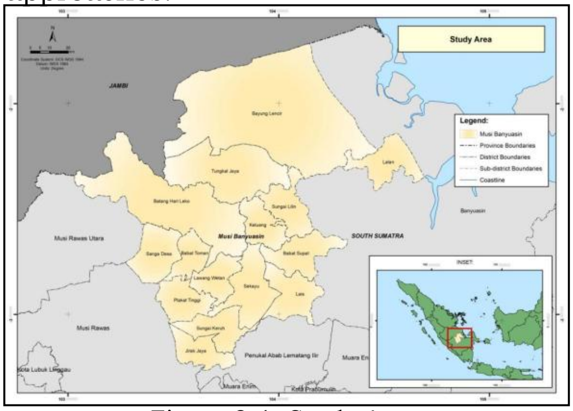

Figure 2-1: Study Area

2.2 Data Sources

This study applies remote sensing techniques and spatial analysis approach to detect and assess the spatial distribution patterns of illegal oil mining activities in Musi Banyuasin Regency, South Sumatra, Indonesia. The methodology consisted of two main stages: (1) acquisition and digitization of illegal oil well locations using a drone platform, and (2) spatial autocorrelation analysis to determine the distribution patterns of the identified wells.

Field data acquisition was carried out using a DJI Phantom 4 Pro drone equipped with a high-resolution camera (20 MP, 1-inch CMOS sensor) to capture detailed aerial imagery over areas suspected of hosting illegal oil mining operations. The drone was flown at an altitude of 100–120 meters above ground level using a grid flight pattern with a minimum image overlap of 70% to ensure complete coverage and high spatial accuracy. The drone flight paths were pre-programmed using automated waypoint navigation to ensure systematic coverage of the study area, particularly zones suspected to contain a high density of shallow illegal oil wells. The flight plan was designed to achieve optimal image overlap and consistent ground sampling distance, enabling the generation of high resolution orthomosaics.

The final orthomosaic products were aligned with existing base maps and projected in a standard coordinate system (e.g., WGS 84 / UTM Zone 48S). This spatial alignment allowed for precise visual interpretation and accurate digitization of surface features. The processed imagery served as the primary data source for identifying, digitizing, and analyzing the spatial distribution of illegal oil wells across the study area. Figure 2-2 shows the study methods.

All UAV flight activities were conducted under valid operational authorization issued by the Regency Government of Musi Banyuasin, which included explicit permission for low-altitude aerial mapping in the designated survey blocks. Prior to field deployment, brief on-site coordination was carried out with village-level representatives and local land managers to ensure situational awareness, avoid disturbance, and maintain safety compliance during data acquisition.

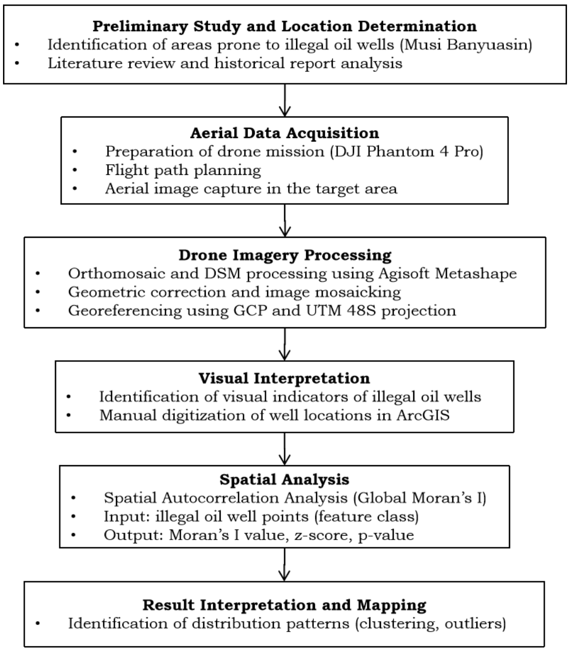

Figure 2-2: Study Methods

2.3 Processing Aerial Data

The aerial imagery captured during the drone surveys was stored on onboard memory and subsequently exported for further processing. Selected image frames were processed using Agisoft Metashape software to generate a seamless orthomosaic through a series of photogrammetric steps, including image alignment, dense point cloud generation, digital surface model (DSM) creation, and orthorectification. The result was a georeferenced high-resolution composite image suitable for spatial analysis.

Following the generation of the orthomosaic, manual digitization of surface features was conducted using ArcGIS software. This process involved identifying and delineating the locations of existing oil well sites based on visual interpretation of surface signatures typically associated with illegal oil extraction activities. The digitized points were compiled into a unified vector dataset representing the spatial distribution of confirmed oil well locations.

Aerial imagery that lacked embedded coordinate references underwent a georeferencing process prior to spatial analysis. Ground control points (GCPs) were established using existing geodetic benchmarks located on permanent infrastructure within the study area. These benchmarks served as reference tie points for aligning the imagery to a spatial coordinate system. The georeferencing process was conducted using the Universal Transverse Mercator (UTM) coordinate system, enabling accurate spatial alignment with other geospatial datasets. This spatial referencing was essential to ensure that the orthomosaic derived from drone imagery could be accurately overlaid with vector-based thematic layers, such as well location data. By anchoring the aerial data to a standardized coordinate framework, the georeferenced imagery became fully integrated into the broader geospatial database.

The resulting orthomosaics had an average ground sampling distance (GSD) of approximately 3.8 cm/pixel. A total of 12 ground control points (GCPs) were used, distributed across the surveyed blocks to maintain geographic balance. Bundle adjustment in Agisoft Metashape achieved a georeferencing RMSE of 1.6 cm. Camera self-calibration based on the Metashape Brown–Conrady lens distortion model was applied during processing to optimize the internal orientation parameters. These parameters collectively indicate that the positional accuracy of the mosaics was sufficient to reliably digitize individual shallow wellheads.

2.4 Processing Spatial Data

Spatial autocorrelation measures the direction and strength of the linear relationship between a variable and the spatial intensity of the same variable across a defined area (Dube & Legros, 2014; Lee & Wong, 2001). It is a fundamental concept in spatial analysis that quantifies the degree of correlation among spatial data points based on their geographic locations (Getis, 2008). Spatial autocorrelation is useful for identifying the spatial distribution of attributes and assessing the interconnectivity of phenomena on the Earth’s surface (Haining, 2009). Specifically, it evaluates the correlation among values of a single variable referenced by location (Griffith, 2000). In spatial autocorrelation analysis, the distribution of spatial phenomena is generally classified into three categories: positive autocorrelation (indicating a positive spatial correlation among features) (Figure 2-3), negative autocorrelation (indicating a negative spatial correlation) (Figure (2-4), and spatial randomness, where no spatial correlation is present (Figure 2-5) (Griffith, 2000).

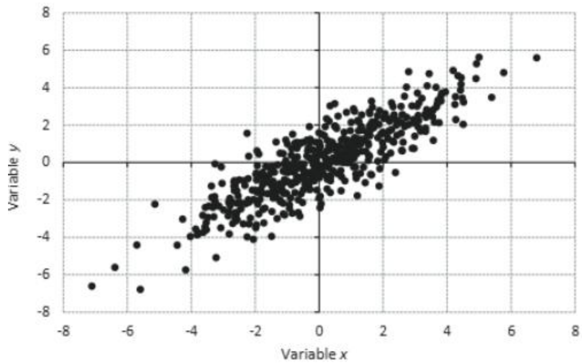

Figure 2-3: Positive Spatial Autocorrelation

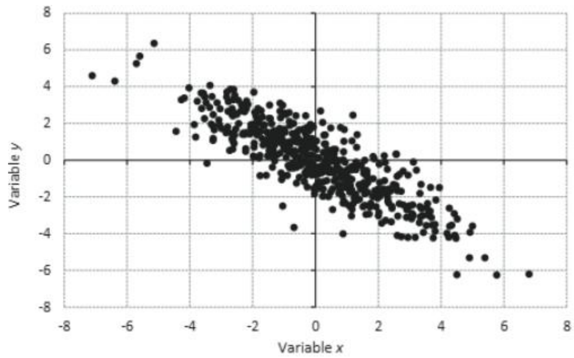

Figure 2-4: Negative Spatial Autocorrelation

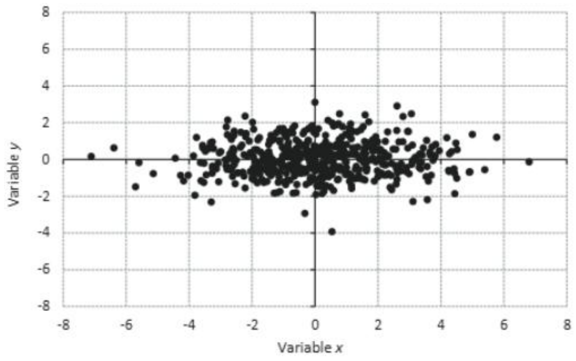

Figure 2-5: No Spatial Autocorrelation

Spatial autocorrelation analysis was performed using ArcGIS Pro software, specifically employing the Spatial Statistics Tools under the Analyzing Patterns module, with the Spatial Autocorrelation (Moran's I) method. The primary input feature class consisted of the digitized point data representing the distribution of illegal oil wells. The input field parameter was defined using the distance between individual points, serving as a proxy for spatial interaction. The processing extent and raster analysis boundaries were set using the shapefile of Musi Banyuasin Regency to constrain the analysis within the study area.

The Moran's I index can be expressed as follows (Chen, 2013):

$$I = z^T W z$$

Where I refers to Moran's I index, $z = [z_1, z_2, \ldots, z_n]$ is a vector of standardized variables (z-scores), $W = [w_{ij}]$ is a globally normalized, symmetric spatial weight matrix of size n × n, and T denotes the matrix transpose. This equation represents a quadratic form commonly used in spatial statistics.

The spatial weight matrix W possesses three key properties:

(1) Global normalization, where the sum of all elements in W equals 1;

(2) Symmetry, such that $W^T = W$;

(3) Non-negativity, meaning all elements in W are greater than or equal to zero.

The standardized variable z has a mean of 0 and a standard deviation of 1 (Chen, 2023).

Moran's I Index in ArcGIS ranges between -1 and +1, where positive values indicate spatial clustering—suggesting that features are more spatially proximate than would be expected under a random distribution. The closer the Moran's I value is to +1, the stronger the clustering pattern. Conversely, negative values indicate a dispersed or repelling spatial pattern, with values approaching -1 denoting stronger dispersion. A value near zero suggests spatial randomness, where features exhibit no discernible spatial pattern.

In this study, spatial relationships were conceptualized using a fixed distance band, with the threshold set at 1,500 meters based on the peak z-score method in ArcGIS Pro to ensure that the spatial scale aligned with the dominant intra-cluster distances observed in the digitized data. A global row-standardized spatial weight matrix was applied so that each feature contributed proportionally to its neighbors regardless of variation in local point densities. This threshold distance was selected after iteratively evaluating alternative distance bands between 800–2,500 meters, where the 1,500-meter band produced the highest statistically stable z-score and minimized sensitivity to edge effects. The use of a globally normalized spatial weights matrix supports comparability across clusters and ensures that the Moran's I inference reflects a consistent neighborhood definition across the entire Musi Banyuasin study area.

2.5 Validating Data

To validate the accuracy and reliability of the spatial data derived from drone-based imagery, an extensive ground truthing effort was conducted. This process involved systematic field verification at a series of georeferenced locations that were previously identified through visual interpretation of high-resolution orthomosaic images. Selected sites, particularly those with a high density of suspected illegal oil wells were visited by the research team to assess the physical presence, operational status, and characteristics of the mapped features. The fieldwork included the collection of photographic evidence, GPS-base coordinate logging, and detailed documentation of well typologies, surrounding land use, and visible signs of recent activity.

3 RESULTS AND DISCUSSION

3.1 Aerial Mapping

The aerial mapping survey, conducted using a DJI Phantom 4 Pro drone, yielded high-resolution imagery that provided a detailed visual record of the physical landscape across several key areas in Musi Banyuasin Regency suspected to harbor illegal oil mining activities. The imagery acquisition covered a broad swath of terrain, including active plantations, secondary forests, abandoned industrial zones, and remote hinterlands with limited road access. In addition to identifying individual well points, the imagery also revealed associated infrastructure such as makeshift access roads, fuel transfer points, and temporary worker shelters (as shown in Figure 3-1). The visual presence of open oil pits and blackened vegetation indicated environmental degradation resulting from surface spills and unregulated waste disposal practices. These indicators not only confirmed the presence of illegal activity but also highlighted the broader ecological risks posed by such operations.

Moreover, some of the detected sites exhibited clear signs of activity during the image capture timeframe, including the presence of vehicles, active smoke plumes, and visible movement of personnel, further confirming their operational status. The ability to detect such transient indicators in still imagery underscores the timeliness and operational relevance of drone-based surveillance in dynamic and high-risk environments.

The integration of drone-acquired imagery with Geographic Information System (GIS) tools enabled precise georeferencing and facilitated the development of a comprehensive spatial dataset. Furthermore, the resulting spatial information can be seamlessly integrated with existing geospatial databases of legally registered oil wells and supporting infrastructure. For instance, spatial comparison with official well inventories, such as those identified by DY-coded facilities, allows for more accurate differentiation between legal and illegal operations (as shown in Figure 3-2). For comparison against legal petroleum infrastructure, the DY-coded well inventory was obtained from the corporate operational GIS database maintained by SKK Migas. Because the drone-derived orthomosaics and the corporate vector asset layers originate from different acquisition sources, a positional reconciliation was applied to avoid false matches. Co-registration was performed using a 10-m radial buffer tolerance to account for small misalignments between the orthomosaic reference frame and the legacy vector well coordinates.

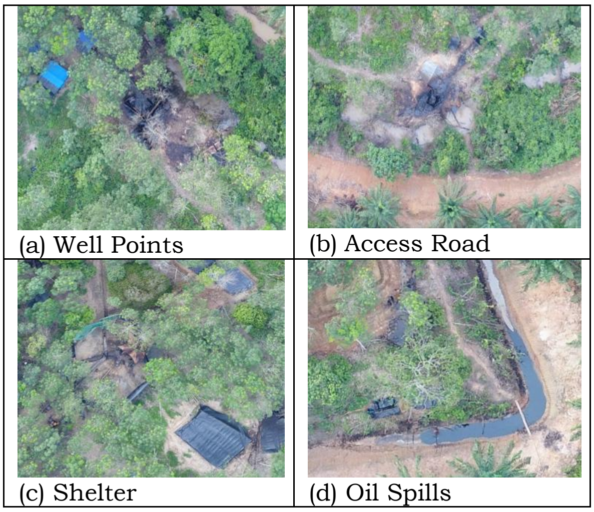

Figure 3-1: Aerial Imagery of Illegal Oil Mining Activities

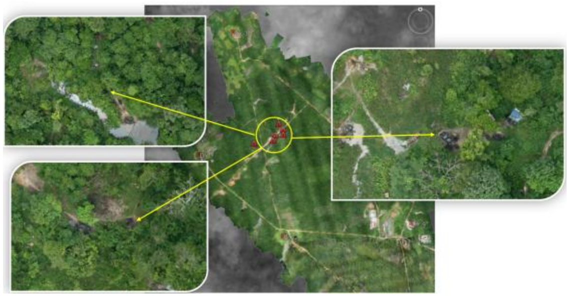
Figure 3-2: Integrated Aerial Mapping

A well was classified as a legal facility if a digitized well point intersected the buffered legal-well footprint. This procedure mitigated minor spatial offsets and ensured that cross-dataset attribution was based on a consistent, operationally defensible matching rule. This integrated approach not only improves the reliability of spatial analysis but also enhances the effectiveness of field validation, supports enforcement efforts, and informs the development of evidence-based policy interventions aimed at regulating unauthorized extraction activities.

3.2 Spatial Distribution of Illegal Oil Wells

The photogrammetric processing of the imagery using Agisoft Metashape software resulted in high-fidelity orthomosaics and digital surface models (DSMs), which served as the primary base maps for feature interpretation. From these orthomosaics, a total of 2,664 illegal oil well sites were visually identified and digitized based on characteristic surface signatures. Spatially, the detected wells were unevenly distributed, with clear concentrations emerging in specific geographic clusters.

The densest occurrences were found in the sub-districts of Tungkal Jaya, Batang Hari Leko, Babat Toman, Sanga Desa, Lawang Wetan, and Plakat Tinggi, which are known from previous studies and government reports to be hotspots of unauthorized hydrocarbon exploitation. Several of these clusters were located within proximity to abandoned legal well sites, suggesting the possible repurposing of older infrastructure for illicit use. Other clusters were detected deep within plantation estates or forest edges, often inaccessible by vehicle and concealed from ground-level observation, which underscores the strategic advantage of aerial surveillance in revealing hidden operations. Figure 3-3 shows the distribution of illegal oil wells from digitization of aerial mapping. Table 3-1 shows the number of illegal oil mining in each sub-district in Musi Banyuasin.

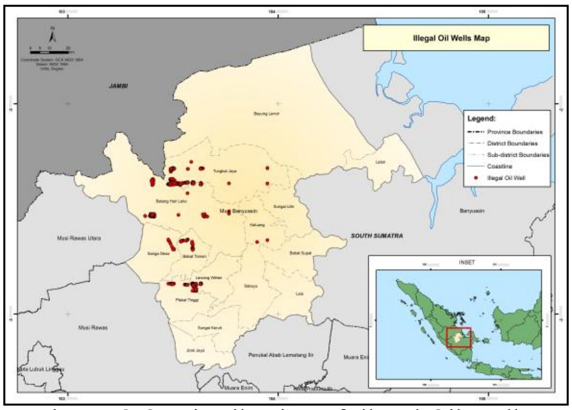

Figure 3-3: Distribution of Illegal Oil Wells

Tabel 3-1: Amount of Illegal Oil Mining

No	Sub-district	Amount of Illegal Oil Wells	Area (km^2)	Density (wells/ km^2)
1	Babat Toman	153	1,291	0.118
2	Babat Supat	0	511	0
3	Batang Hari Leko	426	2,108	0.202
4	Bayung Lencir	0	4,847	0
5	Jirak Jaya	0	299	0
6	Keluang	2	400	0.005
7	Lais	0	755	0
8	Lalan	0	1,031	0
9	Lawang Wetan	1360	232	5.862
10	Plakat Tinggi	63	248	0.254
11	Sanga Desa	15	317	0.047
12	Sekayu	0	701	0
13	Sungai Keruh	0	329	0
14	Sungai Lilin	0	374	0
15	Tungkal Jaya	645	821	0.785
TOTAL		2,664	14,266	0.187

To quantitatively assess the spatial pattern, a Global Moran's I analysis was performed in ArcGIS Pro using the digitized point dataset as the input feature class. The results, presented in Table 3-2, yielded a Moran's I of 0.652075 with a corresponding z-score of 2.199 (p = 0.028). These values indicate statistically significant positive spatial autocorrelation, confirming that illegal wells tend to form spatially clustered groups rather than occurring randomly or being evenly dispersed.

Table 3-2: Moran's I Index of Illegal Oil Mining Distribution

Global Moran's I Summary	
Moran's Index	0.652075
Expected Index	-0.000376
Variance	0.000022
z-score	2.199
p-value	0.028199

The spatial clustering implies that certain environmental or socio-economic factors may be influencing the establishment of illegal wells in specific locations. Upon closer inspection of the mapped distribution, it became evident that the highest concentrations of illegal wells were found within the sub-districts of Lawang Wetan, Tungkal Jaya, and Batang Hari Leko. These areas are characterized by relatively accessible terrain, proximity to former legal oil operations, and historical precedence of artisanal oil extraction practices. In many cases, clusters of illegal wells were situated adjacent to or within the buffer zones of decommissioned oil concessions, suggesting a form of opportunistic exploitation of legacy infrastructure.

Moreover, the spatial clustering of illegal wells often corresponded with areas where enforcement presence is limited, road infrastructure is fragmented, and oversight mechanisms are weak or absent. This spatial relationship indicates that beyond physical accessibility and geological potential, institutional and governance factors may play a pivotal role in shaping the spatial behavior of illegal oil extractors.

3.3 Ground Validation.

The verification process confirmed that the vast majority of features interpreted as illegal oil wells in the imagery corresponded to actual installations in the field. In many cases, structural elements such as derricks, tanks, pipelines, and associated equipment were directly observable and documented. Additionally, ground surveys enabled the distinction between active and inactive wells, based on indicators such as the presence of workers, fresh excavation marks, or oil seepage. These findings provided a critical layer of qualitative validation to support the visual interpretation and spatial modeling conducted in the earlier stages of analysis. Figure 3-4 shows the results of the ground validation of illegal oil mining in several sub-districts.

Figure 3-4: Illegal Oil Mining in Several Sub-district

The validation exercise demonstrated a high level of consistency between the drone-derived spatial data and field observations, reinforcing the methodological rigor of the approach. The comprehensive verification and documentation process not only strengthened the credibility of the resulting maps but also highlighted the effectiveness of combining remote sensing technologies with systematic ground-based assessment. This integrative strategy provides a replicable model for environmental monitoring, regulatory enforcement, and spatial decision-making in regions affected by informal or illegal resource extraction.

In total, 142 mapped well locations were visited during ground validation, representing approximately 5.3% of the 2,664 wells identified in the orthomosaics. Sampling followed a hotspot-focused stratified strategy, with sub-samples drawn from the highest-density clusters rather than random selection, due to practical access limitations and safety considerations associated with active illegal extraction areas. Among the visited locations, 131 were confirmed as active or abandoned illegal wells, resulting in a confirmation rate of 92%. Although sampling was not spatially uniform, the validation coverage included multiple sub-districts and cluster typologies, which increases confidence that the spatial patterns inferred from the remote-sensing data reflect actual on-ground conditions.

4 CONCLUSION

This study demonstrated the effectiveness of integrating drone-based remote sensing and spatial analysis techniques to detect, map, and analyze the distribution of illegal shallow oil wells in Musi Banyuasin Regency, South Sumatra. Through systematic aerial surveys using high-resolution drone imagery, a total of 2,664 illegal oil wells were successfully identified and digitized. The spatial distribution analysis using Moran's I index yielded a value of 0.652075, indicating a statistically significant clustered pattern of illegal oil well locations, particularly concentrated in subdistricts such as Lawang Wetan and Tungkal Jaya. Validation through field verification and ground truth data confirmed a high level of accuracy in the identification process, with direct observation, photographic documentation, and geospatial cross-referencing supporting the reliability of the remotely sensed data.

ACKNOWLEDGEMENTS

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