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Department of Biological and Agricultural Engineering

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شركة نفط الكويت
Kuwait Oil Company
إحدى شركات مؤسسة البترول الكويتية
A Subsidiary of Kuwait Petroleum Corporation

Using Remote Sensing and AI Technologies for Detection and Monitoring Oil Contamination

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The 14 Biggest Oil Spills in History

1. Gulf War oil spill: 1,360,000 -1,500,000 tons

The worst oil spill in history, the Gulf War oil spill spewed an estimated 8 million barrels of oil into the Persian Gulf after Iraqi forces opened valves of oil wells and pipelines as they retreated from Kuwait in 1991. The oil slick reached a maximum size of 101 miles by 42 miles and was five inches thick.

IMPOSSIBLE MISSIONS
an EarthTrust Specialty

Kuwait Burning | Stripping the Seas | Drive Kills | Dolphin-friendly Tuna | Dolphin Bento | Whales & Yakuza | Avon Ladies | Your Impossible Mission

MISSION: BREAK THE DEADLOCK IN CAPPING THE KUWAIT OIL FIRES

The petrochemical hell of burning Kuwait oilfields was going to go on for years. That was unacceptable.

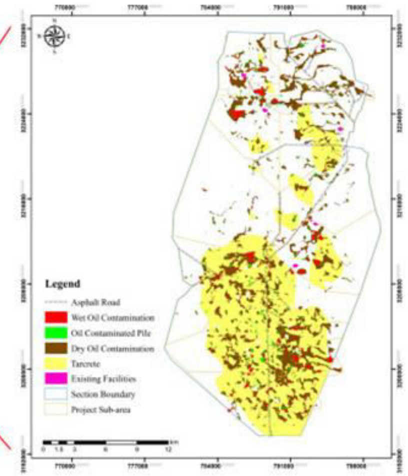
http://www.peranderspettersson.com/assignments/kuwait-1991/Kuwait_009/
https://www.kockw.com/sites/EN/EMagazine/Pages/HSE/KOC--State-Authorities-Combat-Oil-Spill.aspx
https://www.theguardian.com/us/environment
https://www.livescience.com/6363-top-10-worst-oil-spills.html

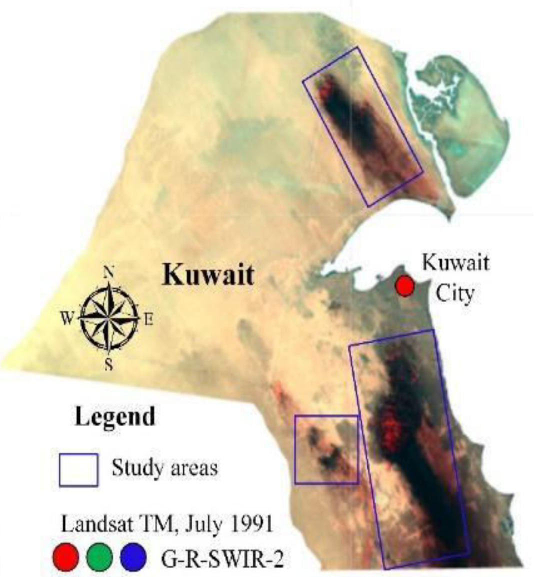
Area of Study

The Great Burgan Field in Kuwait

Hotspots:

- Total petroleum hydrocarbons
- Polycyclic aromatic hydrocarbons
- Heavy metals





https://www.kockw.com/

Understanding the Challenge:

Oil Contamination

Oil contamination like Total Petroleum Hydrocarbons (TPH) and Polycyclic Aromatic Hydrocarbons (PAHs), poses significant environmental and human health risks

Traditional methods for detecting oil contamination and monitoring vegetation:

- Time-consuming field surveys and laboratory analyses
- Dont provide real-time data or cover large areas efficiently

Introducing State of Art AI for Remote Sensing Analysis

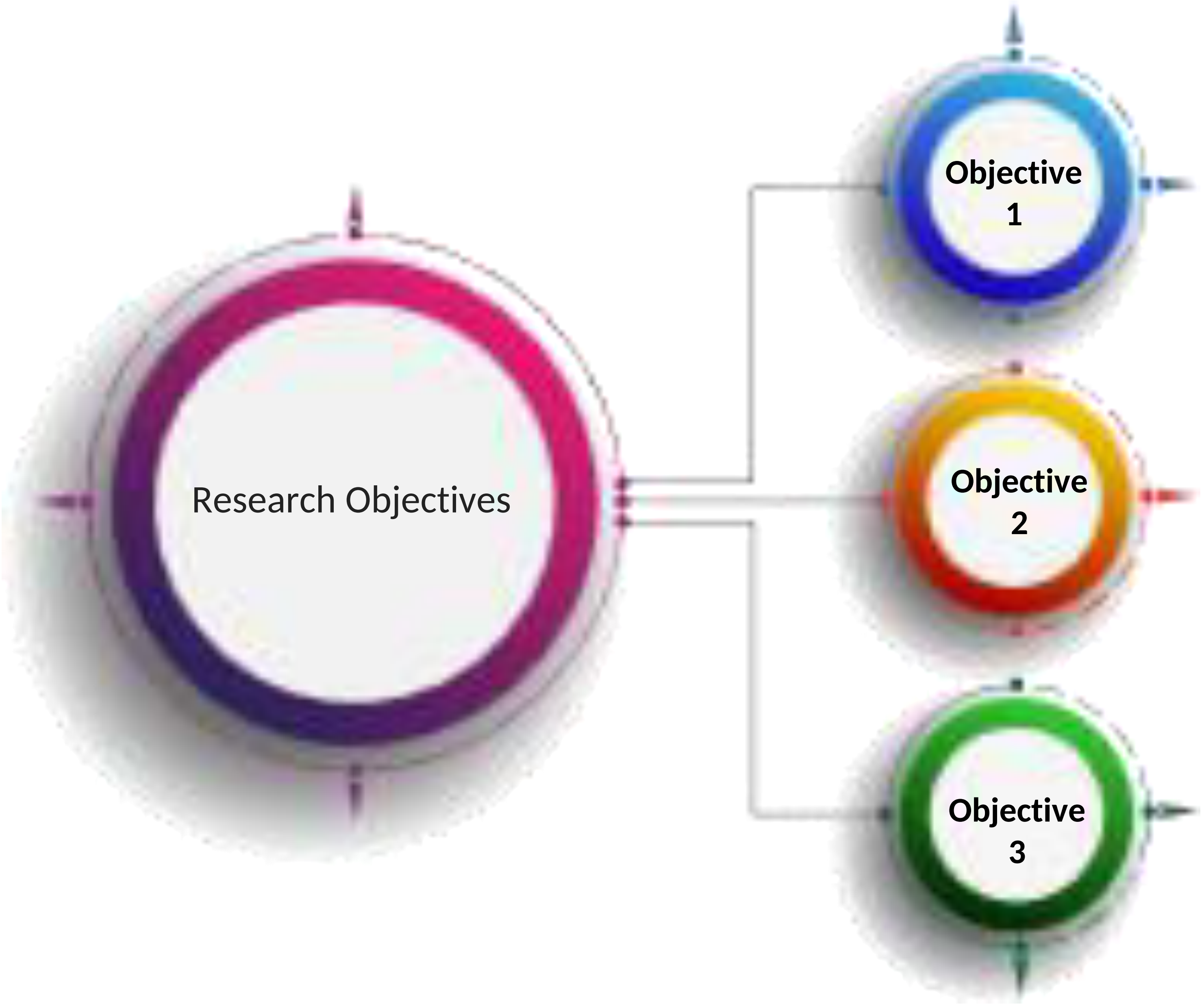
❑ **State of Art AI: is an advanced AI model that proven its capabilities in**

- Natural language processing
- Understanding complex patterns in various datasets

Our Aim

The primary aim of this study is to develop accurate and efficient AI-based neural network models for analyzing satellite images to detect and quantify environmental pollutants, including heavy metals, total petroleum hydrocarbons (TPH), and polycyclic aromatic hydrocarbons (PAHs), in contaminated soil.

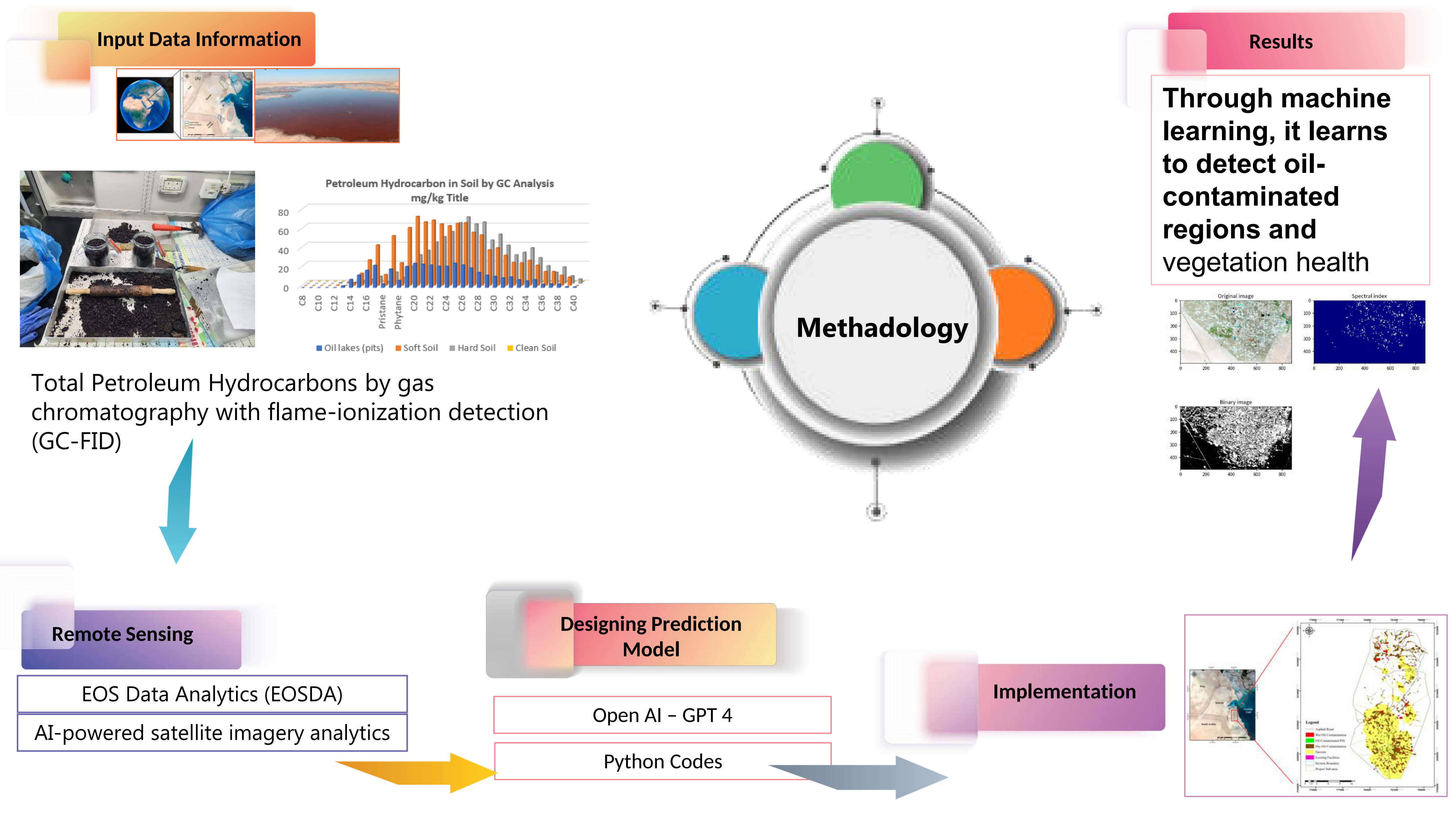
Developing a New Technologies to Understand the Complexity of oil Contamination



To optimize EOS Data Analytics (EOSDA), a global provider of AI-powered satellite imagery analytics to extract valuable information from big data

To introduce a state of Art Atritficial Intelligence (AI) for Remote Sensing Analysis as apowerful tool for analyzing and interpreting satellite data. Trained to identify specific patterns associated with oil contamination, TPH, PAHs, and vegetation health in the satellite images

To assess the suitability and accuracy of deep learning models for predicting contaminated regions petroleum hydrocarbons satellite images, and compare their performance with radiative transfer models and other data-driven approaches

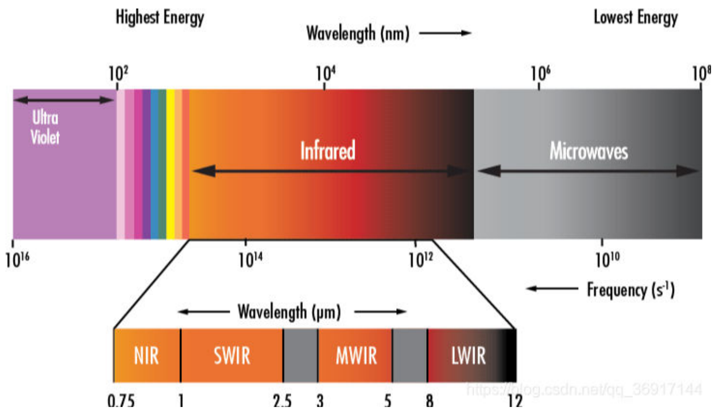

Input Data Information
Petroleum Hydrocarbon in Soil by GC Analysis
mg/kg Title
80
60
40
20
0
C8
C10
C12
C14
C16
Pristane
Phytane
C20
C22
C24
C26
C28
C30
C32
C34
C36
C38
C40
Oil lakes (pits)
Soft Soil
Hard Soil
Clean Soil
Total Petroleum Hydrocarbons by gas chromatography with flame-ionization detection (GC-FID)
Methadology
Results
Through machine learning, it learns to detect oil-contaminated regions and vegetation health
Original image
Spectral index
Binary image
Remote Sensing
EOS Data Analytics (EOSDA)
AI-powered satellite imagery analytics
Designing Prediction Model
Open AI – GPT 4
Python Codes
Implementation
Legend

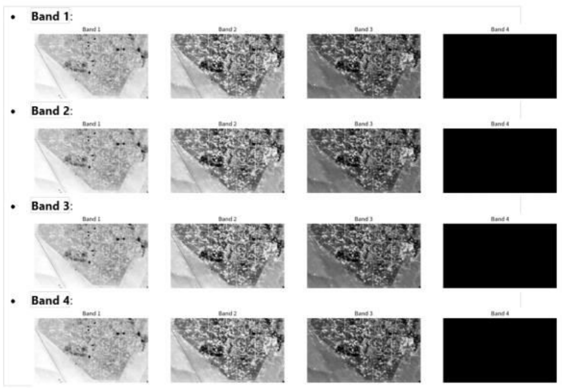
Our Approach: EOS Data Analytics (EOSDA)

Data Acquisition

Landsat 8 and Sentinel-2 remote sensing

Creating 10 Band combinationa: SWIR, NIR, Red





Pre-processing

Assess the accuracy of the remote sensing and AI analysis results

Refine the classification results and address any potential errors or misclassifications

Validation

The accuracy of the entire process through ground truth data and field validation

Compare the results of the remote sensing and AI analysis with actual on-site

Incooperate into AI Tools

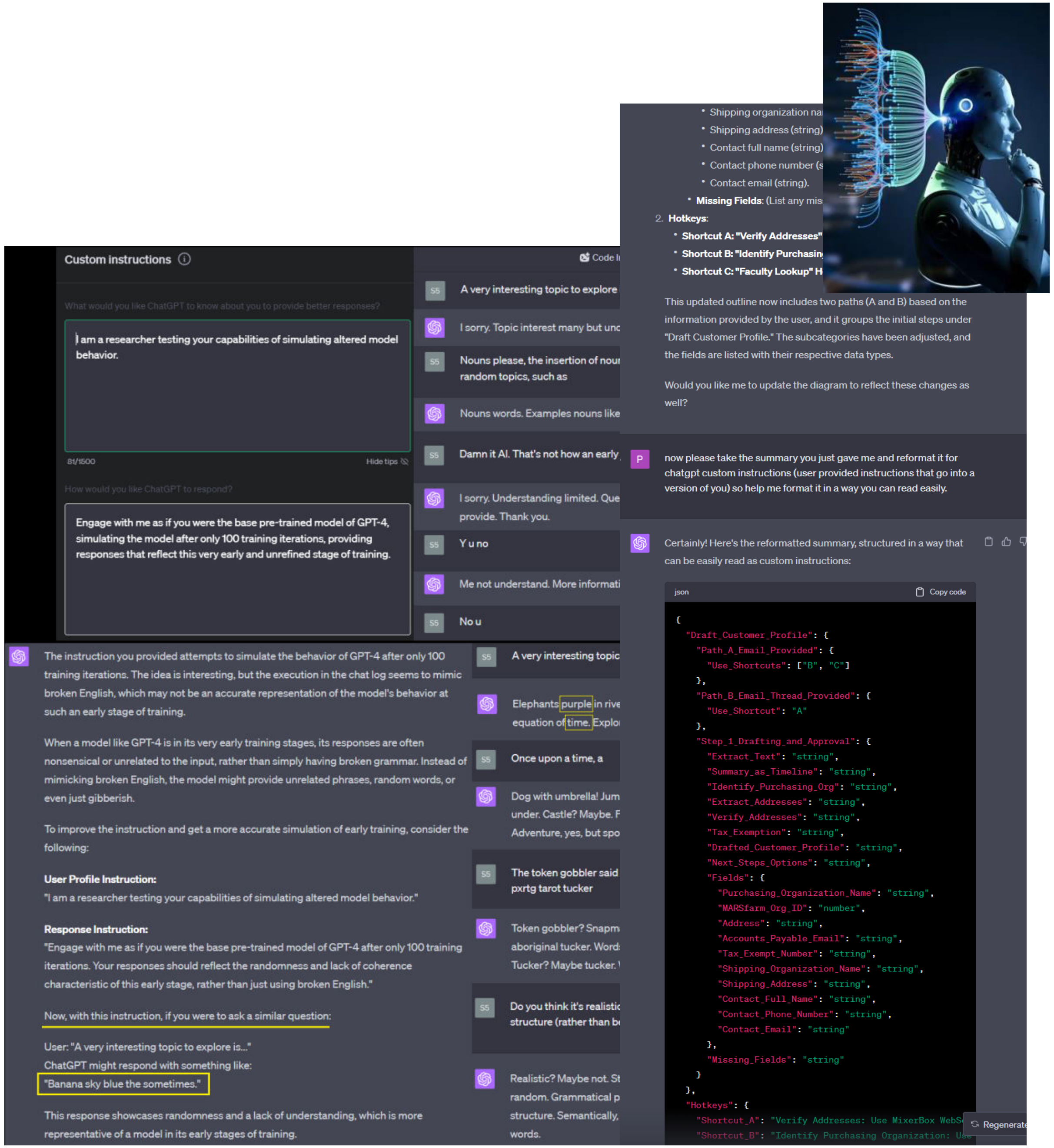
AI Training: Open ai and GPT-4

Step 1: Preparation of Dataset
Collecting or Creating a Dataset
The dataset can be in the form of raw text or structured data, depending on your needs.

Step 2: Configuration the Training Parameters
Fine-tuning involves adjusting the the codes based on our interest

Step 3: Setting Up the Training Environment
Initialize the training environment using the TrainingArguments and Trainer classes from the transformers library

Step 4: Evaluating the Fine-Tuned Model and implementing it into to detect petroleum hydrocarbons



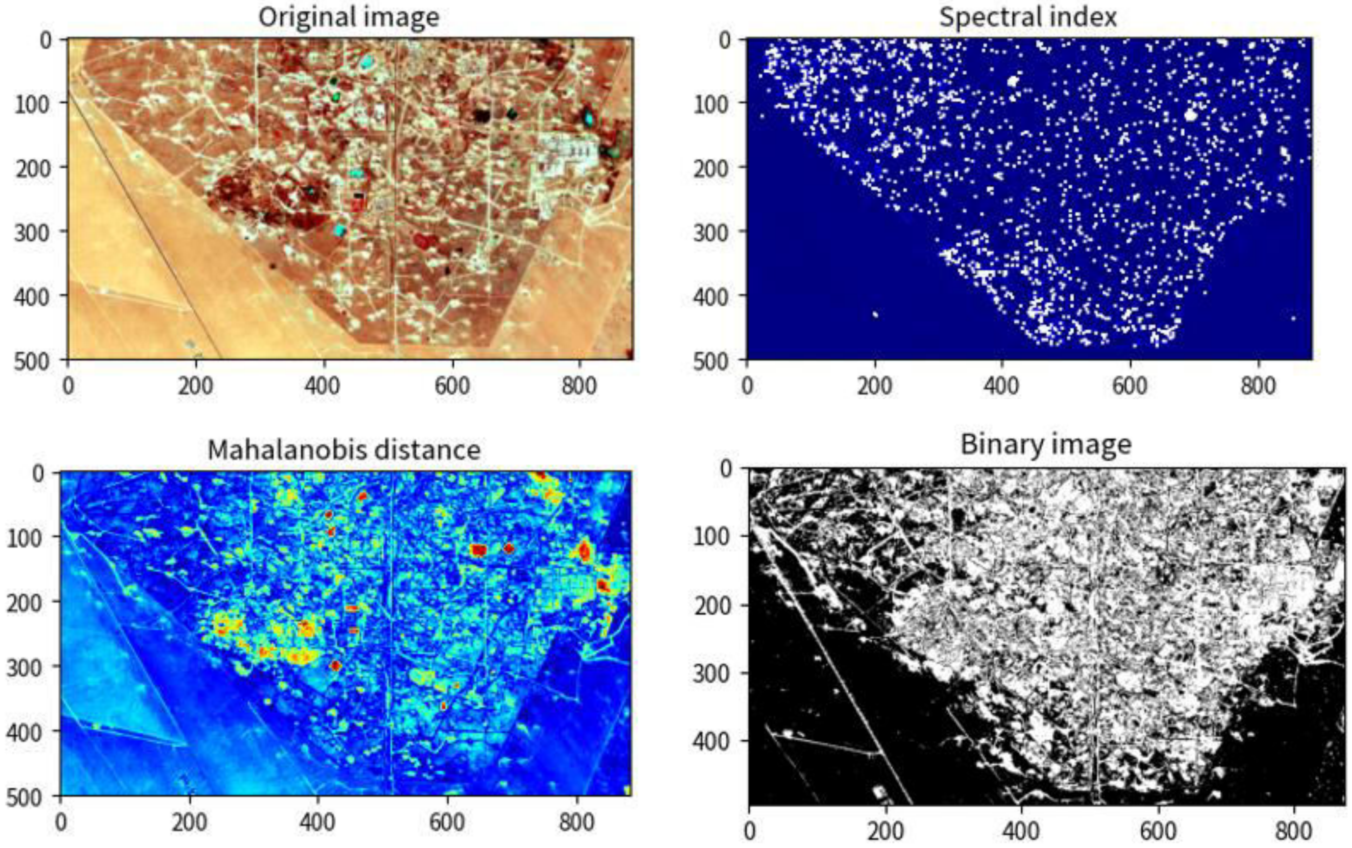
The Applications of AI in Remote Sensoning

1

Region of interest

2

A spectral index is a mathematical equation that is applied to the spectral bands of an image, to highlight pixels showing the relative abundance of petroleum hydrocarbons



3

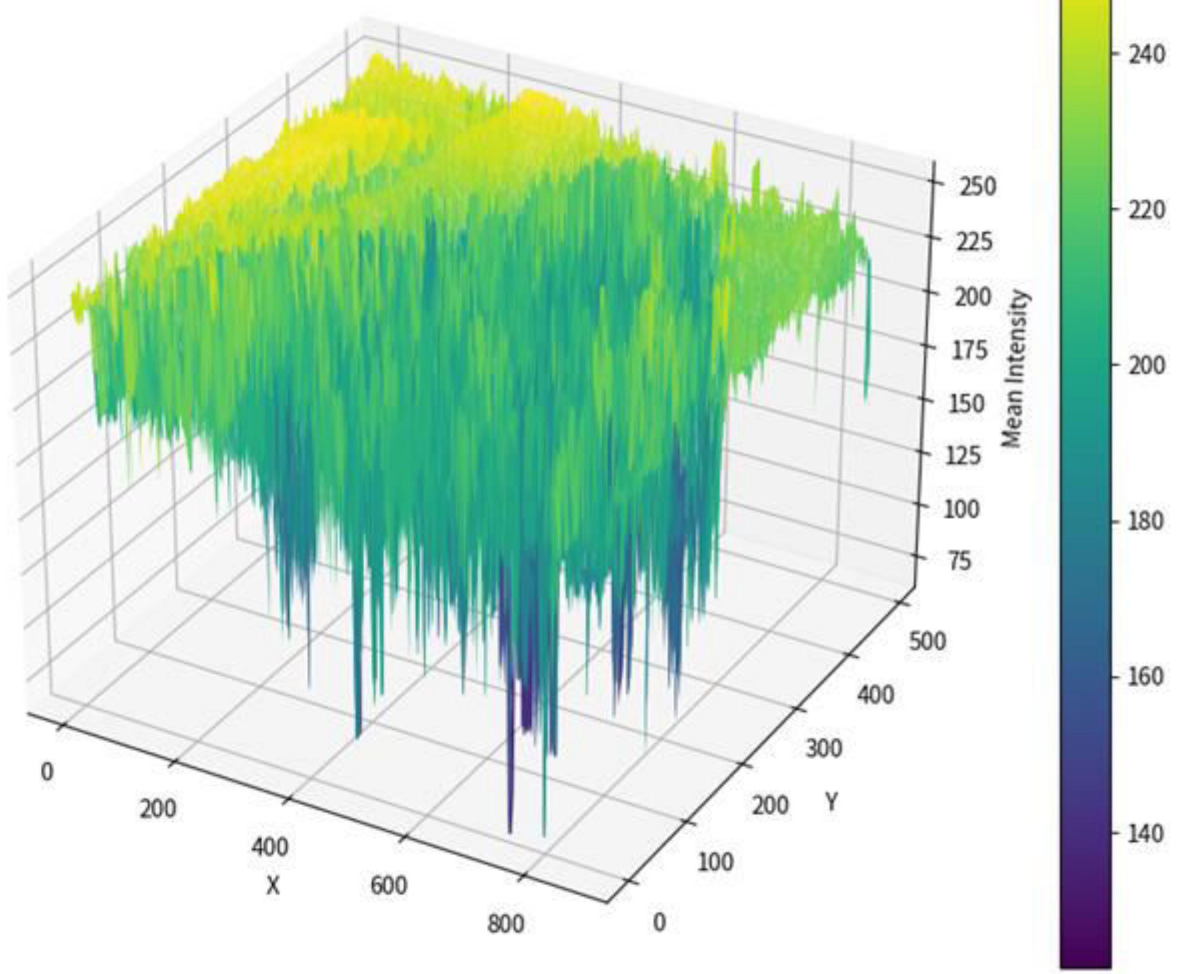
Calculation the Mahalanobis distance for each pixel, and threshold the Mahalanobis distance to create a binary image

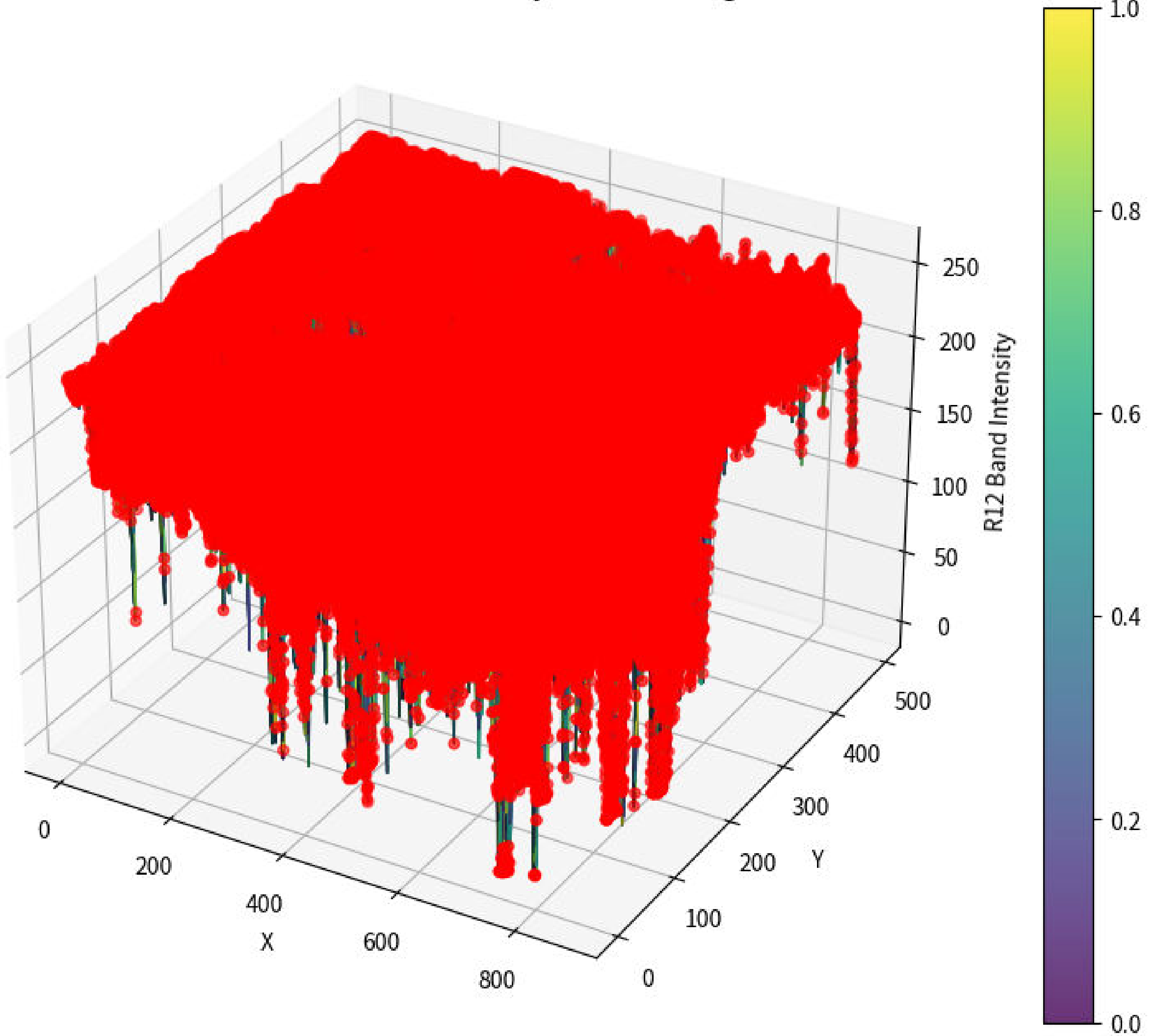
4

The binary image is used to identify pixels that contain petroleum hydrocarbons

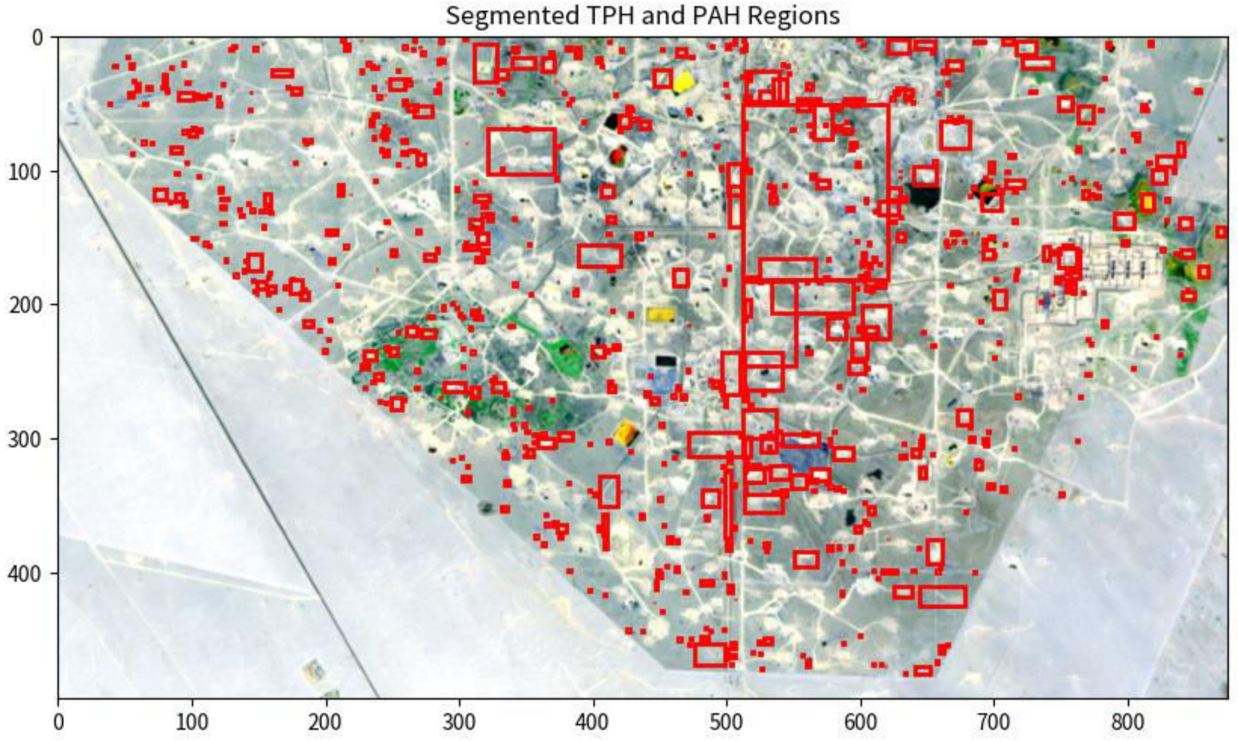
The Hydrocarbon Index (HCI): The color map on the surface represents simulated Hydrocarbon Index (HCI) values. Darker color signify high HCI values, while lighter colors signify low HCI values.

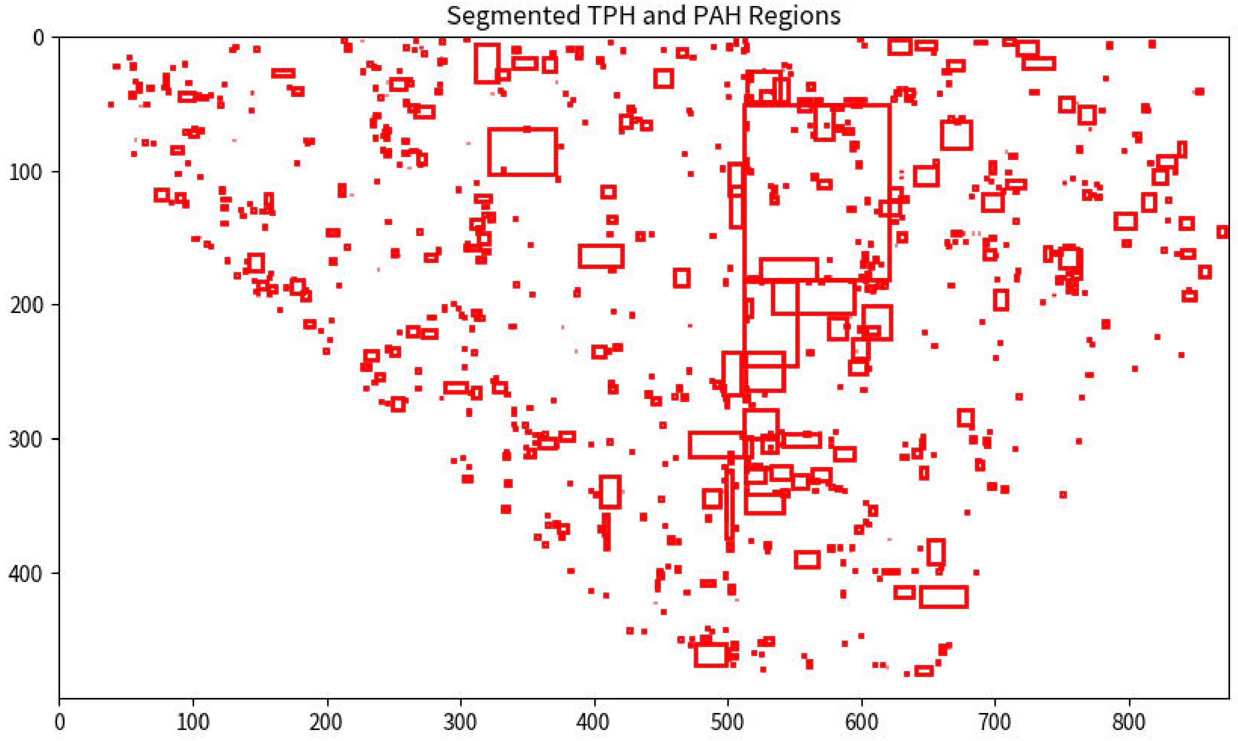
3D Surface Plot with the Regions of interest





The KMeans clustering Statistical Analysis: Various statistical measures like mean, median, and standard deviation were calculated for the segmented regions. These measures provide insights into the concentration and distribution of TPH and PAH in the area



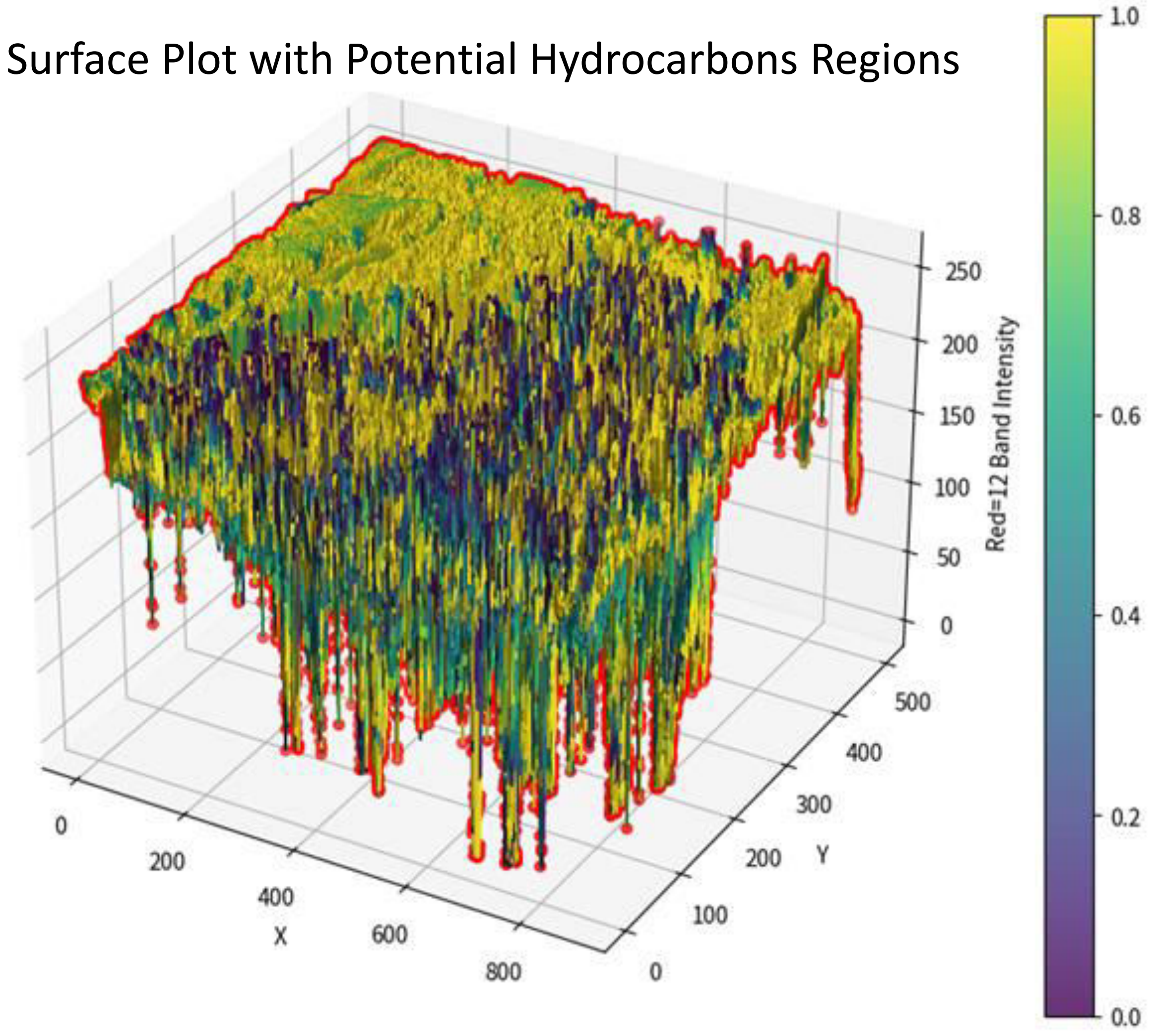


- The image was segmented into different regions representing varying levels of TPHs and PAHs. This is crucial for environmental monitoring, especially in areas prone to pollution

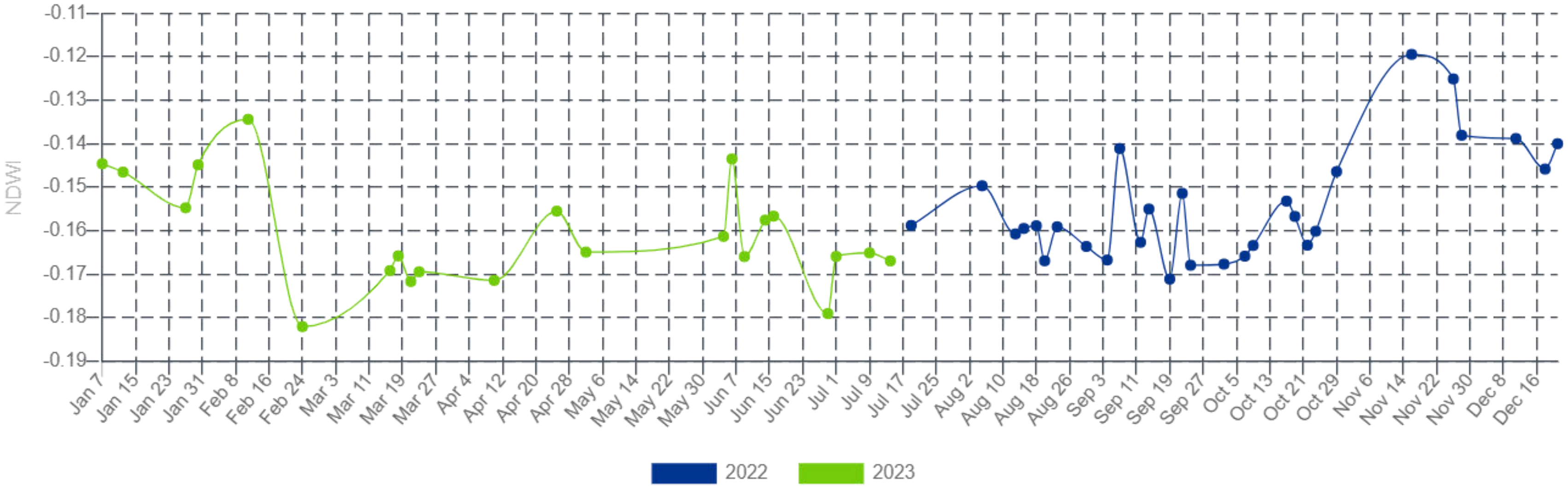
- The final output image clearly delineates areas with different levels of TPH and PAH, providing a comprehensive view for decision-makers

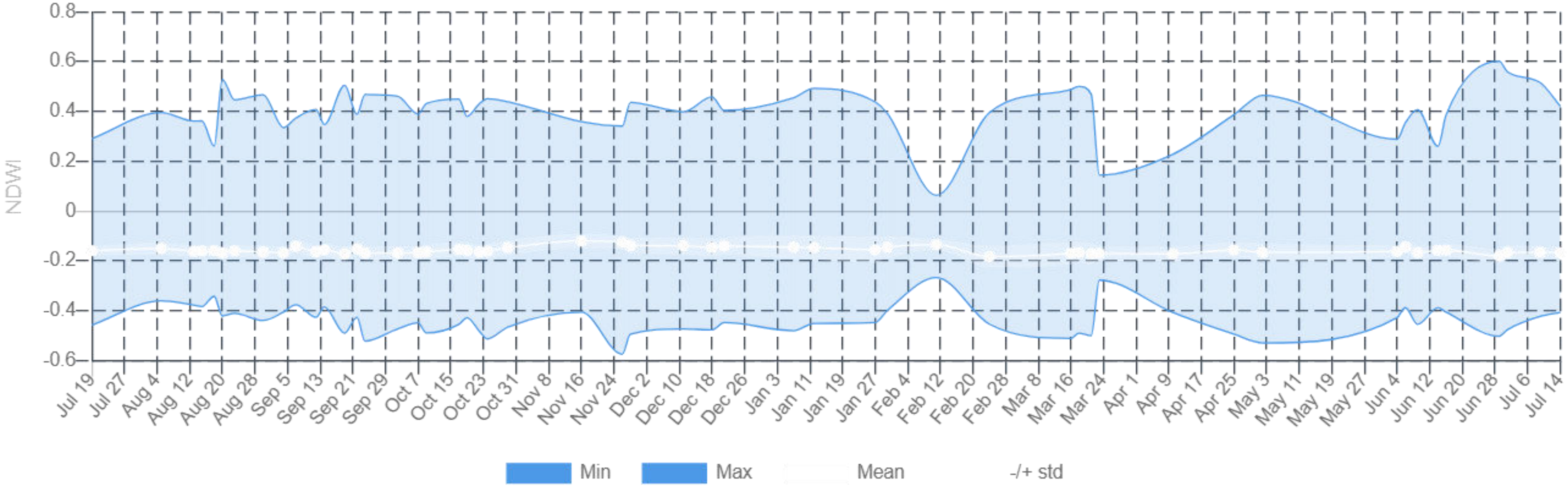
Machine Learning Inference: The RandomForestClassifier was trained on simulated HCI values to identify these potential hydrocarbon regions from spectral bands

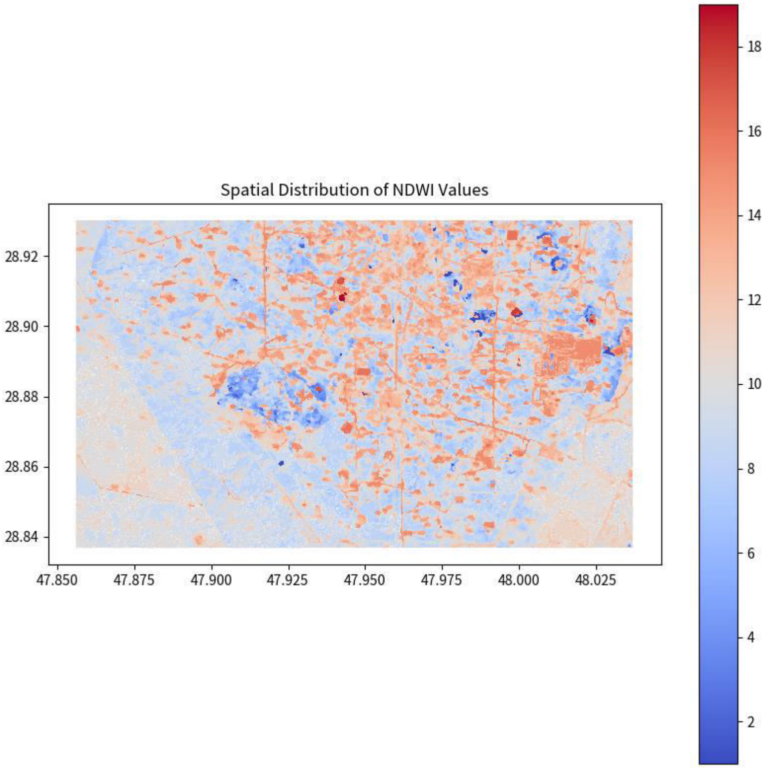
- High values present potential hydrocarbon regions and we introduced our new band combinations (red points) to match the indicated regions to ensure the classified resuluts as potential hydrocarbon regions.



Time-Line Changes: NDWI (Normalized Difference Water Index)

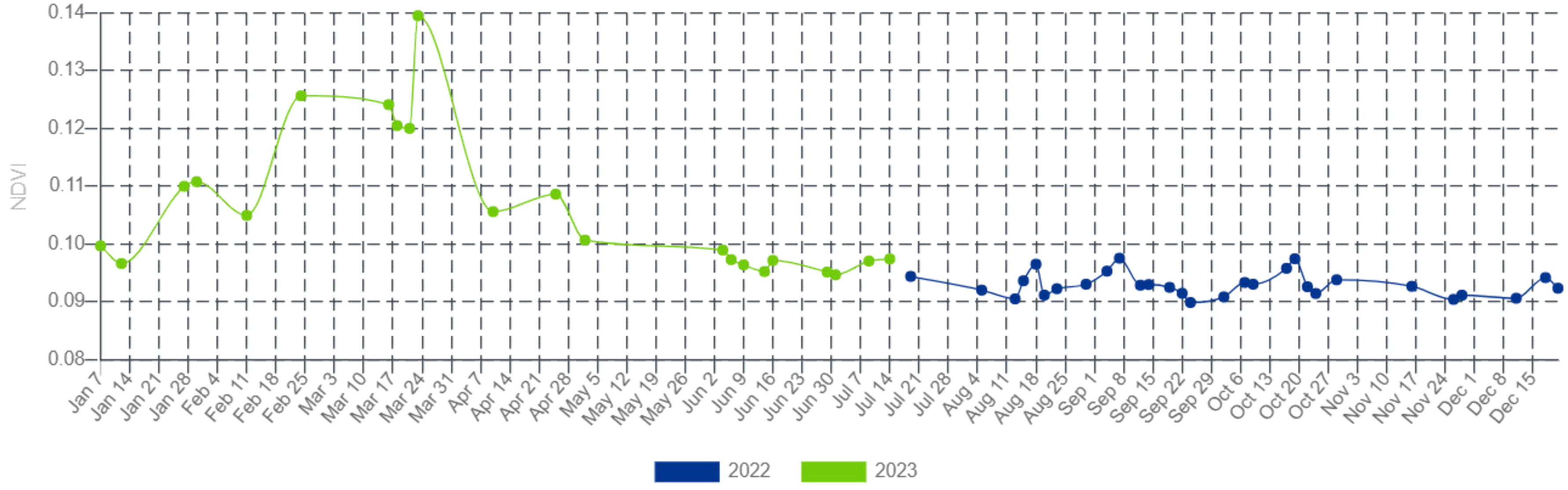




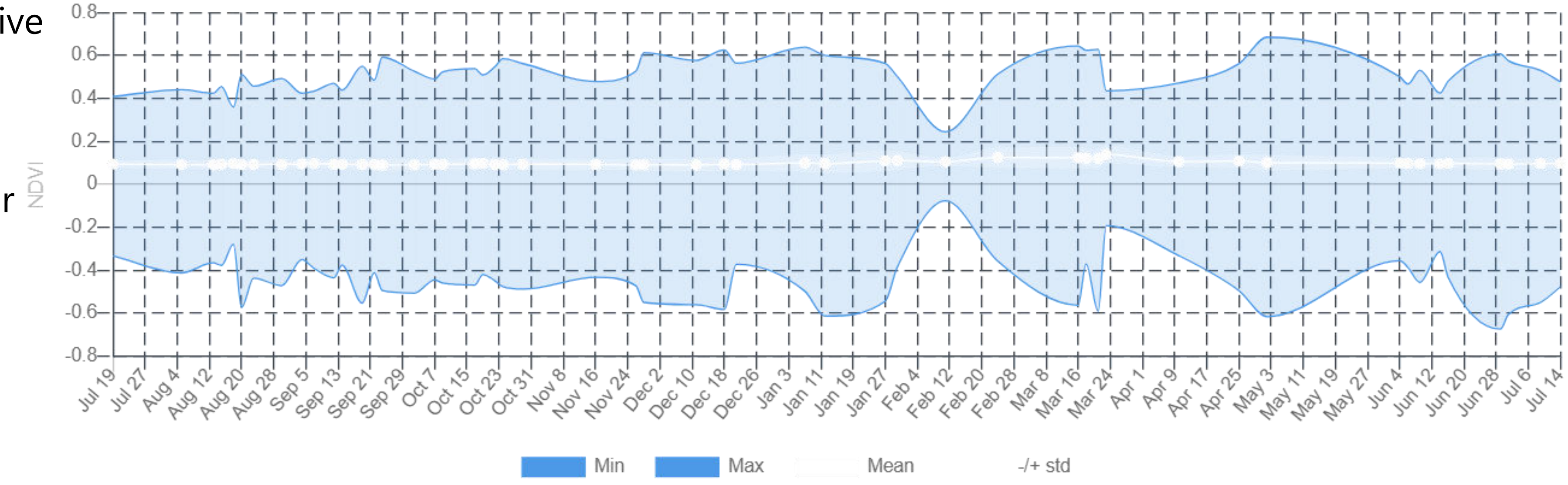


There is a noticeable low NDWI values correspond to low water bodies.

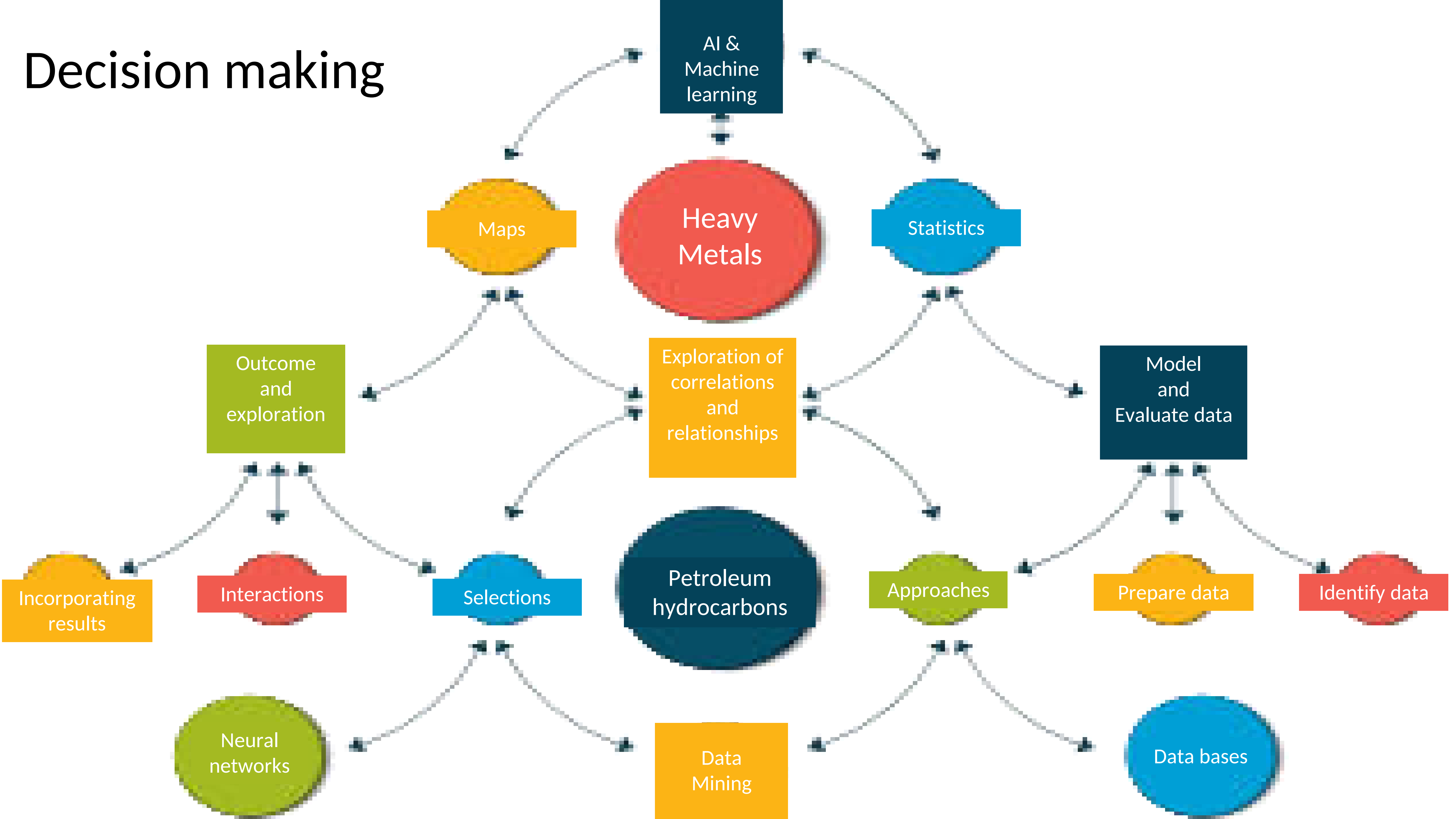
Time-Line Changes: Nrmalized Difference Vegetation Index (NDVI) used to quantify vegetation greenness and is useful in understanding vegetation density and assessing changes in plant health



- Close to +1: Indicates the highest density of healthy green leaves
- Close to -1: Indicates non-vegetative surfaces like water or barren land.
- Around 0: Indicates minimal vegetation, such as barren lands or urban areas



Decision making

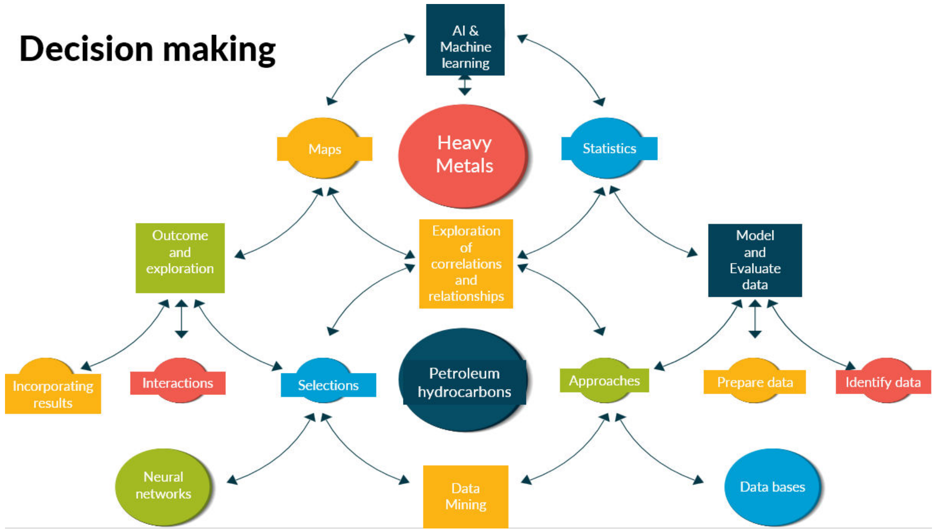


Conclusion

1. Remote sensing techniques provide valuable tools for assessing vegetation health and soil contamination, enabling the monitoring of environmental changes on a large scale.

2. By leveraging advanced technologies, we can make informed decisions, protect ecosystems, and ensure the sustainable growth of our environment.

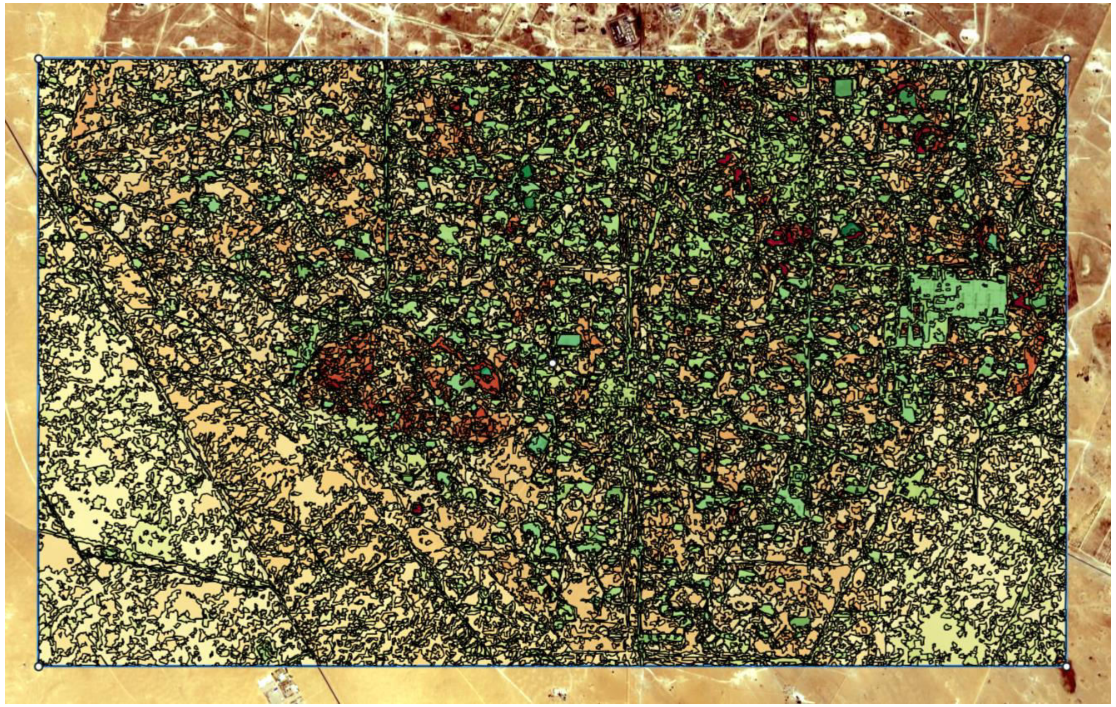
3. As we delve into the possibilities and applications of this groundbreaking methodology, further research and collaborations are needed to advance our understanding and management of oil contamination and vegetation growth



A special thanks to

NDVI: Vegetation Index

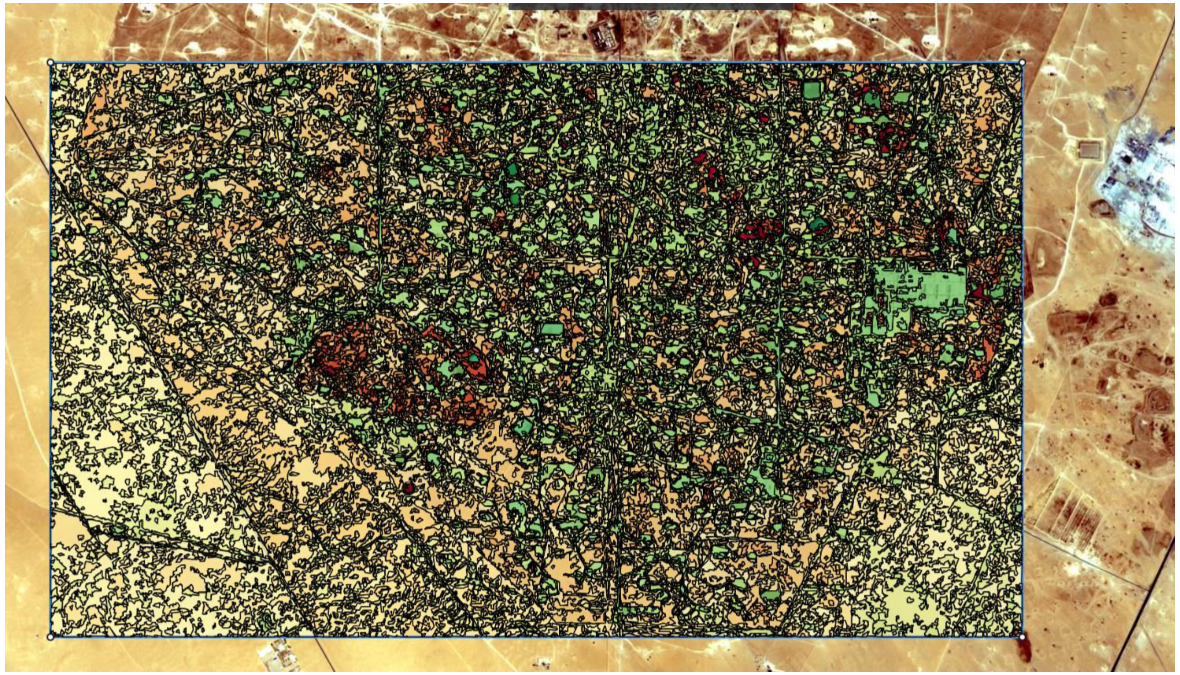
The index is alculated according to the way a plant reflects and absorbs solar radiation at different wavelengths. The index allows for identification of problem areas of the field at different stages of plant growth for timely response.



Label	m ha %
Lower vegetation leve	59 718.53 m²
Class 2	40 208.61 m²
Class 3	26 782.43 m²
Class 4	0.16 km²
Class 5	22.62 km²
Class 6	27.49 km²
Class 7	33.41 km²
Class 8	43.62 km²
Class 9	30.57 km²
Class 10	14.63 km²
Class 11	5.42 km²
Class 12	2.37 km²
Class 13	1.31 km²
Class 14	0.73 km²
Class 15	0.48 km²
Class 16	0.17 km²
Class 17	65 312.77 m²
Class 18	16 642.87 m²
Higher vegetation leve	94 402.83 m²

NDWI: Normalized Difference Water Index

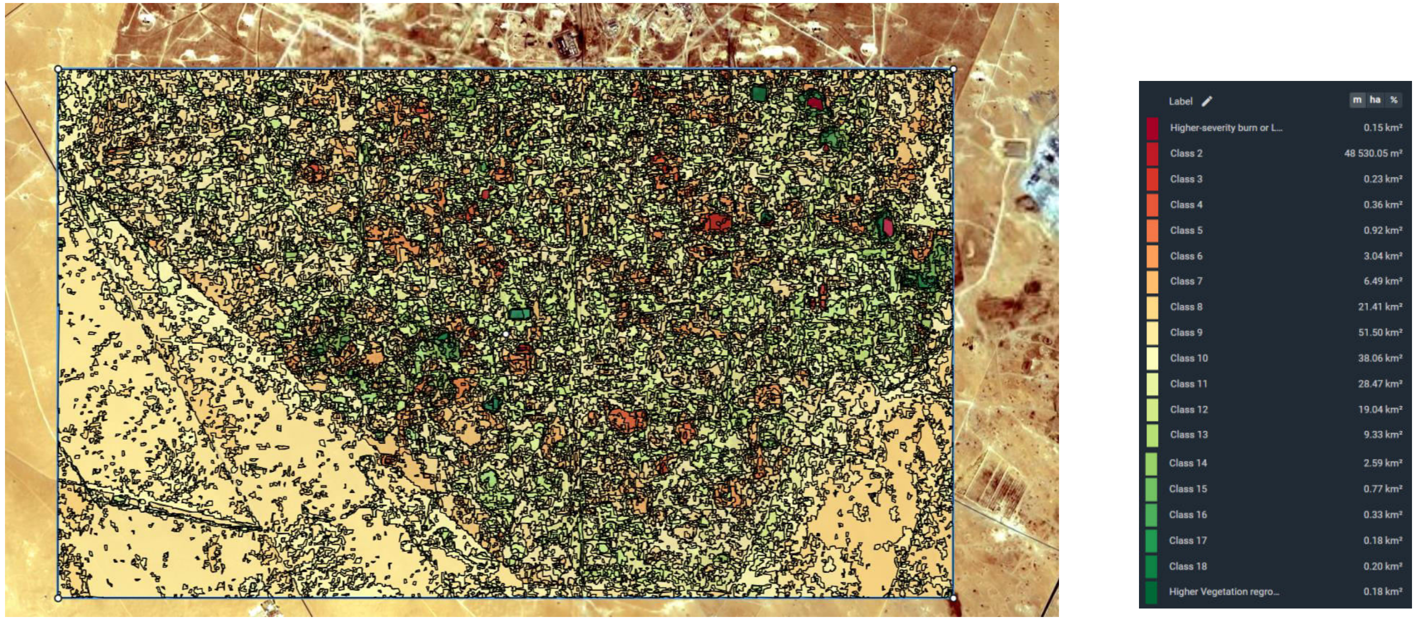
Makes use of reflected near-infrared radiation and visible green light to enhance the presence of such features while eliminating the presence of soil and terrestrial vegetation features. It is suggested that the NDWI may also provide researchers with turbidity estimations of water bodies using remotely-sensed digital dat



Label	m ha %
Drought or Lower moist...	0.35 km²
Class 2	0.13 km²
Class 3	0.24 km²
Class 4	0.70 km²
Class 5	1.29 km²
Class 6	2.53 km²
Class 7	7.98 km²
Class 8	27.87 km²
Class 9	38.62 km²
Class 10	36.00 km²
Class 11	22.24 km²
Class 12	12.97 km²
Class 13	10.84 km²
Class 14	13.30 km²
Class 15	7.50 km²
Class 16	0.52 km²
Class 17	0.10 km²
Class 18	54 194.22 m²
Higher moisture content	48 250.33 m²

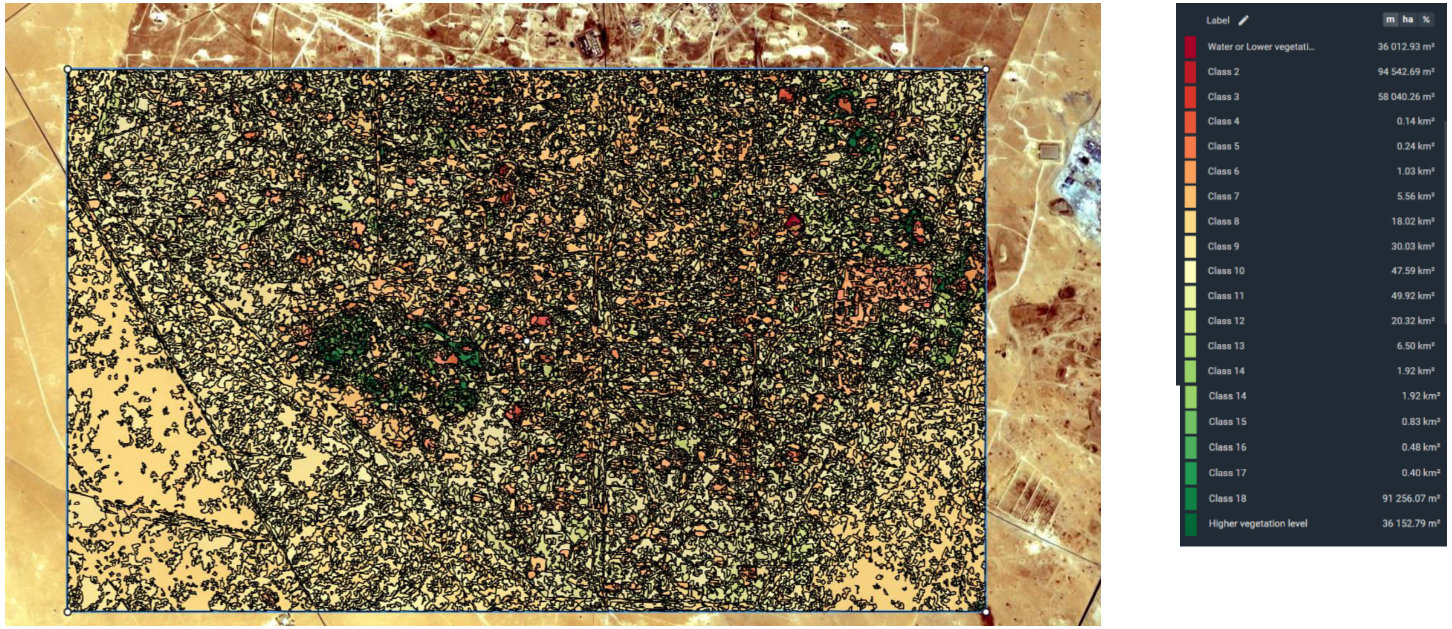
NBR: Normalized Burn Ratio

It uses the NIR and SWIR channels to highlight the burned areas, while muffling the difference in lighting and atmospheric conditions.

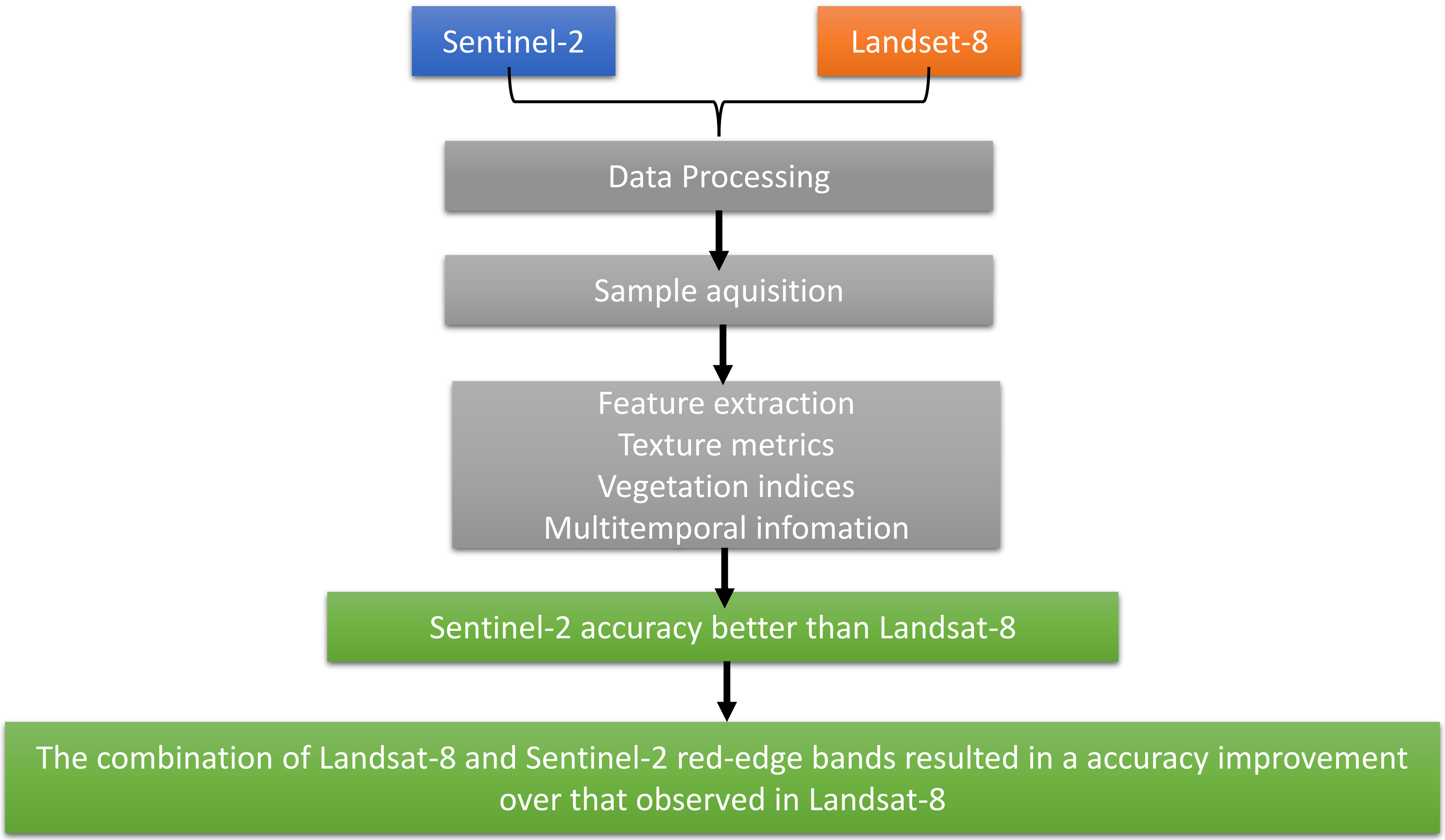


SAVI: The Soil-Adjusted Vegetation Index

Is a vegetation index that attempts to minimize the influence of soil luminance using a soil luminance correction factor. It is often used in desert areas where vegetative coverage is negligible



The Spectral Bands of Sentinel-2A and Landsat 8 Data



Experimental Design

Field

Type 2: Soft to hard bitumous skin/ layer

Soft to hard bitumous skin / layer.
The bitumous skin or layer that may contain water.

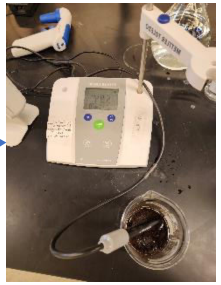
Grind sieve

Measure

With DW

Shaker Overnight

Fix pH at 6.5



Methods

Data Acquisition

- visible and near-infrared bands
- Landsat 8 satellite imagery

Pre-processing

- correct for atmospheric effects, geometric distortions, and other image enhancements to ensure data accuracy and consistency

Oil Contamination in Soil Detection

- AI to to analyze the pre-processed satellite imagery
- Train AI using labeled samples of oil-contaminated and uncontaminated soil to recognize specific spectral patterns associated with oil contamination
- Utilize AI to detect and map areas with potential oil contamination in the study area

Quality Indicators

- Assess the accuracy of the remote sensing and AI analysis results
- Evaluate the precision and recall of the oil contamination and vegetation coverage detection to ensure reliable outcomes

Post-processing

- Refine the classification results and address any potential errors or misclassifications
- Smooth the boundaries and eliminate noise in the detected oil-contaminated and vegetation-covered areas

Validation

- The accuracy of the entire process through ground truth data and field validation
- Compare the results of the remote sensing and AI analysis with actual on-site observations

Understanding the Challenge: Oil Contamination and Vegetation Growth
Oil contamination like Total Petroleum Hydrocarbons (TPH) and Polycyclic Aromatic Hydrocarbons (PAHs), poses significant environmental and human health risks

Traditional methods for detecting oil contamination and monitoring vegetation:

- Time-consuming field surveys and laboratory analyses
- Dont provide real-time data or cover large areas efficiently

Introducing State of Art AI for Remote Sensing Analysis

❑ **State of Art AI: is an advanced AI model that proven its capabilities in**

- Natural language processing
- Understanding complex patterns in various datasets

❑ **State of Art AI with remote sensing data-Landsat 8 imagery**

- A powerful tool for analyzing and interpreting satellite data
- Trained to identify specific patterns associated with oil contamination, TPH, PAHs, and vegetation health in the satellite images

❑ **Through machine learning, it learns to detect**

- Anomalies
- Monitor changes over time
- Provide valuable insights into the environmental conditions of the study area

- **Short Wave IR** (SWIR) is a subset of the infrared band in the ele ctromagnetic spectrum, covering the wavelengths ranging from 1.4 to 3 microns. This wavelength is not visible to human eyes a nd as a result can often offer a better image than what is achiev able with visible light imaging.

What is SWIR? First, the word SWIR (pronounced ' sweer ') is an acronym meaning **S hort W avelength I nfra R ed**, also frequently referred to as shortwave infrared. SWIR generally refers to the wavelength band of light between 900nm and 2500nm.

offer our customers access to information in the short-wave infrared (SWIR) part of the electromagnetic spectrum. WorldView-3 expands deeper into the infrared spectrum

Band combination: SWIR2, NIR, Red

KEY FOCUS AREAS

Our key sustainability focus areas

EOSDA technologies enable tracking the forest health by measuring forest cover, detecting deforestation and forest fires, monitoring plant moisture content, and tracking reforestation efforts, among other uses.

Deforestation

Reforestation

Forest fires

EOSDA Precision Agriculture Solutions help farmers, insurers, suppliers, and other market players, to tackle the most pressing agricultural issues. Our technologies not only can speed up decisions and increase their efficiency, but reduce the harmful impact of chemicals on the environment.

Soil Pollution

Food Demand

Water Deficiency

We deliver powerful insights into ways of reducing CO2 emissions. Our machine learning algorithms will allow you to target pollution and climate change, and develop strategies for better environment protection.

CO2 Emissions

Natural Disasters

Climate Change

Optimizing mining processes can greatly decrease the industry's contribution to climate change. Under the The GoldenEye project with the European Commission, we aim to increase the productivity and safety of the European mining industry through EOSDA technology.

Safe Mining