



Spatio-temporal assessment of surface hydrocarbon contamination in the Agadem oilfield (Niger) using Landsat-derived spectral indices (NDVI and OIS)

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Received 04 Apr 2026,
Revised 19 May 2026,
Accepted 22 May 2026

Keywords:

- ✓ Landsat;
- ✓ Oil Spill Index (OIS);
- ✓ NDVI;
- ✓ Petroleum exploitation;
- ✓ Sahelian environment

Citation: Haladou O. R., Daou I. E., Maârouhi I. M., Assoumane A. S., Tankari D. B. A. (2026) Spatio-temporal assessment of surface hydrocarbon contamination in the Agadem oilfield (Niger) using Landsat-derived spectral indices (NDVI and OIS), *J. Mater. Environ. Sci.*, 17(5), 811-827.

Abstract: Soil contamination by petroleum hydrocarbons represents a critical environmental threat in arid regions, leading to severe land degradation and ecological loss. In the Agadem oil field (eastern Niger), the rapid expansion of extraction activities has raised significant concerns regarding surface pollution and its long-term impact on the fragile Sahelian ecosystem. This study analyzes the spatio-temporal dynamics of this contamination between 2010 and 2025 using Landsat 7 and Landsat 8 satellite imagery processed with ENVI and ArcGIS. The approach is based on the combined use of the Normalized Difference Vegetation Index (NDVI), employed to assess vegetation cover condition, and the Oil Spill Index (OIS), designed to detect areas affected by hydrocarbons. The results reveal a marked regression of dense vegetation and a progressive expansion of degraded areas over the study period. Simultaneously, surfaces associated with high OIS values increase significantly, indicating an intensification of petroleum contamination. Statistical analysis shows a substantial rise in the correlation between NDVI and OIS (r increasing from 0.03 to 0.889; $p < 0.01$), highlighting a strengthening link between oil pollution and ecological degradation. These changes are attributed to the combined effects of root hypoxia, reduced soil infiltration, and the phytotoxicity of hydrocarbons. The study demonstrates that petroleum exploitation constitutes a major driver of soil degradation in Sahelian environments and underscores the relevance of the NDVI–OIS approach as an operational tool for environmental monitoring and decision support in sustainable remediation strategies.

1. Introduction

Globally, it is estimated that millions of tons of petroleum hydrocarbons are released into the environment annually due to extraction, transport, and accidental spills (UNEP 2011). For instance, in major oil-producing regions like the Niger Delta or the Middle East, soil contamination has led to the loss of thousands of hectares of arable land and severe degradation of ecosystem services (Kadafa 2012; Roufaï *et al.* 2025). In arid environments, where the natural recovery of soil is extremely slow,

these impacts are even more devastating, affecting the livelihoods of local populations who depend on scarce natural resources. Consequently, controlling the environmental impacts of mining and oil activities has become a key issue in sustainable development policies, particularly in regions where there is high pressure on natural resources (IGF 2021 & 2024; ONU 2025; Sabine and Paul 2024). While these activities play an important role in economic growth, they are also recognised for their negative effects on ecosystems, particularly through soil degradation, water resource contamination and biodiversity loss (Sabine and Paul 2024). These impacts are of particular concern in Sahelian and arid areas, where soils have low natural resilience and are highly sensitive to anthropogenic and climatic disturbances climatiques (Assane 2018).

Soil-mediated environmental disasters in oil-producing regions often result in long-term loss of land productivity due to the accumulation of toxic compounds such as Polycyclic Aromatic Hydrocarbons (PAHs). These compounds are highly hydrophobic and persistent in soil matrices, strongly adsorbing to soil particles and altering physicochemical properties—such as sorption dynamics—which reduce water infiltration and nutrient availability (Kariyawasam *et al.* 2022; C. Wang *et al.* 2024). Furthermore, PAH contamination disrupts soil microbial communities, diminishing microbial diversity and functional capacity, which further degrades soil health and resilience (Muhammad *et al.* 2024; C. Wang *et al.* 2024). Such transformations create a hostile environment for seed germination and microbial activity, effectively turning fertile zones into barren land. In extensive oil-producing zones, soils act as long-term reservoirs of dangerous hydrocarbons, affecting plant uptake and broader ecosystem functions (Sahith *et al.* 2025).

In this context, satellite remote sensing has established itself as a relevant approach for detecting, monitoring and mapping soil pollution on a large scale and over long periods of time (Nkeiruka *et al.* 2018; Wekpe and Idisi 2024). The use of multispectral images, particularly those from Landsat satellites, not only makes it possible to identify areas affected by oil contamination, but also to analyse their spatio-temporal dynamics (Roy *et al.* 2014). Optical sensors record spectral variations associated with vegetation cover, soil moisture and the presence of hydrocarbon compounds, thus providing indirect indicators of environmental degradation (Kilbride *et al.* 2023).

The interpretation of these data relies heavily on the use of spectral indices. The Normalised Difference Vegetation Index (NDVI) is commonly used to assess the physiological condition of vegetation and detect environmental stress induced by pollution. In addition, several indices specifically dedicated to the detection of hydrocarbons have been developed, such as the Oil Spill Index (OIS), the Normalised Difference Hydrocarbon Index (NDHI), the Hydrocarbon Index (HI), as well as advanced spectral analysis methods such as the Spectral Angle Mapper (SAM) (Abdurahman and Halil 2025; Ghayour *et al.* 2021; Hong *et al.* 2022). These approaches have proven particularly suitable for arid and semi-arid environments, where sparse vegetation cover facilitates spectral discrimination of contaminated soils (Kilbride *et al.* 2023).

Unlike NDVI, which mainly provides information on the indirect effects of pollution through vegetation response, the Oil Spill Index (OIS) allows for more direct detection of hydrocarbons by exploiting their specific optical signatures, particularly in the short-wave infrared (SWIR) bands. Pixels affected by contamination generally exhibit high OIS values, reflecting characteristic absorption features linked to petroleum compounds. Similar indices, such as the Hydrocarbon Index (HI) and the Normalized Difference Hydrocarbon Index (NDHI), which combine specific reflection and absorption bands, have also proven effective in differentiating the spectral signatures of bare soil, vegetation, and polluted areas. Throughout this study, the term OIS is used consistently to refer to the oil-specific spectral response.

Numerous recent studies confirm the relevance of advanced remote sensing approaches for detecting hydrocarbon-impacted environments. [Zakzouk et al. \(2023\)](#) developed novel oil spill indices using Sentinel-2 SWIR bands to detect natural hydrocarbon seepage, demonstrating that SWIR-derived features can sensitively indicate hydrocarbon presence even in sparsely vegetated areas. In the Niger Delta, a recent remote sensing analysis combining vegetation health indices (e.g., NDVI, EVI2, SAVI) with machine learning highlighted significant declines in vegetation health following oil spill events, confirming the persistent impact of petroleum contamination on landscapes ([Adebangbe et al. 2025](#)). Similarly, [Al-Jabri et al. \(2023\)](#) used Sentinel-2 imagery to assess plant stress induced by oil-contaminated produced water in a constructed wetland, emphasizing the effectiveness of multispectral indices for detecting stress patterns linked to hydrocarbon pollution.

Several studies have shown that combining vegetation and hydrocarbon-specific spectral indices significantly improves the reliability of spatial analyses for oil pollution detection. Integrating spectral signatures from SWIR and red-edge bands enhances the identification of hydrocarbon contamination by capturing subtle changes in soil moisture and vegetation stress ([Ashkanani et al. 2025](#)). The Oil Spill Index (OIS) directly targets spectral contrasts associated with hydrocarbon absorption features, offering more direct detection than vegetation-only indices like NDVI. In long-term contaminated soils, hydrocarbon residues alter soil properties and biological activity, which can be reflected in both traditional vegetation indices and dedicated hydrocarbon indices, improving discrimination between stressed and uncontaminated areas ([Bahar et al. 2024](#)).

The Agadem block is situated within the Termit Basin, a major rift structure in eastern Niger. Geologically, it is characterized as a superimposed rift basin with significant hydrocarbon potential in the Upper Cretaceous and Paleogene formations ([Yuan et al. 2022](#)). The region's environment is typically Sahelian-arid, dominated by expansive sand dunes and sparse steppe vegetation, which provides a high spectral contrast ideal for detecting surface oil spills ([Hong et al. 2022](#)).

From a socio-ecological perspective, the area is sparsely populated, primarily by nomadic pastoralist communities whose livelihoods depend on the fragile balance of seasonal pastures and scarce water points. The intensification of oil exploration and the construction of transport infrastructure (pipelines) since the early 2010s have introduced new ecological pressures, making the monitoring of soil health vital for both biodiversity conservation and the preservation of traditional pastoral lands

The main objective of this study is to analyse the spatio-temporal evolution of the NDVI and OIS indices in order to assess the impact of oil exploitation on vegetation and land use in the Agadem region. To do this, a series of Landsat 7 and 8 images covering the years 2010, 2015, 2020 and 2025 was used. This approach makes it possible to simultaneously assess the environmental pressure factor linked to hydrocarbon pollution and the ecological response of ecosystems, thus providing a decision-making tool for the sustainable management and remediation of affected areas.

The use of Landsat sensors is justified by their accessibility, the continuity of their temporal archive and their spatial resolution of 30 metres, which is particularly suited to the analysis of environmental dynamics at the regional scale ([Roy et al. 2014](#)).

2. Methodology

2.1 Presentation of the study area

The study area is located in the Diffa region, in south-eastern Niger, within the Chad Basin ([Figure 1](#)). This region is characterised by an arid to semi-arid climate, marked by low to moderate annual rainfall, ranging from 300 to 350 mm, and high temperatures, with average monthly maximums reaching 41 to 42 °C during the hot season ([Roufaï et al. 2025](#); [Weather Spark 2025](#)).

Vegetation cover is sparse and consists mainly of Sahelian and Saharan species adapted to harsh water conditions. The terrain is generally flat to slightly undulating and dominated by sandy soils with low organic matter content, locally associated with outcropping sandstone formations. The main human activities in the area include oil exploitation, which began in 2010 in the Agadem block, and extensive pastoral practices, which exert additional pressure on natural resources.

Oil exploration in the Agadem block dates back to the 1970s, but industrial production truly accelerated in 2011 with the commissioning of the Agadem-Zinder pipeline and the SORAZ refinery. Managed primarily through partnerships between the Nigerien government and the China National Petroleum Corporation (CNPC), the field has seen a rapid expansion from initial discovery wells to an extensive network of several hundred active production wells across the Termit Basin (Yuan *et al.* 2022). Currently, the area under active work pressure covers thousands of square kilometers, involving heavy infrastructure, access roads, and flowlines that fragment the landscape. The current environmental status is characterized by localized soil contamination around wellheads and transport corridors, which, combined with the extreme aridity, limits the natural attenuation of hydrocarbons and leads to persistent ‘black spots’ of degraded soil (Hong *et al.* 2022).

Geologically speaking, the Agadem Basin is part of the Central African Rift System and offers favourable conditions for hydrocarbon accumulation. Oil reservoirs are mainly associated with Lower and Upper Cretaceous sedimentary formations, resulting from siliciclastic deposits in lacustrine environments linked to rifting phases. The genesis of hydrocarbons is thus closely linked to the accumulation of organic matter and the tectonic-sedimentary dynamics of the basin (Rojas *et al.* 2022). Recent studies based on aerogeophysical data confirm the presence of deep structures, such as horsts and grabens, which promote the migration and trapping of hydrocarbons in the Agadem block (Amadou *et al.* 2023).

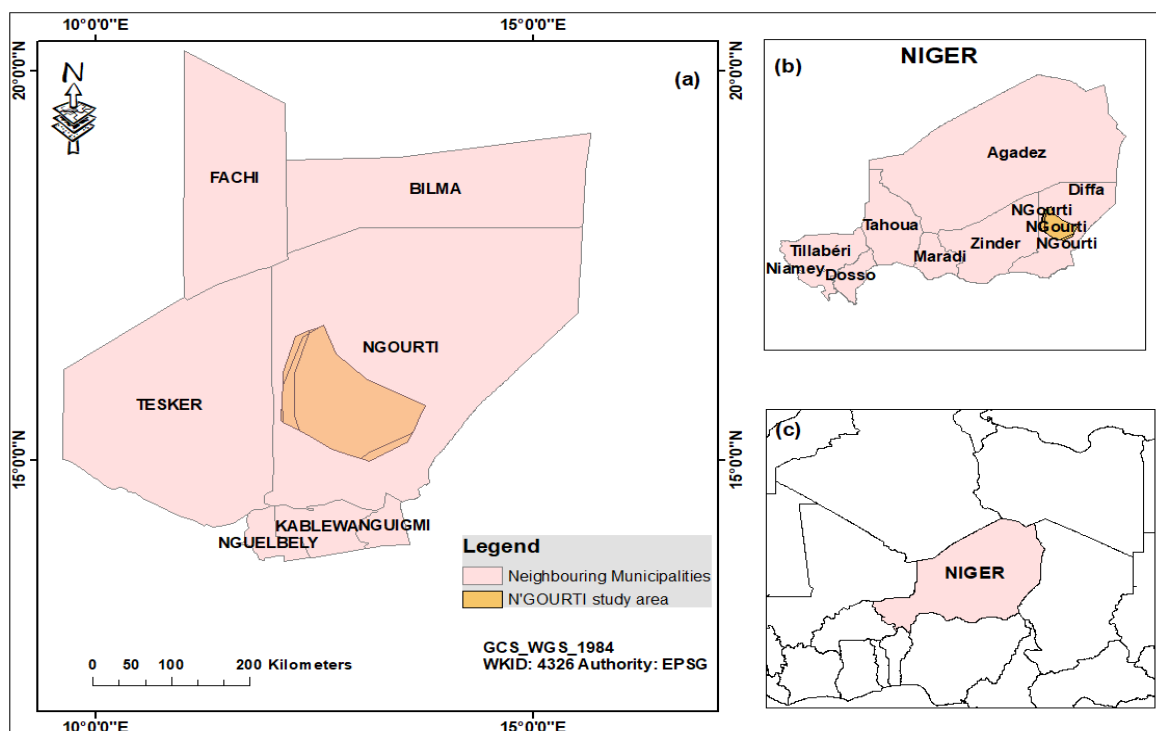


Figure 1 : (c) in West Africa, (b) in Niger and (a) Location of the study area

In this context, the combination of extreme climatic conditions, the intrinsic fragility of desert ecosystems and the potential impacts of oil activities makes the Agadem area a particularly relevant

site for studying soil contamination by hydrocarbons using remote sensing. Work carried out in comparable Sahelian environments has highlighted both a certain resilience of vegetation and an increased sensitivity to anthropogenic and climatic pressures (Wolwäi *et al.* 2023). Furthermore, recent mapping of water-dependent ecosystems in the Sahelian part of Niger provides essential information on vegetation distribution and soil-water interactions in these vulnerable environments (Rambhunjun *et al.* 2024).

2.2 Satellite data

Four Landsat satellite images were used in the spatio-temporal analysis of soil contamination by hydrocarbons (Table 1). The data came from the Landsat 7 ETM+ sensor for 2010 and the Landsat 8 OLI sensor for 2015, 2020 and 2025. All images were downloaded free of charge from the USGS EarthExplorer portal, a platform widely used for large-scale environmental studies (Hong *et al.* 2022). The selected scenes have cloud cover of less than 10%, ensuring radiometric quality suitable for spectral analysis. In order to reduce seasonal effects related to vegetation phenology, all images were acquired during the dry season (January). This choice makes it possible to better isolate the spectral signatures associated with bare soil and oil contaminants, while limiting interference due to seasonal variability in vegetation cover.

The images were processed and analysed using ENVI 5.3 and ArcGIS 10.8 software, commonly used for pre-processing, spectral index calculation and thematic mapping. Several studies have shown that the use of optical images acquired during the dry season improves the reliability of analyses in arid and semi-arid environments, in particular by reducing the impact of cloud cover and facilitating the estimation of biophysical parameters (Kergoat *et al.* 2017; Lo *et al.* 2022).

Table 1: Image references

Year	Satellite image reference
2010	LE07_L1TP_186049_20100113_20200911_02_T1
2015	LC08_L1TP_186049_20150103_20200910_02_T1
2020	LC08_L1TP_186049_20200101_20200824_02_T1
2025	LC08_L1TP_186049_20250130_20250207_02_T1

2.3 Methods

Figure 2 illustrates Methodological workflow for spatio-temporal analysis of vegetation dynamics and soil contamination by hydrocarbons based on Landsat 7 and 8 images.

2.3.1 Pre-processing of satellite data

The selected Landsat 8 and 7 images underwent rigorous pre-processing, including atmospheric, radiometric and geometric corrections to minimize distortions and optimize data accuracy (Assoumane *et al.* 2025; Berra *et al.* 2024; Chakouri *et al.* 2020; Moravec *et al.* 2021). Atmospheric correction, which is essential for obtaining surface reflectance from raw digital values (DN), was

performed using recognized methods such as QUAC, FLAASH, DOS1 and 6S, which are widely used for Landsat and Sentinel-2 (Chakouri *et al.* 2020; Moravec *et al.* 2021; Sola *et al.* 2018). These methods improve inter-sensor comparability and the reliability of spectral indices, even in arid environments (Chakouri *et al.* 2020; Moravec *et al.* 2021). After correction, the relevant spectral bands (blue, green, red, NIR, SWIR1, SWIR2) were extracted for the calculation of the NDVI and OIS indices. The images were cropped to the exact extent of the study area using ArcGIS 10.8 (Moravec *et al.* 2021).

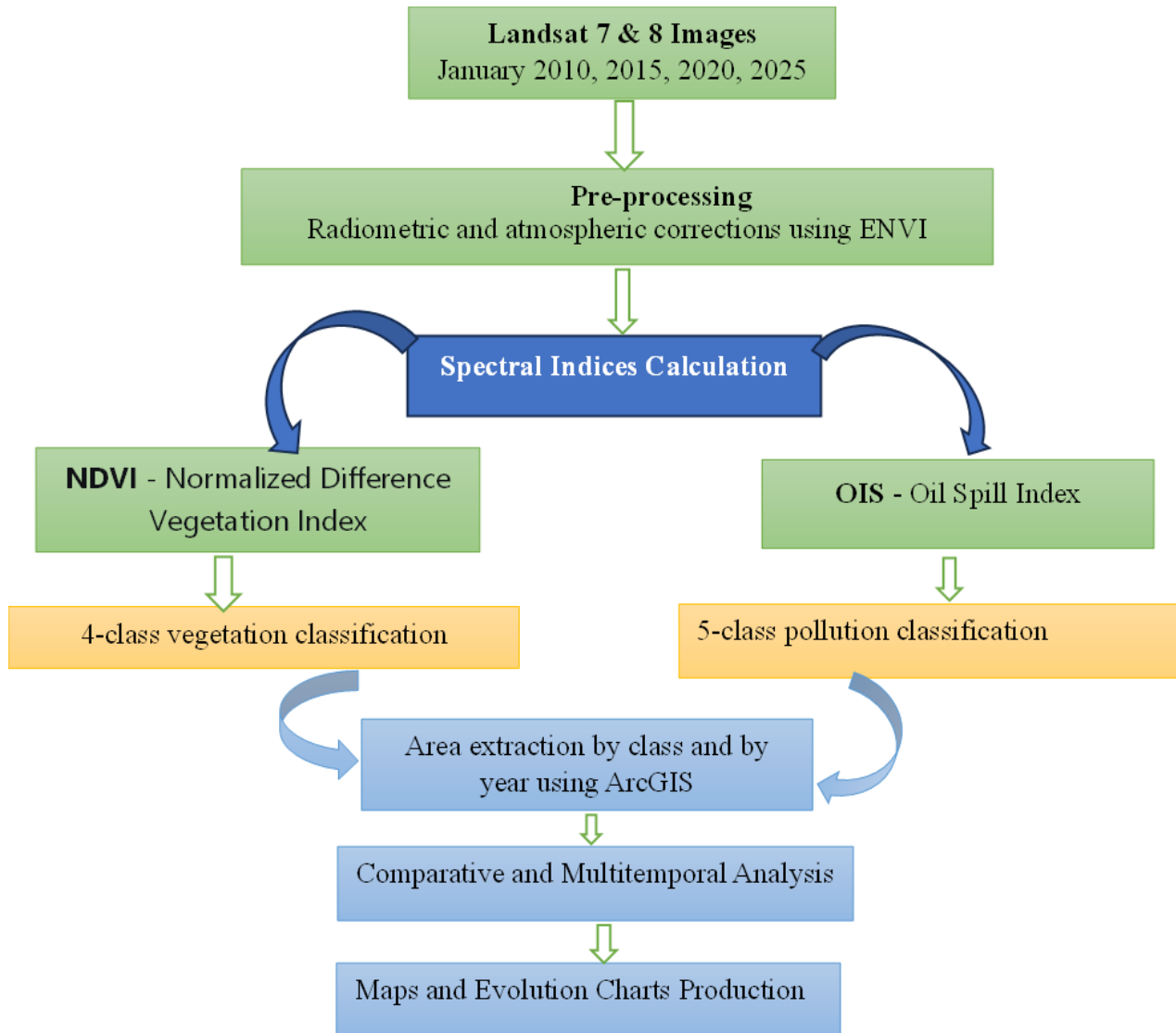


Figure 2 : General outline of the methodology

2.3.2 Calculation of spectral indices

Two indices were calculated to assess vegetation cover and hydrocarbon pollution. The Normalized Difference Vegetation Index (NDVI) was determined using the standard Eqn. 1:

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \dots \dots \dots \text{Eqn.1}$$

For Landsat 8, bands B5 (NIR) and B4 (RED) were used; for Landsat 7, B4 (NIR) and B3 (RED) (Berra *et al.* 2024; Dhillon *et al.* 2022; Moravec *et al.* 2021; Zhang *et al.* 2018). NDVI is recognized for its robustness in quantifying plant vigour and detecting stress, including in desert environments (Adamu *et al.* 2018; Dhillon *et al.* 2022; Moravec *et al.* 2021).

For hydrocarbon detection, the Oil Spill Index (OIS) was adapted by exploiting SWIR bands, which are sensitive to the spectral signatures of hydrocarbons (Adamu, Tansey, et Ogutu 2018). For Landsat 8, SWIR1 corresponds to band 6 (1.57-1.65 μm) and SWIR2 to band 7 (2.11-2.29 μm); for Landsat 7, B5 (SWIR1) and B7 (SWIR2) are used. This approach (Eqn. 2), similar to that applied on Sentinel-2, highlights spectral anomalies related to hydrocarbons (Adamu et al. 2018). The effectiveness of OIS has been demonstrated in arid environments, particularly for the detection of oil seeps (Adamu et al. 2018):

$$\text{OIS} = \frac{(\text{SWIR1} - \text{SWIR2})}{(\text{SWIR1} + \text{SWIR2})} \dots \dots \dots \text{Eqn. 2}$$

2.3.3 Classification and spatial analysis

The NDVI and OIS rasters were classified according to standardized intervals to distinguish between levels of vegetation cover and contamination (Ahmad and al-Sharia 2017). The corresponding areas were calculated using ArcGIS 10.8 to generate usable thematic maps. Finally, the correlation between NDVI and OIS was assessed using Pearson's coefficient in ArcGIS 10.8 to analyze the relationship between vegetation and pollution (Adamu et al. 2015).

2.3.4 NDVI classification

NDVI classification (Table 2) thresholds are commonly used to distinguish between levels of vegetation cover, from bare soil to dense vegetation. Several recent studies confirm the relevance of these intervals, particularly in arid environments.

Table 2: Normalized Difference Vegetation Index (NDVI)

NDVI Interval	Cours	Description	References
-1.00 to 0.00	Bare soil, water, shade	A negative or zero NDVI indicates areas without vegetation.	(Khalil et al. 2024; Kumar et al. 2022; Nadzirah et al.2024)
0.00 to 0.20	Very sparse vegetation or degraded soil	Low photosynthetic activity, often linked to infertile or degraded soils	(Khalil et al. 2024; Kumar et al. 2022)
0.20 to 0.50	Moderate vegetation	Semi-arid areas or sparsely grazed pastures	(Khalil et al. 2024; Kumar et al. 2022)
0.50 to 1.00	Dense and healthy vegetation	Forests, intensive agricultural areas, lush vegetation	(Khalil et al. 2024; Kumar et al. 2022; Nadzirah et al. 2024)

The OIS classification (Table 3) is based on empirical thresholds derived from the analysis of spectral value histograms, a method validated in the literature for the detection of hydrocarbons by remote sensing:

Table 3: Oil Spill Index (OIS) class categories

OIS interval	Cours	Description	References
-1.00 to 0.00	Moist soil, undisturbed, or healthy vegetation	High SWIR absorption, no pollution	(Al-Ruzouq <i>et al.</i> 2020; Tysi�c <i>et al.</i> 2022)
0.00 to 0.20	Slightly impacted soil	Onset of spectral stress or low plant density	(Al-Ruzouq <i>et al.</i> 2020; Tysi�c <i>et al.</i> 2022)
0.20 to 0.40	Moderate stress	Moderate contamination by hydrocarbons	(Al-Ruzouq <i>et al.</i> 2020; Tysi�c <i>et al.</i> 2022)
0.40 to 0,70	Significant soil degradation	Loss of moisture and organic matter	(Al-Ruzouq <i>et al.</i> 2020; Tysi�c <i>et al.</i> 2022)
0,70 to 1.00	Heavily polluted or barren areas	Strong SWIR reflectance associated with oil slicks	(Al-Ruzouq <i>et al.</i> 2020; Tysi�c <i>et al.</i> 2022)

3. Results and Discussion

3.1 Spatio-temporal mapping of NDVI

Figure 3 illustrates the spatio-temporal evolution of NDVI in the study area between 2010 and 2025. The NDVI, a widely used indicator for characterizing photosynthetic activity and vegetation vigour (Tucker 1979), was calculated from Landsat 7 ETM+ and Landsat 8 OLI images, then classified into standardized intervals to enable consistent multi-temporal comparison.

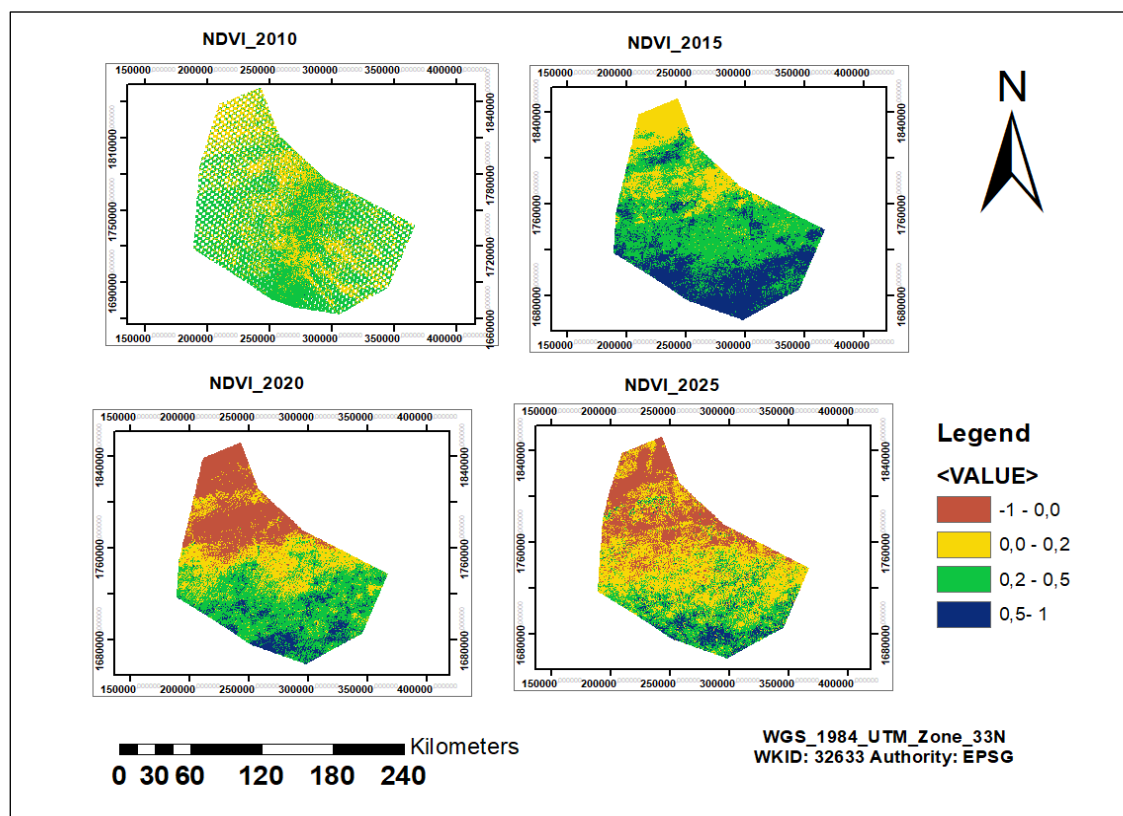


Figure 3: NDVI mapping of the Agadem site over the study period

Spatio-temporal assessment of the NDVI reveals that very low vegetation index values (0.00-0.20) dominate the study area for all years (2010-2025), which is characteristic of arid, nutrient-poor landscapes where vegetation cover remains sparse and uneven (e.g., in arid and semi-arid areas) and is further influenced by environmental stress factors (Khalil *et al.* 2024).

The limited increase in moderate NDVI values (0.20-0.50) observed in 2020 and 2025 suggests localized vegetation growth that could be due to interannual climate variations or changes in land cover dynamics, as documented in semi-arid environments influenced by climatic and anthropogenic factors (Li *et al.* 2025).

High NDVI classes (>0.50), which generally indicate dense vegetation, remain marginal throughout the period, consistent with observations made in regions affected by oil pollution, where vegetation health tends to deteriorate and NDVI values are low.

Negative NDVI values (−1.00 to 0.00) are virtually absent, reflecting a landscape dominated by dry soils and sparse vegetation rather than open water bodies or dense vegetation cover (Anwer *et al.* 2025).

3.2 Spatio-temporal mapping of the OIS index

Figure 4 shows the spatio-temporal evolution of the OIS index for the years 2010, 2015, 2020 and 2025. The OIS is based on the spectral contrast of hydrocarbons in the SWIR bands, enabling the identification of areas affected by oil contamination (Kuta *et al.* 2025).

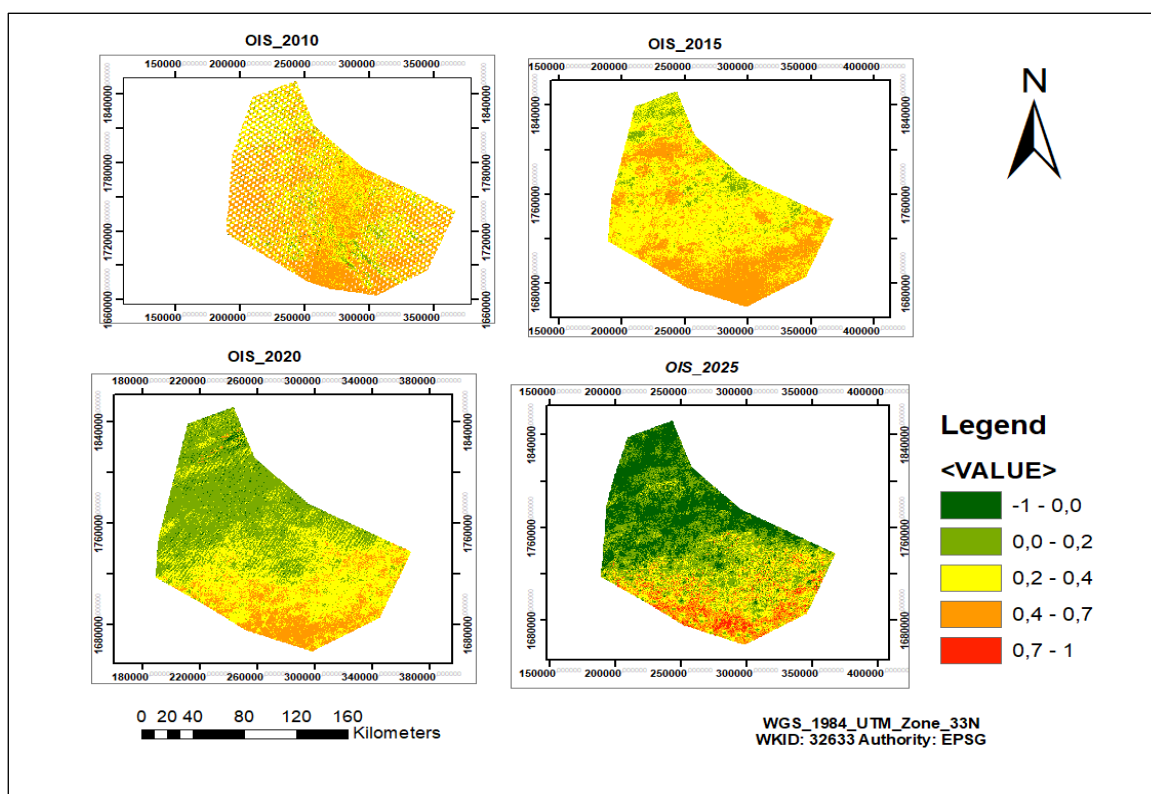


Figure 4: Mapping of the OIS for the Agadem site over the study period

Spatio-temporal analysis of the Oil Spill Index (OIS) between 2010 and 2025 reveals a strong predominance of low values (0.00–0.20), representing more than 99% of the total area of the Agadem oil field. This pattern indicates that the majority of the site shows signs of low or diffuse surface contamination, which is consistent with observations in terrestrial environments where hydrocarbons

do not form continuous slicks but are rather present in a fragmented and localized manner (Mokarram *et al.* 2025).

Moderate contamination levels (0.20–0.40) cover small areas in 2010, 2015 and 2020, but show a notable increase in 2025, suggesting a localized expansion of moderately contaminated areas. Recent studies integrating remote sensing and machine learning approaches show that the spatial evolution of oil pollution can be captured by combining spectral indices with supervised classifications, confirming the value of spectral indicators for tracking the extent of polluted areas over time (Ashkanani *et al.* 2025).

The high to very high classes (0.40–0.70 and 0.70–1.00) are consistently very small in area (<10 ha) for all dates studied. These areas correspond to fragmented hotspots, often associated with oil extraction infrastructure or convenient spill sites, highlighting the importance of remote sensing in identifying point sources of pollution. This behaviour of high-intensity hydrocarbon spectral signatures has been documented in terrestrial and marine contexts, where indices derived from SWIR/NIR bands facilitate the distinction between polluted and natural areas (Zakzouk *et al.* 2023).

The 0.40–0.70 class, which consistently has the smallest spatial extent, appears to correspond to a transitional state between moderate and extreme contamination, indicating areas where hydrocarbons are present but not intense enough to produce strong spectral signatures. This type of gradation is consistent with recent integrated monitoring results using spectral indices and advanced classifications to map degrees of hydrocarbon pollution over long periods (Mokarram *et al.* 2025).

Overall, OIS maps highlight a pattern of contamination dominated by low-intensity signals, with localized hotspots rather than areas of widespread pollution. This spatially diffuse distribution punctuated by intensive hotspots has been observed in several studies using time series of satellite imagery to track the long-term impact of hydrocarbons on land surfaces (Ashkanani *et al.* 2025).

3.3 Statistical Analysis of Areas by NDVI Class

Table 5 shows the change in area (in hectares) associated with the different NDVI classes between 2010 and 2025. Quantitative analysis of areas by NDVI class clearly confirms the trends observed on the NDVI maps and highlights a landscape dominated by very sparse vegetation, characteristic of arid Sahelian environments such as the Agadem oil field. In 2010, the dense vegetation class (NDVI 0.5–1.0) covered approximately 2,474 ha, representing a limited but notable proportion of the vegetated areas. This sporadic presence of high NDVI values may be associated with localized areas of temporary vegetation, favoured by exceptional water conditions or the proximity of topographical depressions conducive to moisture accumulation, as observed in other arid regions studied by remote sensing (Goyena *et al.* 2023).

Table 5: Periodic distribution of areas (in ha) of NDVI classes at the Agadem site

NDVI class	2010	2015	2020	2025
-1 to 0.00	3923.42	15.35	8.48	4.88
0 to 0.2	1548193.04	1896513.66	1886331,57	1902987.55
0.20 to 0.0	682.19	297.06	2110.88	15452.36
0.50 to 1	2474.69	6.72	8.83	8.58
Total	1555273.34	1896832.79	1888459.76	1918453.36

From 2015 onwards, this class experienced a very marked decline, with an area of less than 9 ha, and remained marginal until 2025. This trend reflects a rapid loss of dense vegetation, probably linked to a combination of climate variability, increasing anthropogenic pressure and the expansion of oil infrastructure. Recent studies show that in arid oil-producing areas, dense vegetation is particularly vulnerable to mechanical disturbance and soil degradation (Ding *et al.* 2024; Koshim *et al.* 2022).

The very low vegetation class (NDVI 0.0–0.2) is largely dominant throughout the study period. Its surface area increases from 1,548,193 ha in 2010 to 1,902,987 ha in 2025, representing an increase of more than 350,000 ha. This dominance reflects the predominance of bare soil, very sparse vegetation and degraded areas, typical of arid ecosystems subject to continuous anthropogenic pressure (Li *et al.* 2025).

The moderate vegetation class (NDVI 0.2–0.5) shows non-linear dynamics over the period studied. After a very small area in 2015 (297 ha), it shows a gradual increase from 2020 onwards, reaching 15,452 ha in 2025. This trend suggests a localized recovery of vegetation cover, which may be linked to temporarily favourable climatic conditions, natural regeneration processes or relatively lower anthropogenic pressure in certain areas. Similar observations have been reported in the Sahelian regions, where the increase in intermediate NDVI classes is interpreted as a sign of partial vegetation recovery in arid contexts subject to high climatic variability (Quan *et al.* 2022).

Finally, the negative NDVI class (–1 to 0), associated with temporary water bodies, highly degraded bare soil or barren surfaces, decreased sharply between 2010 (3,923 ha) and 2025 (<5 ha). This decrease may reflect the increasing scarcity of open water surfaces in the arid context of the region, but also improved spectral discrimination of bare surfaces, as highlighted in recent methodological studies on the evolution of satellite sensors (Ding *et al.* 2024; Qi Wang *et al.* 2020).

3.4 Statistical Analysis of Areas by OIS Class

Table 6 shows the change in area (in hectares) associated with the different Oil Spill Index (OIS) classes between 2010 and 2025.

Table 6: Periodic distribution of areas (in ha) of OIS classes at the Agadem site

OIS class	2010	2015	2020	2025
-1 to 0.00	4202.11	4.59	26.53	2.61
0.00 to 0.20	1542989.62	1896828.33	1887875.90	1863903.74
0.20 to 0.40	1503.43	60.66	617.86	54549.71
0.40 to 0.70	0.09	0.75	5.49	8.79
0.70 to 1	2495.35	5.28	9.21	1.17
Total	1551190.60	1896899.61	1888535.00	1918466.03

Analysis of areas classified according to the Oil Spill Index (OIS) shows a clear and persistent predominance of low values (0.00–0.20), representing more than 95% of the total area for all the years studied. This spatial configuration indicates that oil contamination in the Agadem field is mainly diffuse and low in intensity, rather than widespread or continuous. Recent studies show that, in onshore oil fields in arid environments, hydrocarbons are generally detected as weak and fragmented spectral signals, linked to discontinuous deposits or partially degraded historical contamination (Hu *et al.* 2023).

The intermediate (0.20–0.40) and high (>0.40) contamination classes occupy significantly smaller areas, confirming the localized nature of the affected zones. However, a significant temporal evolution is observed for the 0.20–0.40 class, whose surface area increases sharply between 2020 (617.86 ha) and 2025 (54,549.71 ha). This expansion suggests a spatial extension of moderate contamination, potentially linked to the intensification of oil activities, the opening of new access roads or the gradual dispersion of hydrocarbons on the surface under the effect of climatic and wind conditions (Koshim *et al.* 2022). Conversely, high to very high contamination classes (>0.40) remain extremely marginal throughout the study period, although their presence is recurrent. Their limited spatial extent indicates that large or highly concentrated spills remain rare and spatially limited. Nevertheless, these areas constitute critical environmental hotspots, generally associated with extraction infrastructure, storage areas or one-off incidents, and must be subject to targeted monitoring (Adebangbe *et al.* 2025; R. Dean *et al.* 2024). The persistence of a very small surface area for class 0.40–0.70, often identified as the smallest in spatial extent, suggests that it corresponds to a transitional state between moderate and heavy contamination. This behaviour is consistent with recent models of surface hydrocarbon dispersion, where spectral signatures evolve rapidly under the effect of evaporation, oxidation and partial burial of pollutants (Mokarram *et al.* 2025).

3.5 Correlation between NDVI and OIS indices

Pearson's correlation analysis between NDVI and the Oil Spill Index (OIS) (Figure 7) highlights a marked temporal evolution in the relationship between vegetation cover and surface oil contamination in the Agadem field.

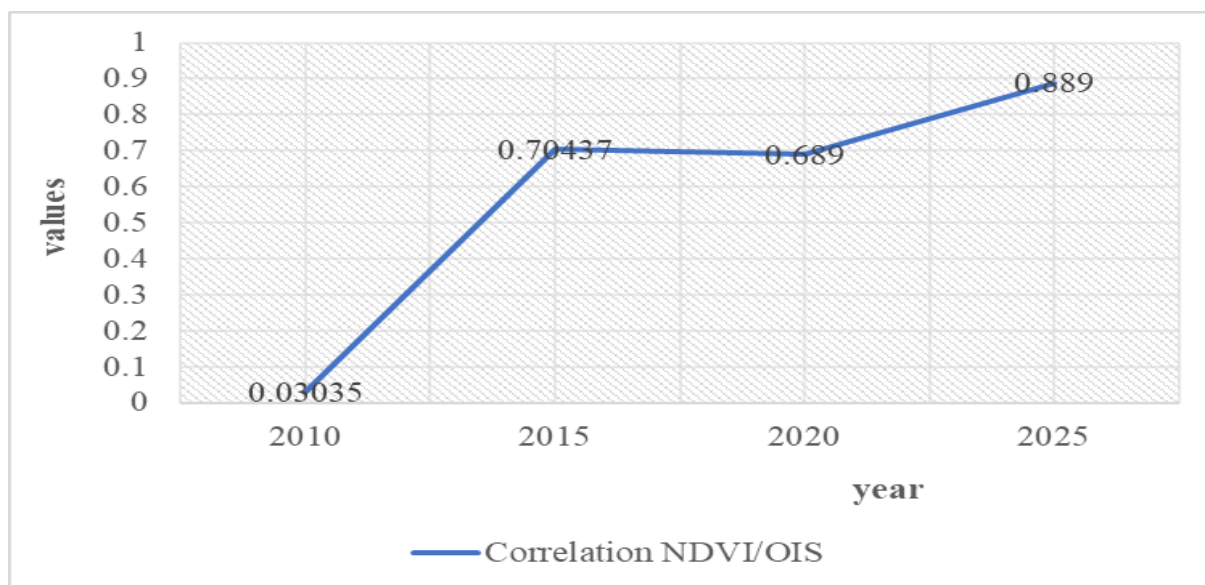


Figure 7: Correlation between NDVI and OIS images

In 2010, the correlation observed was very weak and insignificant ($r = 0.03$; $p > 0.05$), indicating statistical independence between the spatial distribution of vegetation and the spectral signatures associated with hydrocarbons. This situation is characteristic of the initial phases of oil exploitation, where natural vegetation is mainly controlled by climatic and edaphic factors, while oil contamination remains sporadic and insufficiently widespread to significantly influence NDVI dynamics. These observations are confirmed by Hou *et al.* (2025), who state in their studies that, in contexts of low anthropogenic disturbance, NDVI variations are mainly determined by natural factors such as

precipitation and climate variability, and can evolve largely independently of anthropogenic pollution indices when these disturbances are limited or localized (Hou *et al.* 2025).

In 2015, the correlation became strong and statistically significant ($r = 0.704$; $p < 0.01$), reflecting a growing interaction between vegetation dynamics and surface oil contamination. This corroborates the study by Kuta *et al.* (2025), which shows that in exploited oil areas, the impact of oil spills on vegetation becomes detectable by remote sensing and manifests itself in significant statistical relationships between vegetation indices and pollution-related indices (Kuta *et al.* 2025).

In 2025, the correlation reached a very high and highly significant level ($r = 0.889$; $p < 0.001$), indicating a strong spatial dependence between NDVI and OIS. This positive relationship, observed in arid contexts, has been associated with an adaptive response of certain forms of persistent vegetation exposed to moderate levels of oil contamination (Kuta *et al.* 2025).

It is important to emphasize that this positive correlation does not reflect an improvement in ecological status, but rather an increasing spatial overlap between areas with low vegetation cover and moderately contaminated surfaces. Thus, the NDVI–OIS correlation should be interpreted as an indirect indicator of the cumulative impact of oil activities, and not as a direct causal relationship between contamination and plant growth, in accordance with recent methodological recommendations in environmental remote sensing.

Conclusion

The diachronic analysis of Landsat 7 and 8 images made it possible to analyze the spatio-temporal dynamics of surface contamination by hydrocarbons and changes in vegetation cover in the Agadem oil field (Niger) between 2010 and 2025, based on spectral indices derived from Landsat images, notably the NDVI and the Oil Spill Index (OIS).

The results show a persistent dominance of low NDVI values (0.00–0.20) throughout the study period, reflecting a landscape largely characterized by sparse vegetation, typical of arid Sahelian environments. Moderate and dense vegetation classes remain spatially limited and unstable over time, although a slight increase in intermediate NDVI values is observed from 2020 onwards, suggesting a localized rather than widespread recovery of vegetation.

At the same time, OIS analysis reveals a marked predominance of low levels of surface contamination, covering more than 95% of the study area. However, the significant increase in areas associated with moderate contamination between 2020 and 2025 indicates a gradual spatial expansion of affected areas, probably linked to the intensification of oil activities and the dispersion of hydrocarbons on the surface. Areas of high contamination remain very limited in space, appearing as localized hotspots, but nevertheless constitute significant sources of environmental degradation.

The NDVI–OIS cross-analysis and the evolution of Pearson's correlation highlight a growing spatial dependence between vegetation and oil contamination over time. The shift from a weak and insignificant correlation in 2010 to a strong and then very high correlation in 2015 and 2025 reflects the gradual anthropization of the landscape, where vegetation distribution is increasingly influenced by areas disturbed by oil exploitation. This positive correlation does not reflect an improvement in ecological status, but rather a spatial co-location between sparse vegetation and diffuse contamination, characteristic of onshore oil fields in arid environments.

Overall, this study demonstrates the relevance of using NDVI and OIS together for long-term monitoring of the environmental impacts of oil activities using multispectral satellite data. The

proposed approach makes it possible to identify both general trends in degradation and critical areas requiring targeted monitoring. These results provide a solid scientific basis for environmental monitoring, sustainable management of oil sites and the orientation of future ecological rehabilitation strategies in arid regions of Niger and other similar contexts.

Acknowledgement: The authors thank the University of Diffa for its support.

Disclosure statement: *Conflict of Interest:* The authors declare that there are no conflicts of interest.

Compliance with Ethical Standards: This article does not contain any studies involving human or animal subjects.

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