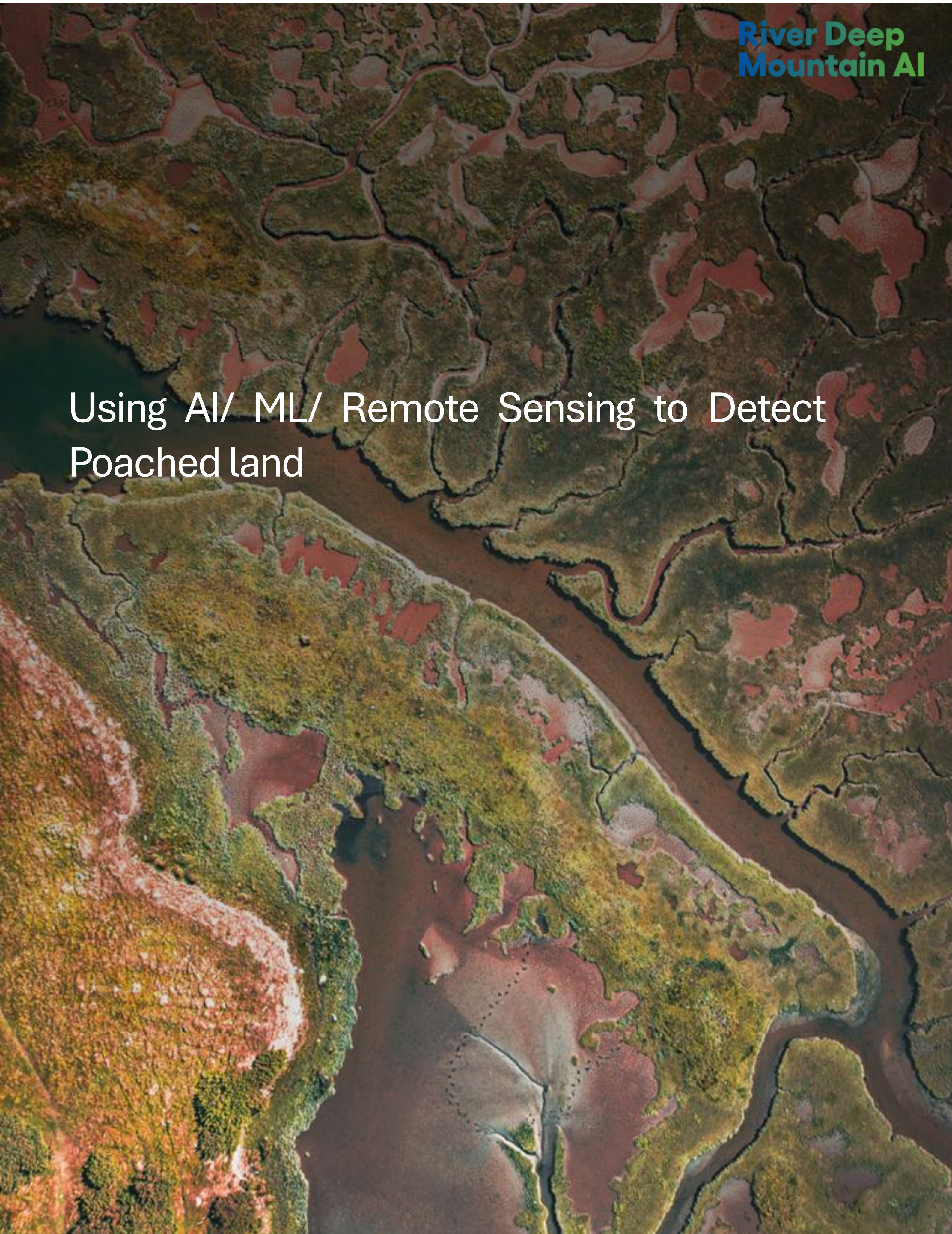
River Deep Mountain AI



Using AI/ ML/ Remote Sensing to Detect Poached land

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1. Introduction

Poached land is typically defined as ‘the physical breakdown of soil caused by the trampling of livestock’, resulting in soil compaction, vegetation loss, and increased erosion and runoff. However, for the purposes of this report, the term poaching is an all-encompassing word to describe disturbed ground (a potential source of diffuse water pollution), which could be caused by livestock or other activities such as rutting from farm vehicles. Poaching poses a significant threat to environmental sustainability, particularly in ecologically sensitive and agricultural regions. The impacts of poaching reduce land productivity, degrade ecosystems, and contribute to potential water quality pollution, especially in rural and peri-urban landscapes.

Traditional field-based monitoring methods are often resource intensive and limited in scale, prompting the need for automated, scalable solutions. In this context, satellite remote sensing offers a powerful platform for continuous Earth observation, providing high-resolution spatial and temporal data. When combined with Artificial Intelligence (AI) and Machine Learning (ML), remote sensing enables advanced image analysis and pattern recognition, allowing for the detection of subtle environmental changes associated with poached land—such as soil exposure, vegetation stress, and surface texture anomalies.

Recent studies have demonstrated the growing potential of these technologies. Tripathy et al. (2024) evaluated the Segment Anything Model (SAM) by Meta AI for delineating smallholder agricultural field boundaries using 2m SkySat imagery. Despite not being trained on remote sensing data, SAM achieved 58% accuracy in boundary detection without requiring extensive labelled datasets. This highlights its utility in low-resource settings, making it relevant for identifying poached land where visual degradation is evident.

Similarly, Trujillano et al. (2024) applied SAM to drone imagery in a public health context, identifying mosquito breeding habitats. While SAM facilitated rapid feature identification, its accuracy varied with landscape complexity and prompt methods, emphasising the need for human oversight in complex terrains like poached pastures.

On the environmental impact side, Zhang et al. (2022) used mechanistic modelling to show that poorly managed livestock farming significantly contributes to diffuse water pollution through sediment and nutrient runoff. Their findings underscore the importance of detecting and managing poached land to mitigate pollution at both farm and watershed scales.

Further supporting this, Greenwood and Meusburger (2018) employed radioisotope tracers (Cs-134 and Co-60) to measure soil redistribution in livestock-poached areas. Their results confirmed that poached zones remain long-term sediment sources, with increasing soil loss due to reduced surface roughness—highlighting the need for early detection to prevent irreversible degradation.

Finally, the GLAS model evaluation (ADAS, 2017) reinforced the importance of policy-driven land monitoring, demonstrating how remote sensing and modelling can assess the effectiveness of sustainable agriculture schemes and quantify reductions in pollutant losses.

Together, these studies provide a strong foundation for integrating AI/ML with remote sensing to monitor poached land. Such tools support proactive land management, policy decision-making, and environmental compliance, contributing to ecological resilience, food security, and climate change mitigation.

1.1. Research Gap

Despite advancements in AI and remote sensing for agricultural and environmental monitoring, there is a lack of dedicated approaches for detecting poached land. Existing methods focus on broad land cover changes or field boundary mapping, often overlooking the subtle, irregular, and transient features of poaching. Current AI models are not specifically trained to identify surface indicators like trampling scars or compacted soil. Additionally, while the environmental impacts of poached land are well recognised, scalable, satellite-based detection methods remain underdeveloped. This limits early intervention and sustainable land management, especially in resource-constrained regions.

2. Approach and Methodological Exploration

To address the challenge of detecting poached land from satellite imagery, we have employed three distinct approaches based on: Remote Sensing, GeoAI, and a Hybrid method combining AI with Remote Sensing. Each approach was selected to overcome specific limitations related to scalability, accuracy, and usability. Remote Sensing techniques offer broad coverage and temporal insights, while GeoAI leverages spatial intelligence and machine learning for pattern recognition. The Hybrid approach integrates the strengths of both, enabling more precise and adaptable detection. These varied strategies were essential to ensure both a technically robust and practical solution for real-world applications. Details on the data sources and methodologies used in each approach are discussed below.

3. Data Sources

Since the current use case is being tested using different approaches, different datasets are required. Table 1 summarises these different data sources used under different approaches.

Table 1. Data sources used to across different approaches

Approach 1 (Remote Sensing)	Approach 2 (GeoAI)	Approach 3 (Hybrid)
1. Sentinel-2 satellite imagery: Provides surface reflectance in 13 spectral bands 2. OpenStreetMap (OSM) Layers: grassland and meadow were used from OSM land-use data.	Images used through Leaflet (Web Map Service)	1. 10-m Sentinel-2 imagery 2. Sentinel 2 Deep Resolution 3.0 (S2DR3 1m imagery 3. Dynamic World V1: A global land cover dataset 4. OpenStreetMap (OSM) road layer: Used to identify and exclude anthropogenic features like roads and infrastructure.

4. Approach-1: Detection of Poached land using Remote Sensing Indices

The detection of poached land using remote sensing techniques is underpinned by several ecological and land-use assumptions. Seasonal dynamics are considered critical, with poaching more frequently observed during wetter periods when elevated soil moisture reduces the soil's resistance to mechanical pressure. Soil condition is a key factor; soft and saturated soils are especially vulnerable to poaching due to their limited structural integrity, which makes them less capable of withstanding the impact of livestock or agricultural machinery and-use practices—particularly the intensity and timing of grazing—are believed to significantly influence the spatial extent and distribution of poached areas within grassland ecosystems (Bilotta et al., 2007). These assumptions form the conceptual foundation for interpreting remote sensing data in the context of poaching detection.

Building on these assumptions, this study proposes the development of a remote sensing-based model to identify potential poached land within grassland and meadow ecosystems. The model leverages spectral indices derived from satellite imagery to assess surface conditions and detect areas susceptible to poaching. Indices such as the Normalised Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI), Bare Soil Index (BSI), and Normalised Difference Moisture Index (NDMI) are particularly valuable in this context (see Table 2). These indices analyse surface reflectance across various spectral bands, enabling the detection of vegetation health, soil exposure, and moisture content—key indicators associated with poaching activity.

Table 2. Remote sensing indices used in this approach

Index	Formula	Thresholds	Purpose
Normalized Difference Vegetation Index (NDVI)	(NIR–RED)/(NIR+RED)	> 0.4	Vegetation health
Soil Adjusted Vegetation Index (SAVI)	(NIR–RED)/(NIR+RED+L) ×(1+L)	> 0.4	Vegetation health (soil-adjusted)
Normalized Difference Moisture Index (NDMI)	(NIR–SWIR)/(NIR+SWIR)	> 0.4	Moisture level in vegetation
Bare Soil index (BSI)	(SWIR+RED–NIR–BLUE)/(SWIR+RED+NIR+BLUE)	> 0	Bare soil exposure

However, in grassland environments, NDVI alone may not effectively capture poached areas, especially where vegetation cover is sparse or where soil moisture plays a critical role. Therefore, a suitability analysis using SAVI and NDMI is being prioritised.

- SAVI adjusts for soil brightness and is particularly useful in areas with low vegetation cover, making it more sensitive to subtle changes in plant health and soil exposure.
- NDMI, on the other hand, is sensitive to vegetation water content and can help detect water stress in plants, which is often associated with poached or compacted soils during wet seasons.

By integrating SAVI and NDMI into the analysis, the model aims to provide a more accurate representation of poached land, especially in conditions where traditional vegetation indices may fall short.

4.1. Methodological Framework

4.1.1. Time Series Analysis and Transition to Suitability Modelling

The rationale for adopting a suitability analysis approach was not straightforward. An initial attempt was made to derive and analyse a time series of remote sensing indices from satellite imagery, aiming to understand the temporal variability in grassland and meadow conditions prior to applying any suitability thresholds. The goal was to identify consistent patterns or seasonal trends that could inform the detection of poached land. However, the analysis did not reveal any discernible or reliable patterns that could be used to guide threshold selection or model calibration.

As a result, the focus was shifted toward a suitability analysis approach, utilising remote sensing indices to directly assess surface conditions and identify potential poached areas based on spectral characteristics.

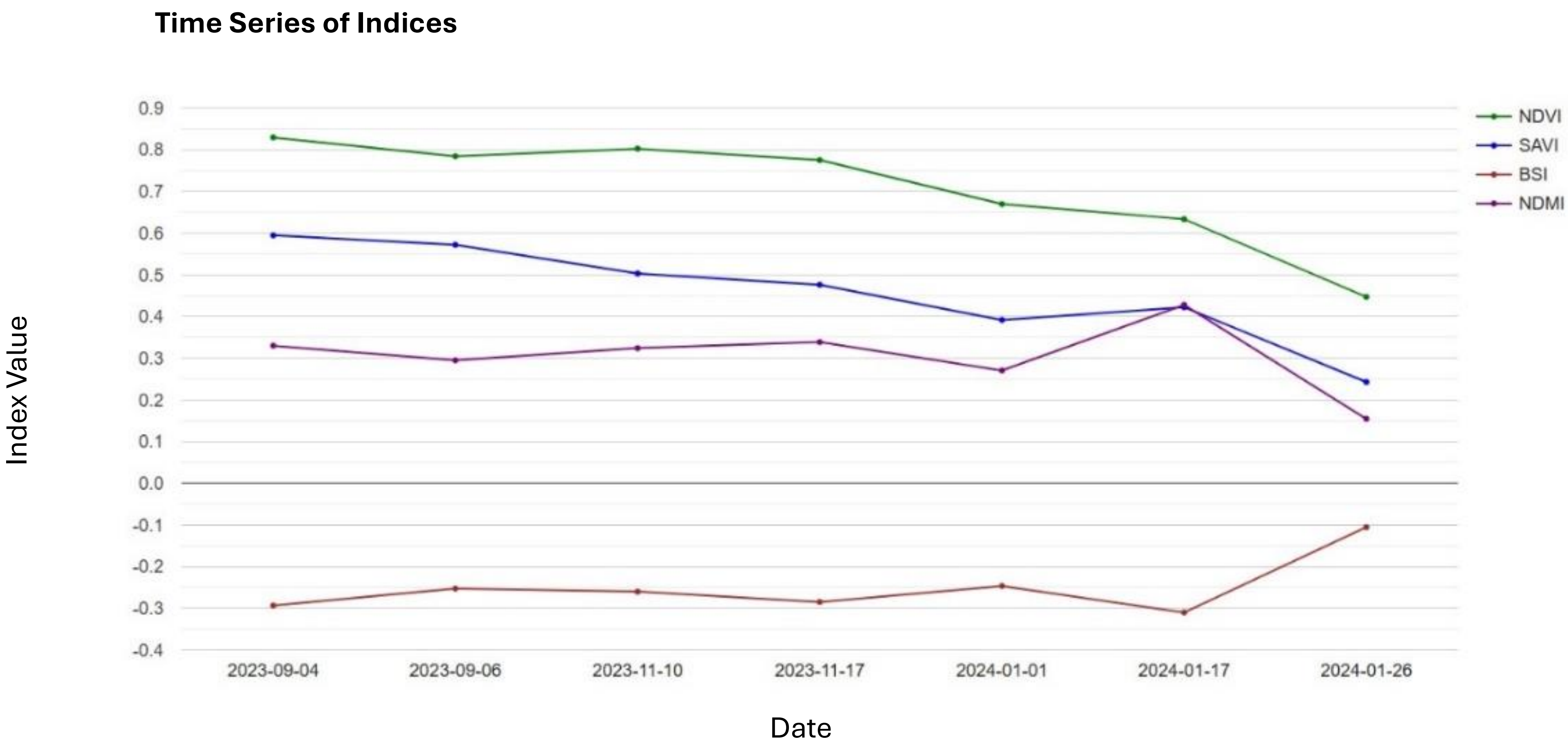


Figure 1. Time series of remote sensing indices derived from Sentinel 2 imagery during winter (Sep. 2023 to Jan. 2024)

As per the variability of all remote sensing indices in Figure 1, it has been noticed that:

- NDVI and SAVI Trends: Both NDVI (green) and SAVI (blue) show relatively stable fluctuations over time, but no clear seasonal pattern or consistent drop that could be directly linked to poaching events or soil degradation. This supports the observation that NDVI alone may not be sufficient for identifying poached areas in grasslands.
- NDMI Behaviour: The NDMI (red) line shows more variability, which could be indicative of changing moisture conditions. This aligns with the assumption that NDMI is useful for detecting water stress, which is often associated with poached land during wet seasons.
- BSI Observations: BSI (purple) remains relatively low and stable, suggesting limited bare soil exposure during the observed period. This could mean that poaching effects are subtle or masked by vegetation, further justifying the need for a suitability analysis rather than relying solely on time series trends.

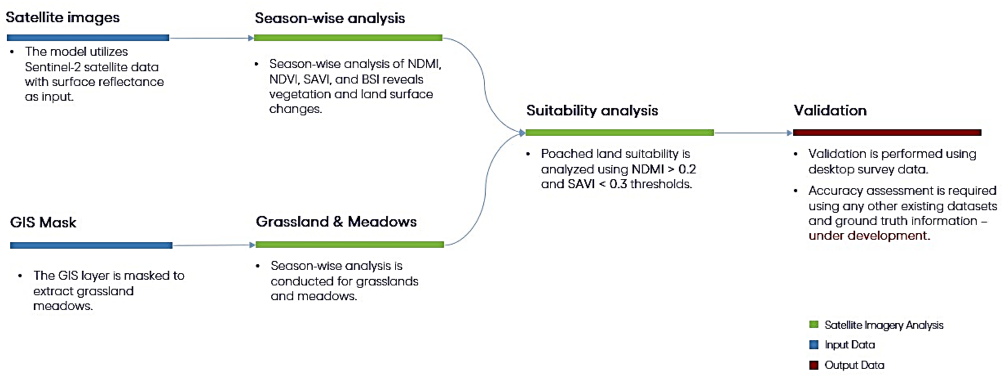


Figure 2. Remote Sensing-based methodology of suitability analysis

A suitability analysis was conducted using specific threshold criteria informed by remote sensing principles rather than seasonal trends. Areas with NDMI values greater than 0.2—indicating relatively moist conditions—and SAVI values less than 0.3—suggesting sparse vegetation—were flagged as potentially poached (Figure 2).

Figure 3. Potential poached land detected through suitability analysis

It is important to note that areas not flagged in this analysis do not necessarily indicate the absence of poaching. Rather, they may reflect limitations such as the lack of spatial resolution in Sentinel imagery, reduced spectral separability, or the timing of satellite capture. Several poached locations might exist but were not detected due to insufficient visibility or a lack of distinguishable indicators in the available imagery.

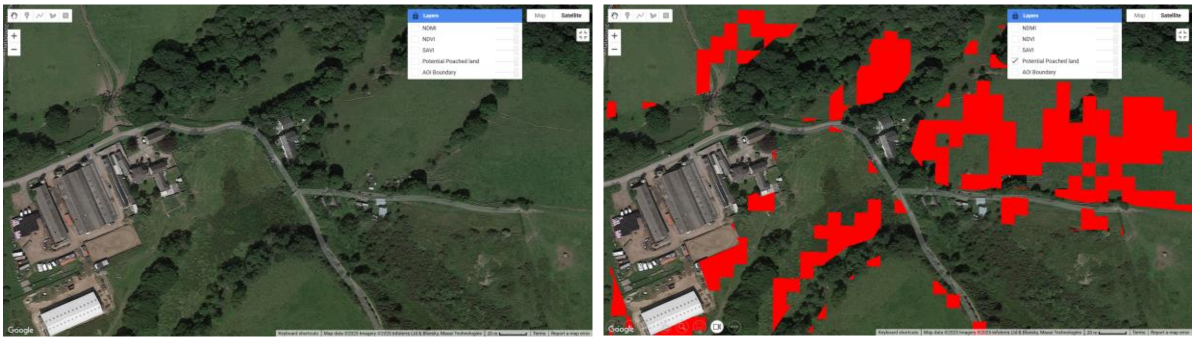


Figure 4. Poached land detected through Sentinel 2 image and overlayed on basemap

The results of the suitability analysis, based on variations in SAVI and NDMI, identified several locations within grasslands exhibiting high moisture and low vegetation cover (Figure 3 and Figure 4). Upon inspection using high-resolution basemaps, many of these areas were found to be situated near farmyards, suggesting they are potential zones of poached land.

4.1.2. Limitation of Spatial Resolution in Detecting Poached Land

One of the key limitations in using the Sentinel-2 satellite imagery for detecting poached land in grassland environments is its spatial resolution. The Sentinel-2 provides imagery at 10-m resolution for key bands used in vegetation indices, such as NDVI, SAVI, and NDMI. Each pixel represents 100 m^2 on the ground.

Given that poached land patches are typically small, often ranging between 50 to 100 m^2, they may:

- Occupy only part of a single pixel, making them difficult to distinguish from surrounding healthy vegetation or soil.
- Be spectrally mixed with adjacent land cover types, reducing the clarity and accuracy of index-based detection.
- Go undetected entirely if their size falls below the pixel resolution or if they are scattered in a non-contiguous pattern.

As a result, the detection and delineation of small-scale poached areas using the Sentinel-2 data is inherently challenging. This limitation necessitates either the use of higher-resolution imagery (e.g., from commercial satellites or UAVs) or the development of enhanced analytical techniques, such as sub-pixel classification or data fusion, to improve detection accuracy.

5. Approach-2: GeoAI-Based Segmentation Using the Segment Anything Model (SAM)

Given the limitations associated with the spatial resolution of the Sentinel-2 imagery and the absence of consistent patterns in time series analysis, a second approach was adopted utilising geospatial artificial intelligence (GeoAI). This method leverages the Segment Anything Model (SAM), an advanced segmentation framework developed by Meta AI, and implemented within a GeoAI toolkit created by

Dr. Qiusheng Wu. SAM enables flexible, prompt-based image segmentation, making it particularly suitable for delineating complex land surface features such as poached areas. This approach aims to enhance the precision of land cover classification by integrating AI-driven segmentation with high-resolution geospatial data.

The segmentation process is:

- Manual (requiring human-guided input during the image processing workflow) but intuitive, enabling precise delineation of poached land patches based on visual interpretation (using foreground/background markers to guide segmentation).
- Built on Leaflet with high-resolution Web Map Service (WMS) basemaps, which enhances the visibility of fine-scale features not captured by coarser satellite imagery like Sentinel-2.
- Flexible, as it does not rely on fixed classification schemes, making it suitable for detecting irregular and context-specific features like poached land.

5.1. Methodological Framework

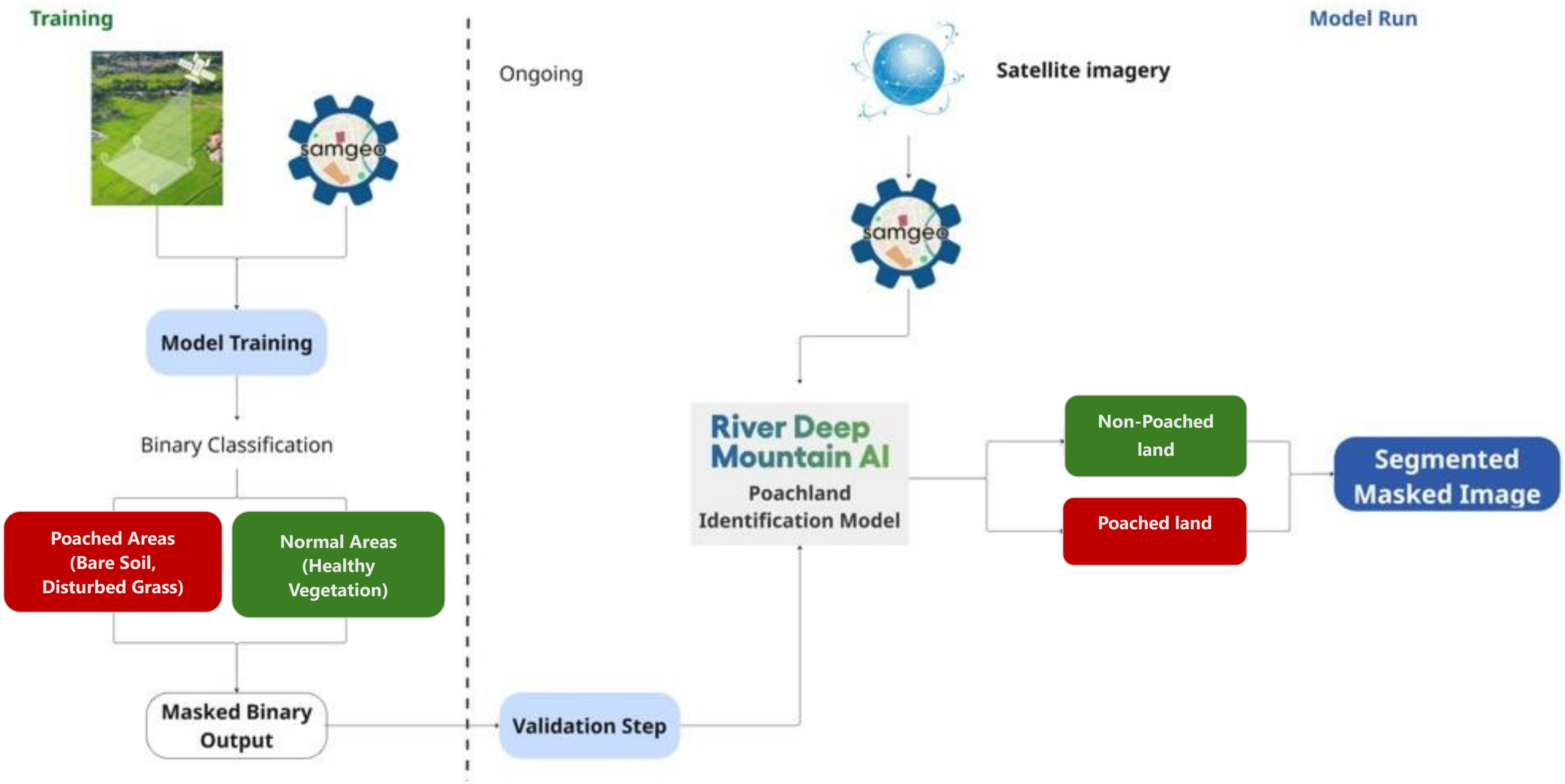


Figure 5. Methodology of the poached land detection using GeoAI

Figure 5 shows overall methodology of SAM Geo model. The training and execution of the SAM Geo model to identify the poached land is described broadly as follows:

Training manual annotation: Foreground and Background

Figure 6 and Figure 7 demonstrates how the annotation has been done. Users manually click on the map to define:

- Foreground points: Areas that represent the object of interest (e.g., poached land).
- Background points: Areas that should be excluded (e.g., healthy vegetation, water bodies, roads).
- These points serve as prompts for the SAM model to understand what to segment.

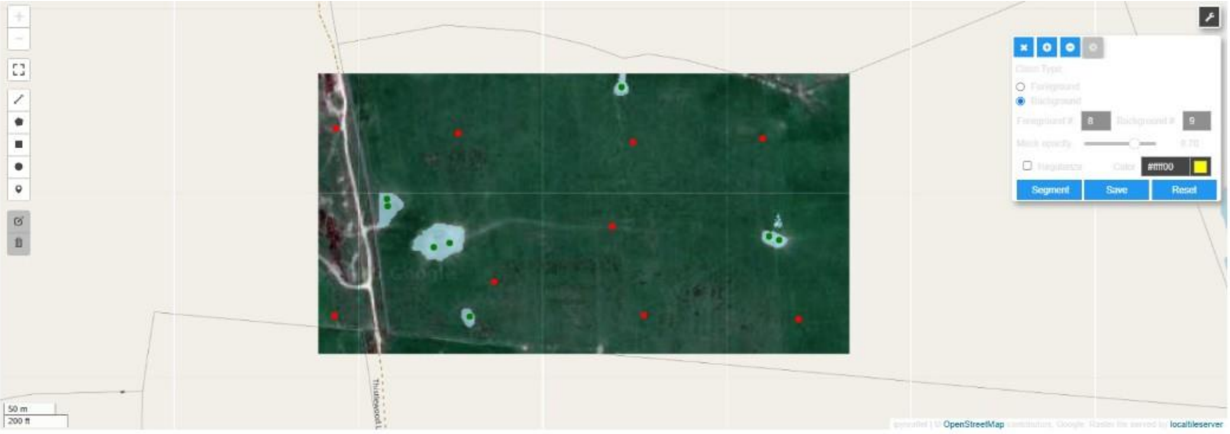


Figure 6. Labelling poached lands using SAM Geo

Segmented multiple poached land patches

Masking Outcome

Light-blue shaded areas represent **detected mask regions** – this is where the model believes poached land exists, based on your prompt guidance.

8 foreground points and **7 background points.**

The **mask opacity** is set to 0.70, allowing you to semi-visually validate mask coverage against the underlying satellite image.

Color	Meaning	Action
White	Poached land (detected)	Extract / Analyze
Black	Normal land (ignored)	Mask out / Ignore

White Areas (Pixel value = 1 or 255)
Black Areas (Pixel value = 0)

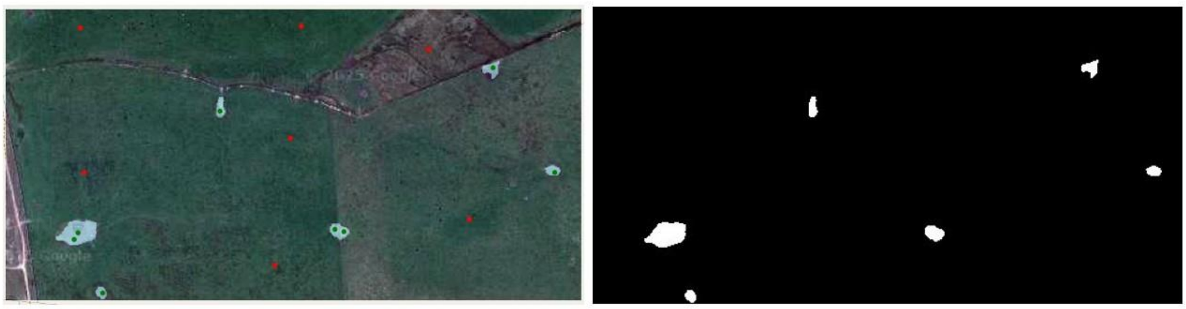


Figure 7. Classifying image into binary image to differentiate poached land (white) from non-poached land

SAM-Based Segmentation

- The Segment Anything Model (SAM) uses these prompts to generate a segmentation mask.

- SAM is capable of zero-shot segmentation, meaning it does not require prior training on specific classes—it segments based on the visual cues provided by the user.

Output Generation

Figure 8 shows the resulting segmentation mask is displayed on the map.

Users can export the mask as:

- GeoJSON for GIS analysis,
- Shapefile for desktop GIS software,
- Or GeoTIFF for raster-based workflows.

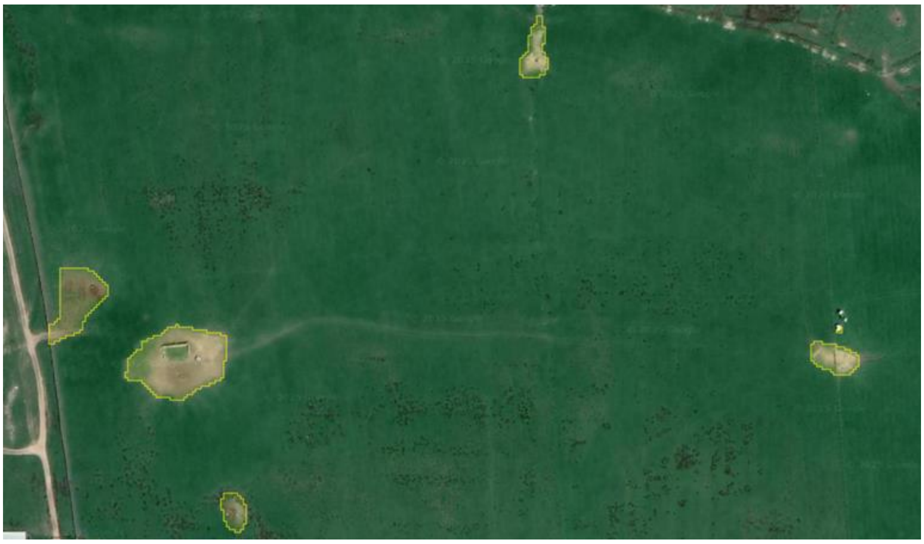


Figure 8. GeoAI output in geometric form (GIS format)

Model performance

To evaluate the effectiveness of the segmentation model in identifying poached land, we used standard classification metrics derived from the confusion matrix: accuracy, precision, recall, and F1 score. These metrics were computed for two test areas: Poached Land 1 and Poached Land 2.

Performance metrics from two test sites (P1 and P2) show high overall accuracy—98.3% and 91.8%, respectively (Figure 9) - driven largely by a high volume (number of manually identified areas) of correctly identified non-poached land. However, the model suffers from low recall (34.5% for P1 and 13.5% for P2), indicating it misses a significant number of poached areas despite achieving relatively high precision (69.9% and 64.6%) (Figure 10).

Poached lands	True Positive Rate (TPR)	Positive Predictive Value (PPV)	Dice Similarity Coefficient	Accuracy	Satellite	Mask Image
P1	0.3455	0.6988	0.4624	0.9834		
P2	0.1353	0.6462	0.2238	0.9154		

Figure 9. Model performances for in different test sites

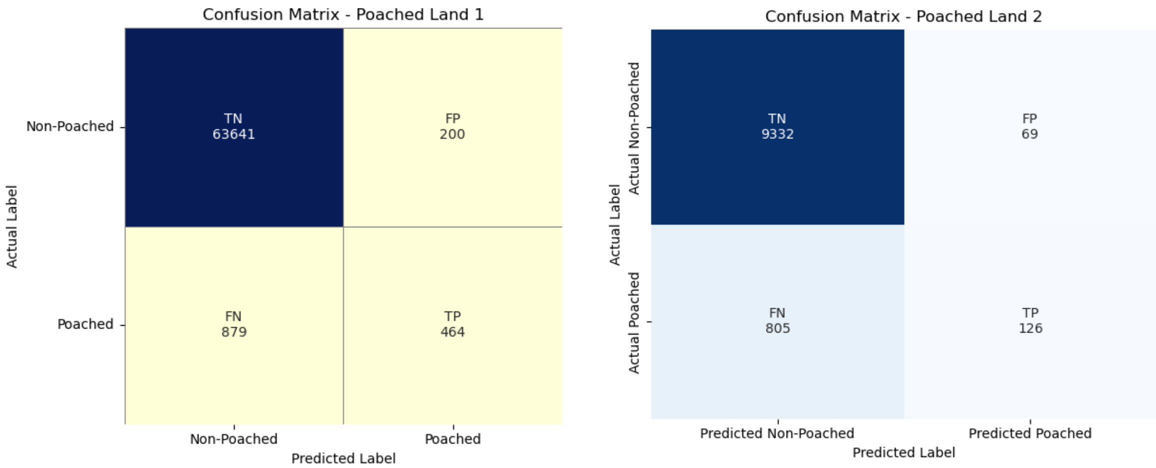


Figure 10. Confusion matrix of poached land 1 and 2. Abbreviations: TP – True Positive, TN – True Negative, FP – False Positive, FN – False Negative.

While the segmentation model performs well in avoiding false positives, it underperforms in detecting all poached areas, especially in more challenging or less distinct regions. This highlights the need for better training data and enhanced feature selection.

Limitations:

- **Limited Automation:** The process involves manual steps in training sample preparation and validation, which restricts scalability and real-time application.
- **High Computational Requirements:** The use of AI/ML models, especially for image segmentation and classification, demands significant GPU resources, which may not be feasible for all users or organisations.
- **Cost:** As poached land is seasonal and inconsistent spatially, continuous monitoring, generating many high-resolution images over time, is required to detect poaching. While scaling up this approach is possible, it may not be cost effective.

5.2. Summary: Limitations of Approach 1 and 2

- Approach 1: The remote sensing-based method using the Sentinel-2 indices (NDVI, SAVI, NDMI) was constrained by spatial resolution (10 m), making it difficult to detect small poached patches (50–100 m^2).
- Approach 2: The GeoAI approach, while flexible and interactive, relies on manual segmentation and WMS basemaps without other temporal images, limiting its scalability and seasonal interpretation.

6. Approach-3: Hybrid Method Integrating AI-Upscaled Imagery, Machine Learning, Remote Sensing, and GIS

To overcome the limitations of the previous methodologies, a hybrid approach was developed that integrates AI-upscaled satellite imagery, machine learning algorithms, remote sensing indices, and GIS-based spatial analysis. This method leverages the enhanced spatial detail and visual clarity provided by AI-upscaled Sentinel-2 imagery. Machine learning models are then applied to classify land cover and detect poached areas based on spectral and spatial patterns. Remote sensing indices—such as NDVI and BSI - are used to extract key surface characteristics related to vegetation health and soil exposure. Finally, GIS concepts are employed to spatially analyse and validate the results, enabling a more accurate and context-aware detection of poached land across any ecosystems.

6.1. Methodological Framework

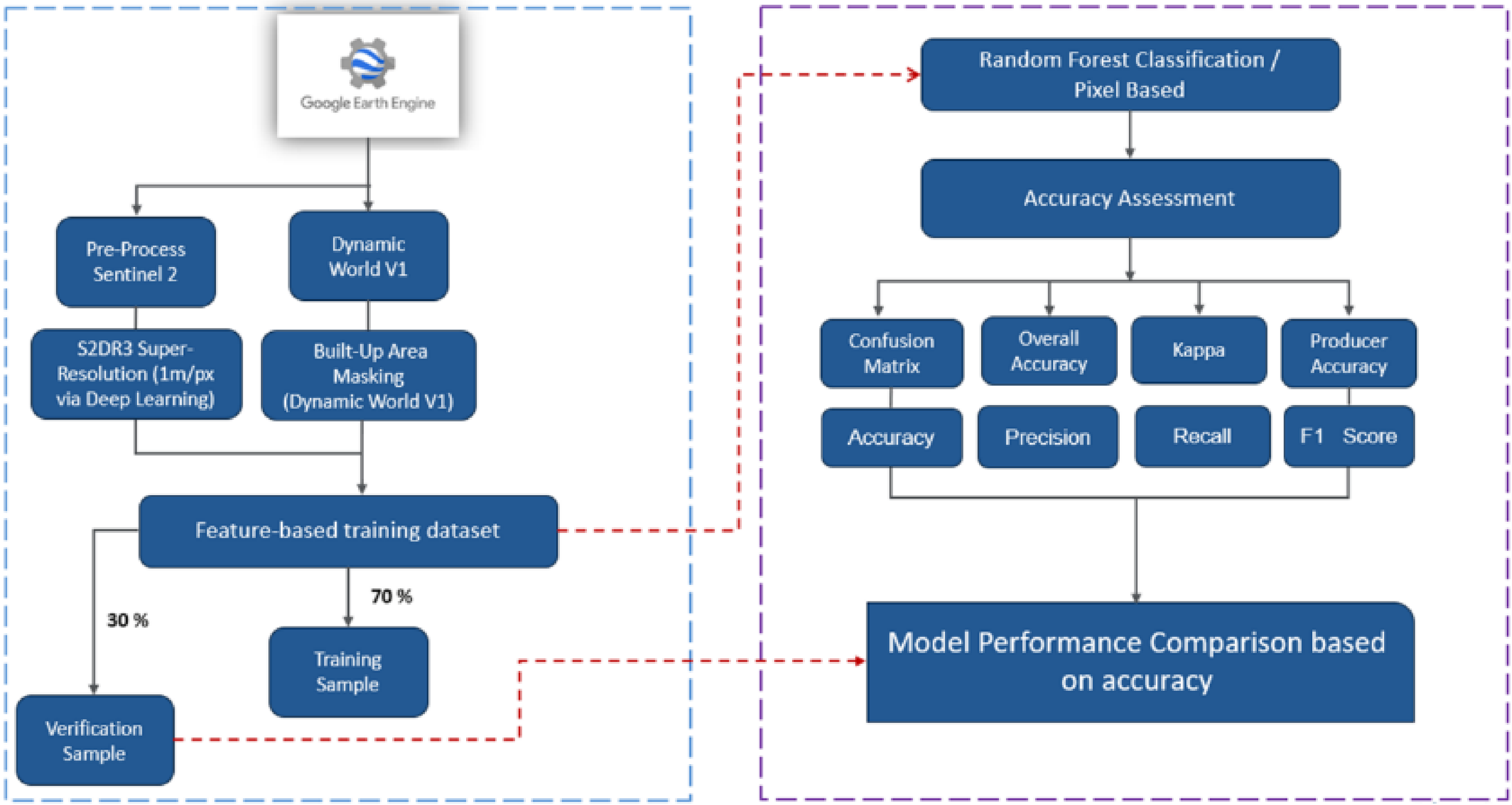


Figure 11. Hybrid model framework to identify poached land

This methodology in Figure 11 outlines a structured approach to evaluate the performance of a classification model using satellite imagery and geospatial data within the Google Earth Engine (GEE) environment. The process integrates data preprocessing, machine learning, and accuracy assessment techniques as follows:

6.1.1. Enhancing Sentinel-2 image spatial resolution to 1 m

The workflow begins with the preprocessing of the 10-m Sentinel-2 satellite imagery. This step typically includes enhancement of imagery (Figure 12) using a Sentinel 2 Deep Resolution 3.0 (S2DR3) tool, which increases the spatial resolution from 10 meters to 1 meter per pixel. The model uses a convolutional neural network (CNN) trained on globally sampled data. This allows it to generalise across diverse geographic regions and land cover types without needing retraining. S2DR3 processes all 12 spectral bands of the Sentinel-2 Level-2A data, ensuring spectral consistency across the visible, near-infrared, and shortwave infrared bands.

Sentinel 2 image at 10 m

Upscaled Sentinel 2 image at 1 m

Figure 12. S2DR3 enhancement of 10m Sentinel 2 to 1m dataset

6.1.2. Creation of Feature-Based Training Dataset

A training dataset is constructed using the processed imagery and auxiliary data. This dataset is then split into:

- 70% Training Sample: Used to train the classification model.
- 30% Verification Sample: Reserved for validating the model's performance.

6.1.3. Random Forest Classification

A Random Forest classifier is applied to the training sample. This pixel-based classification method uses an ensemble of decision trees. The image was classified into five land cover classes e.g. poached land, bare cropland, cropland, trees, waterbodies (Figure 13 and Figure 14) to reduce the misclassification with poached fields. For improved interpretability, the five defined classes have been consolidated into two broader categories: poached and non-poached land.

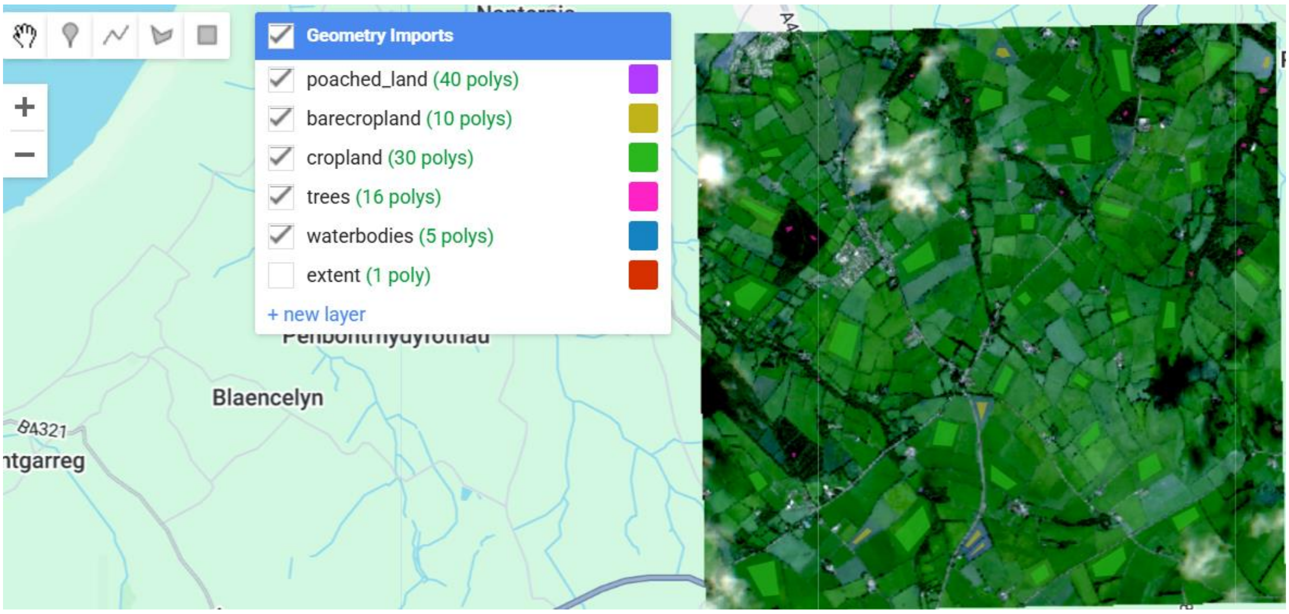


Figure 13. Training samples containing poached and non-poached field

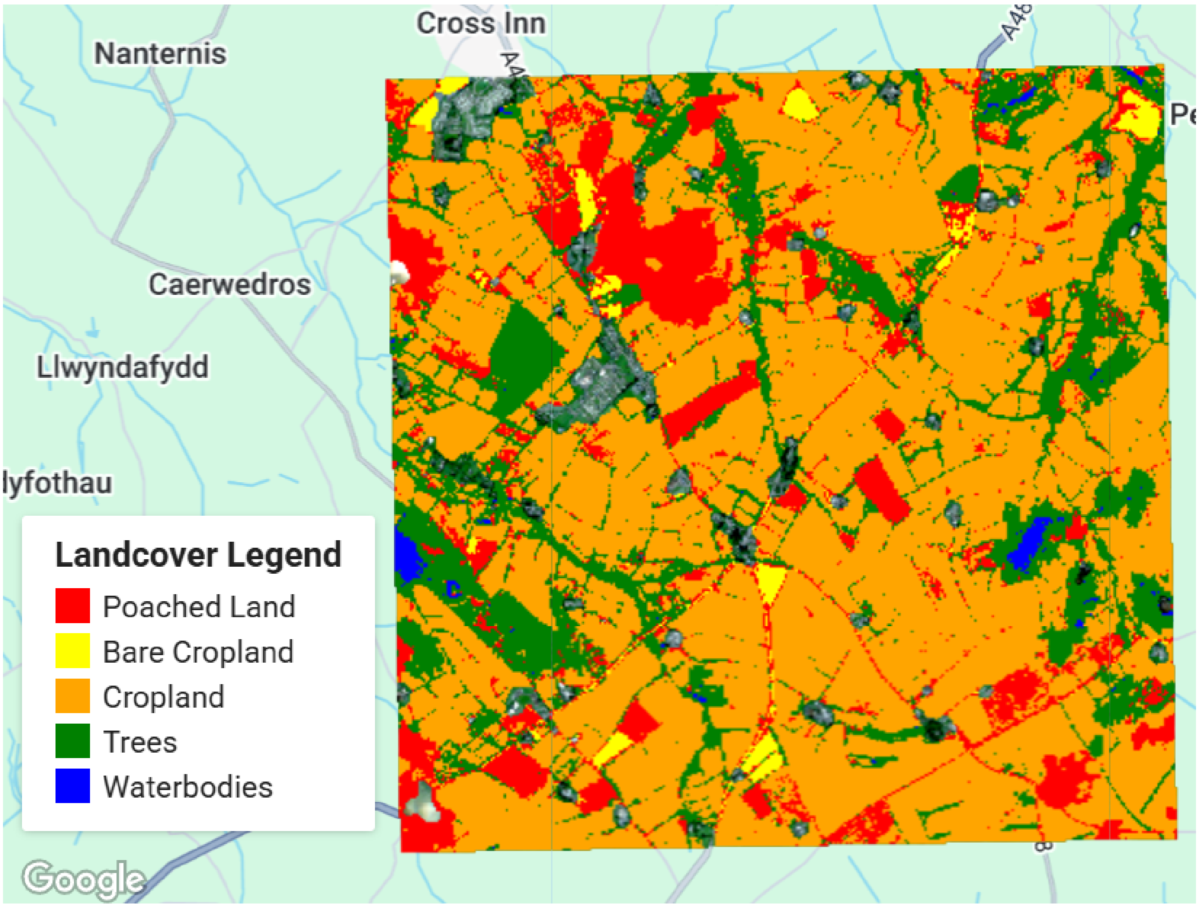


Figure 14. Classified image showing poached land in red colour

Model performance:

These results suggest the model is relatively good at identifying non-poached land but has room for improvement in accurately identifying poached areas, especially in reducing false positives (Figure 15).

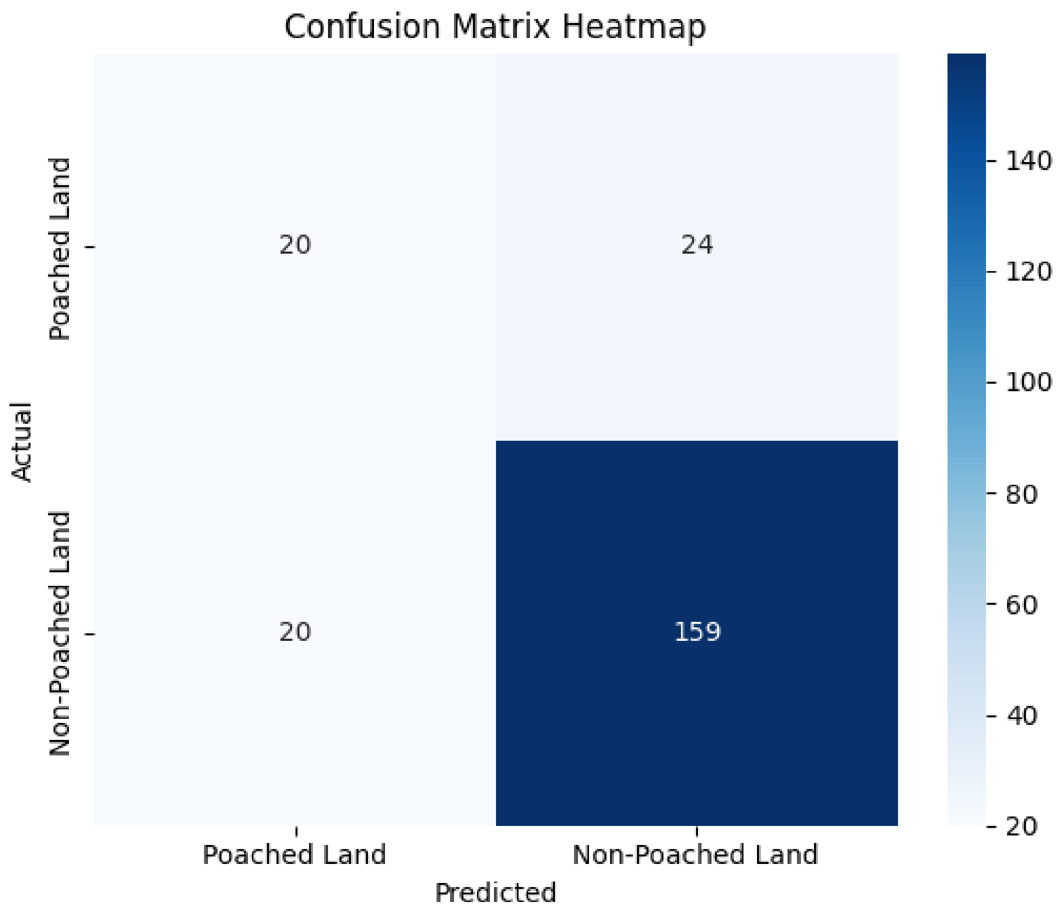


Figure 15. Confusion matrix showing classification accuracy

Table 3. Accuracy Matrices for Classification

Accuracy	0.803
Precision	0.455
Recall	0.5
F1 Score	0.47

6.2. Optimised Hybrid Model for Poached Land Detection:

While the proposed hybrid method—combining AI-enhanced spatial resolution of Sentinel-2 imagery with Random Forest classification—has demonstrated considerable potential in effectively visualising many poached land areas, it also presents certain limitations. Notably, the model tends to misclassify bare croplands, built-up areas, and roads as poached land, thereby increasing the rate of false positives.

To address these inaccuracies, additional refinements have been incorporated into the current approach. These enhancements aim to improve classification precision by minimizing misclassification of non-poached features. The improved methodology is illustrated in Figure 16.

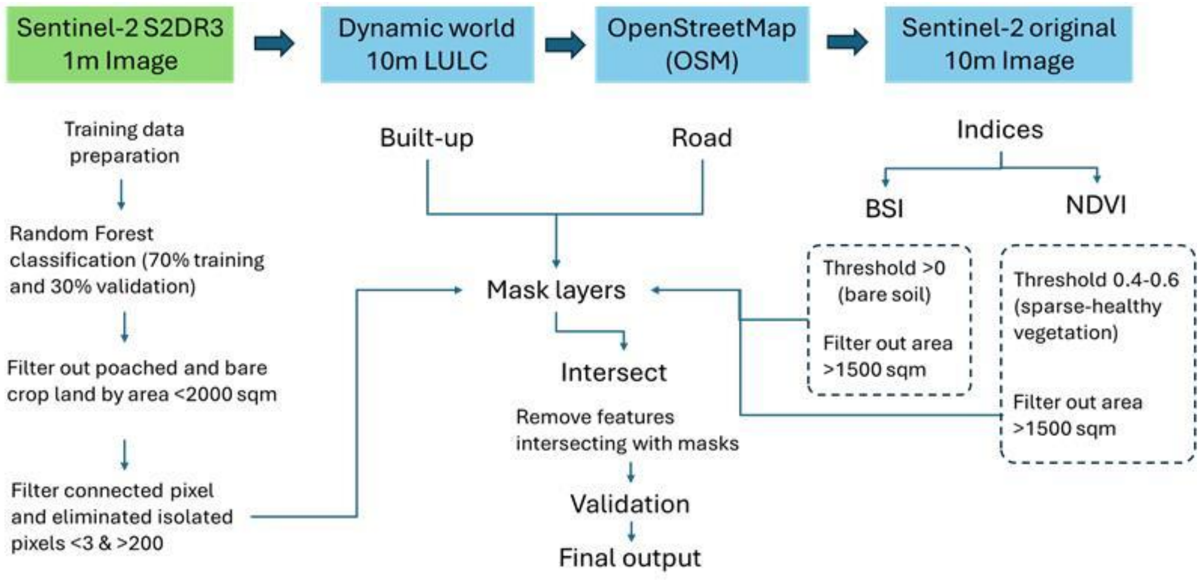


Figure 16. Hybrid methodology to identify poached land from satellite images

6.2.1. S2DR3 1m image classification and refinement

Similarly to the original method described in section 6.2.3, the classification of poached land begins with high-resolution S2DR3 1m imagery, which captures fine-scale spatial details essential for identifying subtle land disturbances. Using this imagery, training data is prepared to distinguish poached from non-poached areas. A Random Forest classifier is then applied, trained on 70% of the data and validated on the remaining 30%. To refine results and reduce noise, post-classification filters were applied.

- Predicted poached land patches and bare cropland areas exceeding 2,000 m^2 were excluded.
- Connected pixel filter eliminates isolated clusters with fewer than 3 pixels or more than 200 pixels.

A minimum area threshold of 2000 m^2 ensured in filtering to eliminate large patches unlikely to represent true poaching. While not a hard threshold, this value was determined based on visual inspection of outputs and used as a practical upper limit. Clusters with fewer than 3 connected pixels were removed to eliminate noise or stray misclassified regions and clusters with more than 200 connected pixels were filtered out in some cases to avoid including large, overly generalized regions.

This approach leverages the precision of S2DR3 imagery while applying spatial constraints to improve classification accuracy and reduce false positives.

6.2.2. Multi-Resolution Fusion for Reducing False Positives in Poached Land Detection

High-resolution (1 m) imagery, such as S2DR3-upscaled Sentinel-2 data, provides detailed spatial information that is useful for identifying fine-scale surface features. However, in vegetated croplands, this granularity can lead to misclassification. Specifically, small bare patches within predominantly vegetated farmland may be incorrectly classified as poached land, resulting in elevated false positive rates.

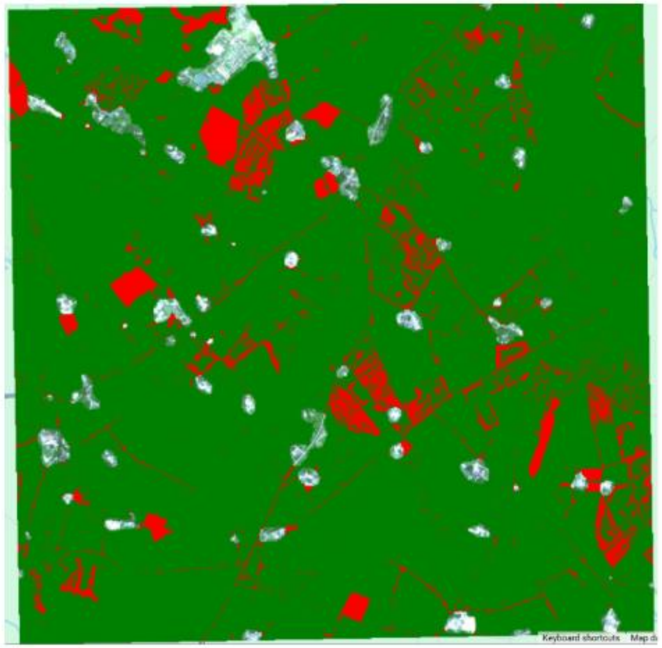
To address this issue, a masking strategy was employed using standard 10 m Sentinel-2 imagery. The coarser resolution of the 10 m data aggregates reflectance over larger pixel areas, effectively capturing the dominant land cover type. In this context, vegetated croplands with minor bare patches are consistently classified as non-poached, based on majority reflectance. By applying a mask derived from the 10 m imagery to the 1 m classification output, misclassified bare patches were filtered out, significantly improving detection accuracy.

Further refinement was achieved by incorporating spectral indices such as the Normalized Difference Vegetation Index (NDVI) and the Bare Soil Index (BSI). NDVI was used to confirm the presence of healthy vegetation, while BSI helped identify exposed soil surfaces. Isolated pixels with low NDVI and high BSI values—indicative of bare patches within otherwise vegetated areas—were systematically removed from the poached land classification. This dual index filtering approach enhanced the robustness of the model by reducing noise and improving spatial coherence in the final output.

6.2.3. Eliminate false positives from impervious surfaces

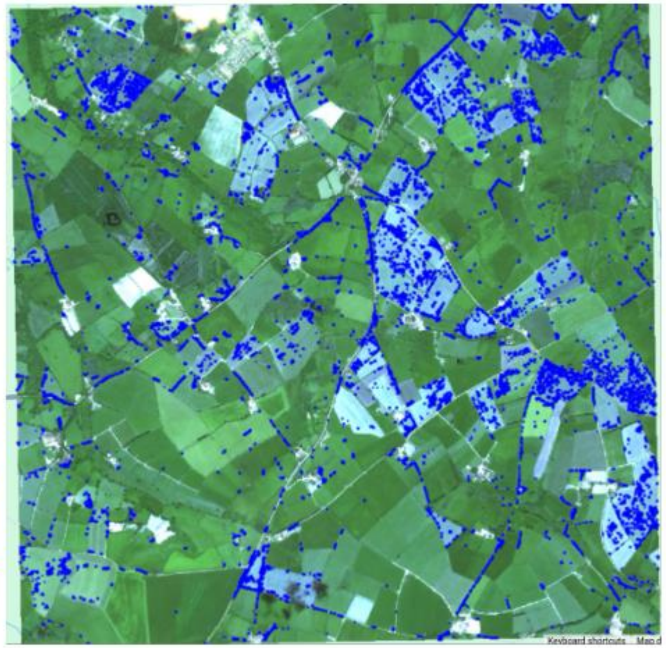
To further reduce false positives, especially those caused by impervious surfaces like roads and buildings, the workflow incorporates a road layer from OpenStreetMap (OSM) and a built-up layer from Dynamic World land-use data within Google Earth Engine (GEE). These layers are used to mask out roads and urban areas, ensuring that such features are not misclassified as poached land. This combination of high-resolution imagery, machine learning, spatial filtering, and contextual masking significantly improves classification accuracy (Figure 17).

RF classification
Red: Poached land
Green: Non-poached land
Mask : Built-up



Filter out poached land and bare crop land by area
Threshold < 2000 sq m

Eliminate isolated pixels classified as Poached land (Threshold < 3 pixels)



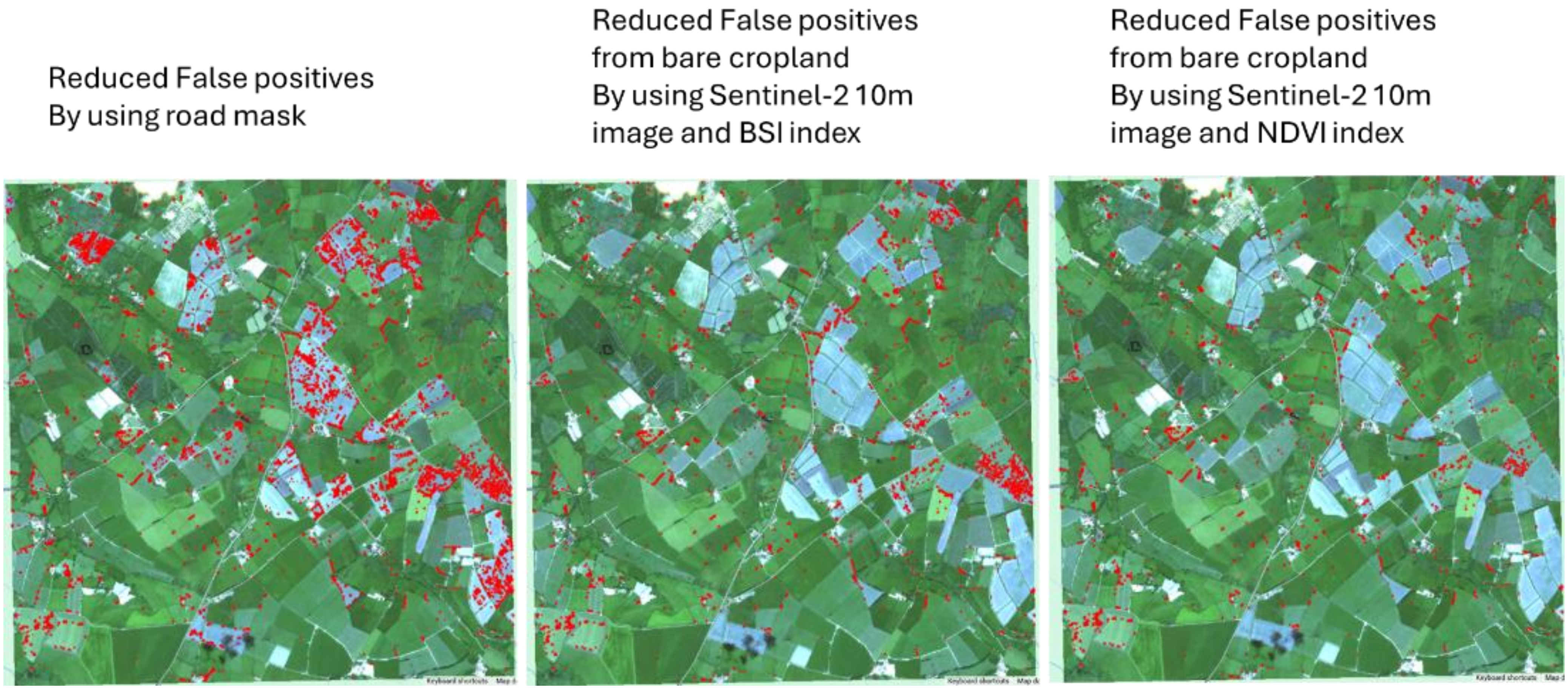


Figure 17. Poached land extracted from classified image using multi-step filtering (read from top-left to bottom-right)

6.3. Accuracy assessment:

Evaluating the accuracy of poached land detection is essential to ensure the reliability and applicability of the proposed methodologies. Given the complexity of distinguishing poached areas—often characterized by subtle spectral and spatial variations—standard classification metrics such as accuracy, precision, recall, and F1 score are employed. These metrics provide a quantitative basis for assessing the model's ability to correctly identify poached versus non-poached land, while also highlighting areas where misclassification may occur. The assessment is conducted using confusion matrices derived from validation datasets, enabling a detailed comparison between predicted and actual land conditions.

6.3.1. Methods of assessing results

The illustration below demonstrates how the accuracy of the poach land classification model was evaluated using a pixel wise comparison between model prediction and ground truth labels. The known locations of poached land and non-poached land were first identified and marked. To obtain the ground-truth labels, visual interpretation of high-resolution imagery from Google Earth Pro was carried out, identifying features such as soil exposure, vegetation loss, and hoof marks. These locations were then cross-checked in the S2DR3 upscaled imagery to ensure the presence of distinct spectral signatures suitable for model learning. Only sites that met both visual and spectral criteria were selected as ground-truth. Additionally, reference sites shared by ADAS were used to guide and standardize the interpretation process.

As shown in Table 3 the True Positives, True Negatives, False Positives and False Negatives were identified and recorded in the confusion matrix to calculate the relevant matrices.

Table . Poached land confusion matrix framework

PREDICTED	ACTUAL	
	Poached land	Non-Poached land
Poached land	True Positive	False Positive
Non-Poached land	False Negative	True Negative

True Positive:

The model predicted poached land presence around the selected location, at least 4-5 pixels have been classified as poach land, aligning with the ground truth (Figure 18).

Figure 18. Expected poached land detection (True positive)

True Negative:

The model correctly identified non-poached land regions such as waterbodies and urban areas (Figure 19).

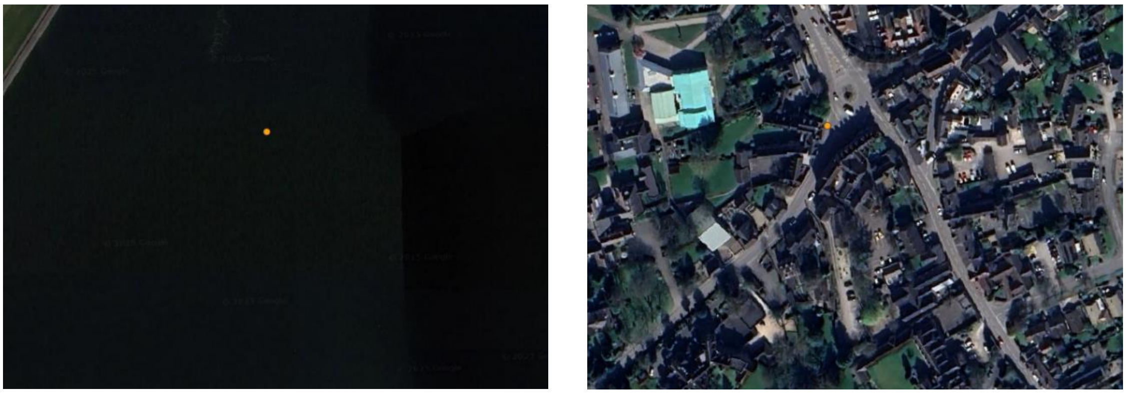


Figure 19. Expected non-poached land detection (True negative)

False Positive:

The model incorrectly predicted poach land regions that are non-poach land, Around the selected ground truth point, at least 5-10 pixels have been wrongly classified (Figure 20).

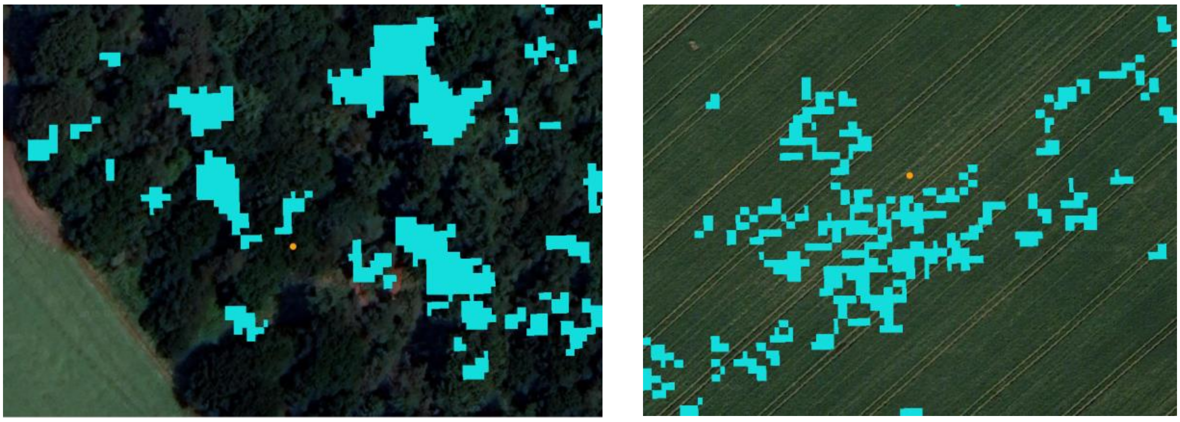


Figure 20. Incorrect poached land detection (False positive)

False Negative

The model failed to detect poached land at the selected location. Although the ground truth marks this area as poached land, the model did not classify it as such (Figure 21).

Figure 21. poached land present but no detection (False negative)

We have compared both the methods in approach 3 from the accuracy point of view to understand any further improvement post refinement of the process and it shows significant improvement in Table 4.

Table 4. Comparison of accuracy assessment

Classification methods		**Actual**		Accuracy	Precision	Recall	F1 score
RF (Initial)		Poached	Non-Poached				
Predicted	Poachland	20	24	0.80	0.45	0.50	0.48
	Non-Poachland	20	159				
Hybrid							
Predicted	Poachland	23	8	0.87	0.74	0.56	0.65
	Non-Poachland	17	151				

Following the hybrid approach, we have selected S2DR3 images for other regions in UK Figure 22.

Table 5. Model performance for each image classification

	Accuracy Matrices				Major Land Use				
Image_Id	Accuracy	Precision	Recall	F1 Score	Crop	Builtup Area	Rangeland	Trees	Water
802edbf32-20200601_MS	65.10%	63.22%	61.11%	62.15%	92.20%	3.25%	2.92%	1.26%	
a70305cf5-20241126	44.68%	41.94%	27.66%	33.33%	31.44%	15.60%	19.26%	31.77%	
cdb6cb5c0-20241126	53.70%	54.55%	44.44%	48.98%	90.27%	2.86%	2.59%	4.26%	
acfe8817a-20231130	74.00%	73.08%	76.00%	74.51%	71.60%	4.50%	13.08%	10.42%	
cb53cbfa7-20231130	69.72%	68.42%	73.24%	70.75%	96.14%	1.83%	0.78%	1.21%	
d9be38caa-20231130	64.12%	67.14%	55.29%	60.65%	78.36%	2.59%	4.54%	14.49%	
efade6075-20231130	58.64%	60.00%	48.75%	53.79%	68.14%	6.14%		15.78%	5.37%
12d149628-20231130	62.73%	63.16%	60.00%	61.54%	68.78%	2.81%	13.28%	14.97%	
dc0a3a63a-20231130	65.50%	63.48%	73.00%	67.91%	25.22%	0.61%	69.11%	5.04%	
802edbf32-20210613_MS	87.44%	74.19%	57.50%	64.79%	88.02%	2.37%	4.05%	5.50%	

Table 5 shows that the model performs best in crop-dominated landscapes, where poached land is more visually distinct. Performance drops in images with mixed land use (e.g., trees, rangeland), likely due to spectral confusion between natural and disturbed surfaces.

The relatively high F1 score in crop-heavy areas suggests the model is well-calibrated for agricultural regions but may need additional features or contextual layers (e.g., NDVI, land-use masks) to improve generalisation in more complex environments.

6.4. Validation Using High-Resolution Imagery

To assess the accuracy of poached land detection, we compared the results derived from upscaled 1-meter Sentinel-2 multispectral imagery with a very high-resolution (50 cm) Vexcel image acquired on 7 September 2021. While the detection process primarily relies on visual cues from the upscaled Sentinel-2 data, its effectiveness is constrained by the sensor's inherent spatial resolution and the complex surface reflectance characteristics of poached areas. These limitations can lead to misclassification or omission of subtle features.

To enhance interpretability and validate the model outputs, we overlaid the detection results onto the higher-resolution Vexcel imagery. Due to cloud cover constraints, it was not feasible to obtain imagery from both sources on the same date. Therefore, the Sentinel-2 image used corresponds to 1 October 2021 (Figure 23).

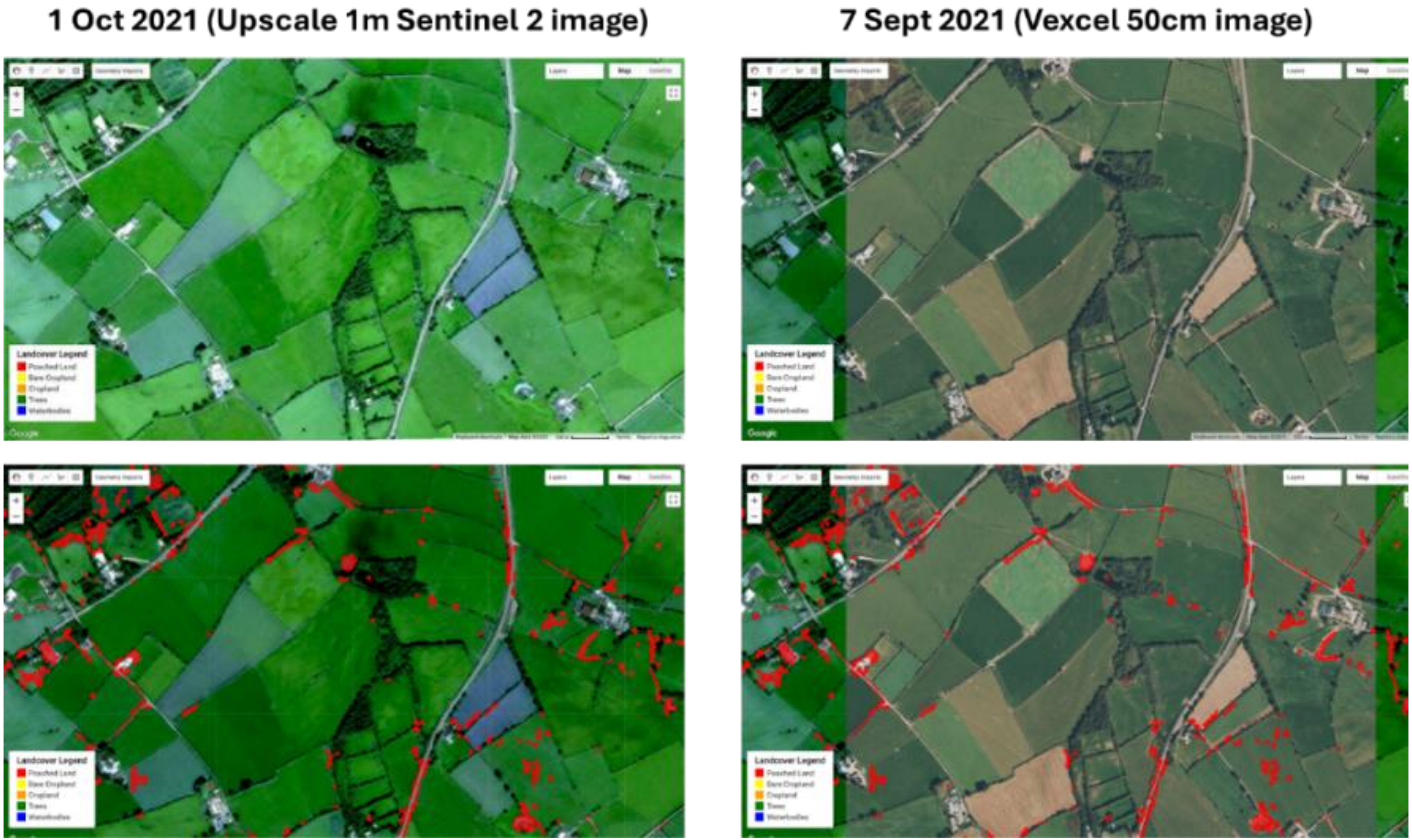


Figure 22. Comparing model output with very high-resolution imagery

As illustrated in Figure 23, the model successfully identified the majority of clearly visible poached areas, demonstrating its potential effectiveness despite the spatial limitations of the input data.

6.5. Overall Performance evaluation:

Table 6. Combined error matrix summary

	Actual Poached Land	Actual Non-Poached Land
Predicted Poached Land	397 (True Positive)	241 (False Positive)
Predicted Non-Poached Land	273 (False Negative)	587 (True Negative)

As shown in Table 7, the model performs better at identifying non-poached land (TN = 587) than poached land (TP = 397), which is common in imbalanced or complex classification tasks. The relatively high number of false negatives (273) suggests that the model may be under-sensitive to poached land, potentially due to overlapping spectral characteristics with other land types. The false positives (241) indicate that some non-poached areas are being misclassified, possibly due to bare soil, construction, or other impervious surfaces that resemble poached land in imagery. In Table 8, the model achieved an overall accuracy of 65.69%, with a precision of 62.23%, indicating moderate reliability in identifying poached land. A recall value of 59.25% reflects the model's tendency to miss some actual poached areas (possibly due to lack of spatial clarity in terms of resolution), and an F1 score of 60.70% suggests a balanced but improvable performance in minimizing both false positives and false negatives.

Table 7. Overall Model performance metrics

Metric	Value	Explanation
Accuracy	65.69%	This means the model correctly classified about two-thirds of all cases. It's a moderate level of accuracy, indicating room for improvement.
Precision	62.23%	Of all the areas predicted as poached land, about 62% were poached. This shows the model is somewhat reliable in its positive predictions, but still produces a significant number of false positives.
Recall	59.25%	The model correctly identified about 59% of all actual poached land. This suggests it is missing a substantial portion of true poached areas (false negatives).
F1 Score	60.70%	The F1 score balances precision and recall. A score around 60% indicates the model is moderately effective but not optimal for either minimising false positives or false negatives.

7. Key Strengths

a. The model effectively combines the Sentinel-2 10m imagery for contextual filtering (NDVI, BSI, land-use masks) with S2DR3 1m imagery for high-resolution classification, leveraging the strengths of both spatial scales.
b. The use of NDVI and BSI thresholds to mask out marginally vegetated and bare soil areas (with area filters >1500 m^2) helps reduce false positives, especially in agricultural and transitional landscapes.
c. Incorporating OpenStreetMap road data and Dynamic World built-up layers ensures impervious surfaces are excluded from classification, improving precision by avoiding misclassification of roads and buildings as poached land.

d. The model applies spatial filters to remove small or isolated patches (< 2,000 m^2 or <4 pixels), enhancing the spatial coherence of the output and reducing noise.
e. With an overall accuracy of 65.69%, precision of 62.23%, and F1 score of 60.70%, the model shows consistent performance across crop-dominated areas and is scalable using Google Earth Engine.

8. Limitations

a. S2DR3 is available for testing and evaluation purposes. Any commercial use of this tool may require purchasing a license, which may increase the cost of the project.
b. S2DR3 may perform better in an agricultural setting rather than in an urban landscape.
c. A recall of 59.25% indicates the model misses a significant portion of actual poached land, which could be critical in some uses of the outputs such as identifying locations for catchment walkovers or conservation applications.
d. Performance drops in heterogeneous landscapes (e.g., mixed rangeland, tree cover, or bare soil), where spectral confusion leads to misclassification, despite masking efforts.
e. The model's accuracy relies heavily on carefully tuned thresholds (e.g., NDVI 0.4–0.6, BSI >0) and area-based filtering, which may not generalise well across different regions or seasons.
f. The workflow may require retraining or re-thresholding when applied to new geographies or imagery sources, limiting its plug-and-play applicability.
g. The F1 score suggests the model is not yet optimal in balancing false positives and false negatives, especially in edge cases or complex land cover transitions.

9. References

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