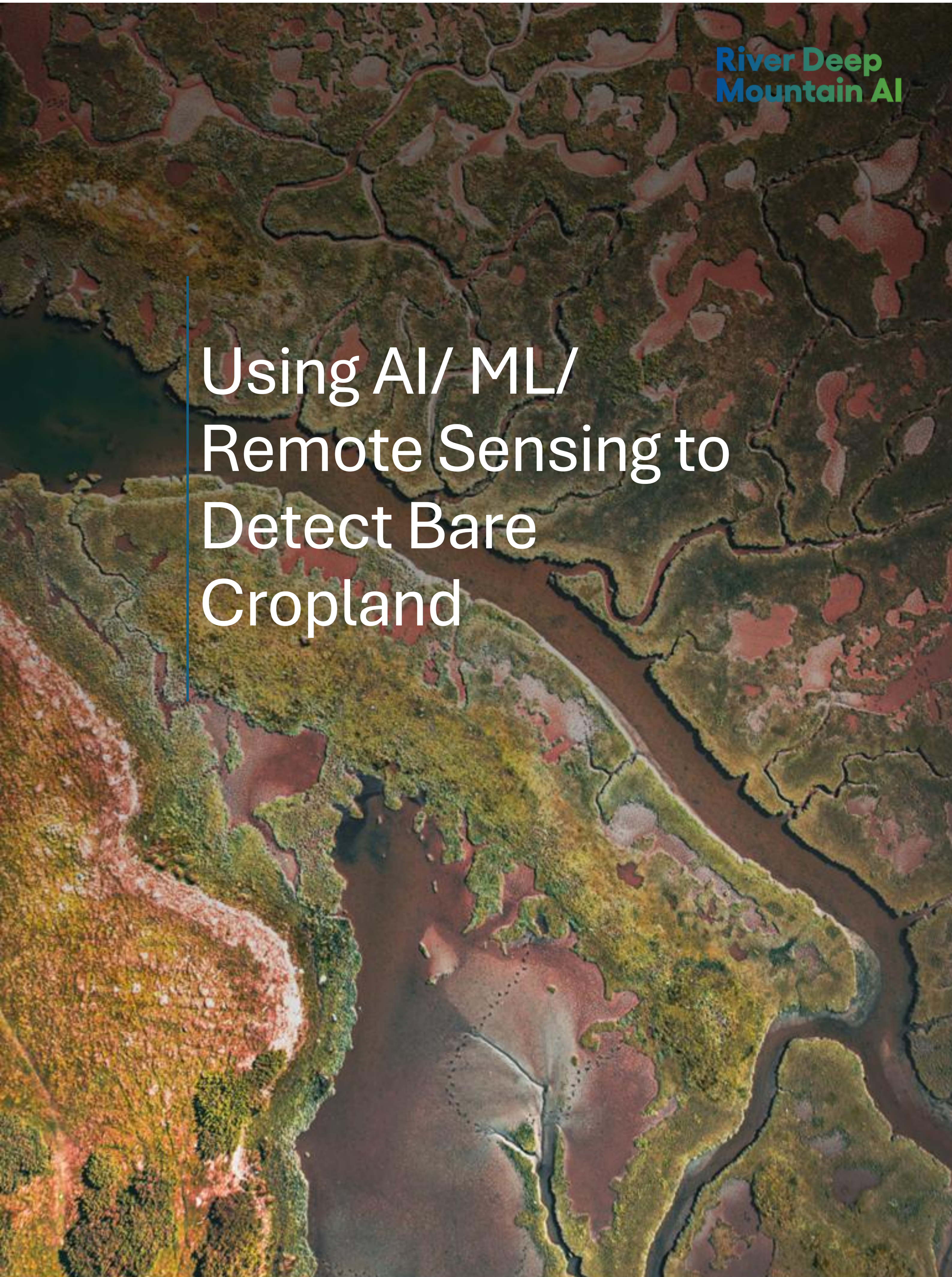
River Deep Mountain AI

Using AI/ ML/ Remote Sensing to Detect Bare Cropland



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1. Introduction

Water pollution continues to pose a serious global threat, impacting rivers, lakes, estuaries, and coastal ecosystems. A major contributor to this issue is non-point source pollution—also referred to as diffuse pollution. Non-point sources of water pollution are those that don't originate from a single, discrete source, but are rather contaminants introduced to the watercourse over a large area. As such, non-point pollution is much more difficult to identify and manage compared to point sources. Agricultural runoff is a key component of this type of pollution. During certain periods in the farming cycle, such as post-harvest or pre-planting, croplands are often left bare, making them particularly vulnerable to erosion and the leaching of nutrients and agrochemicals.

These exposed soils, especially during rainy seasons, can significantly accelerate the transport of sediments, fertilizers, and pesticides into nearby water bodies. Monitoring such bare cropland areas is therefore essential for identifying potential pollution hotspots and informing mitigation strategies.

To support this effort, an Open Bare Cropland Detection Model has been developed, leveraging satellite-derived spectral indicators to evaluate bare soil exposure, vegetation cover, and surface conditions such as snow and moisture presence. Combined with weather data, the model enables accurate monitoring of surface dynamics throughout the seasons. This enhances the ability to track fallow periods, detect land degradation, and inform sustainable land and water quality management strategies.

The following section outlines the data sources, processing techniques, and analytical steps taken to monitor bare soil exposure.

2. Summary of data exploration

2.1. Data Sources and Preprocessing

- **Satellite Data**: Sentinel-2 Level-2A surface reflectance and Harmonized products were used, providing atmospherically corrected and orthorectified imagery at 10–20 m resolution with 13 multispectral bands and 5 days revisit frequency.

Table 1. Sentinel 2 Image spectral band specifications

Band	Description	Wavelength (μm)	Resolution (m)
Band 1	Coastal aerosol	0.443	60
Band 2	Blue	0.490	10
Band 3	Green	0.560	10
Band 4	Red	0.665	10

Band	Description	Wavelength (μm)	Resolution (m)
Band 5	Vegetation Red Edge	0.705	20
Band 6	Vegetation Red Edge	0.740	20
Band 7	Vegetation Red Edge	0.783	20
Band 8	NIR	0.842	10
Band 8A	Vegetation Red Edge	0.865	20
Band 9	Water vapour	0.945	60
Band 10	SWIR - Cirrus	1.375	60
Band 11	SWIR	1.610	20
Band 12	SWIR	2.190	20

- **Temporal Scope**: Imagery was selected for key agricultural periods—winter to early spring (Nov/Dec-Feb/March), mid-summer (Jun-Aug), and post-harvest (Sept-Nov)—to capture seasonal variations in land cover.
- **Geographic Focus**: Data was collected for selected agricultural catchments in England e.g. Browney, Pont and Lyne Druridge.

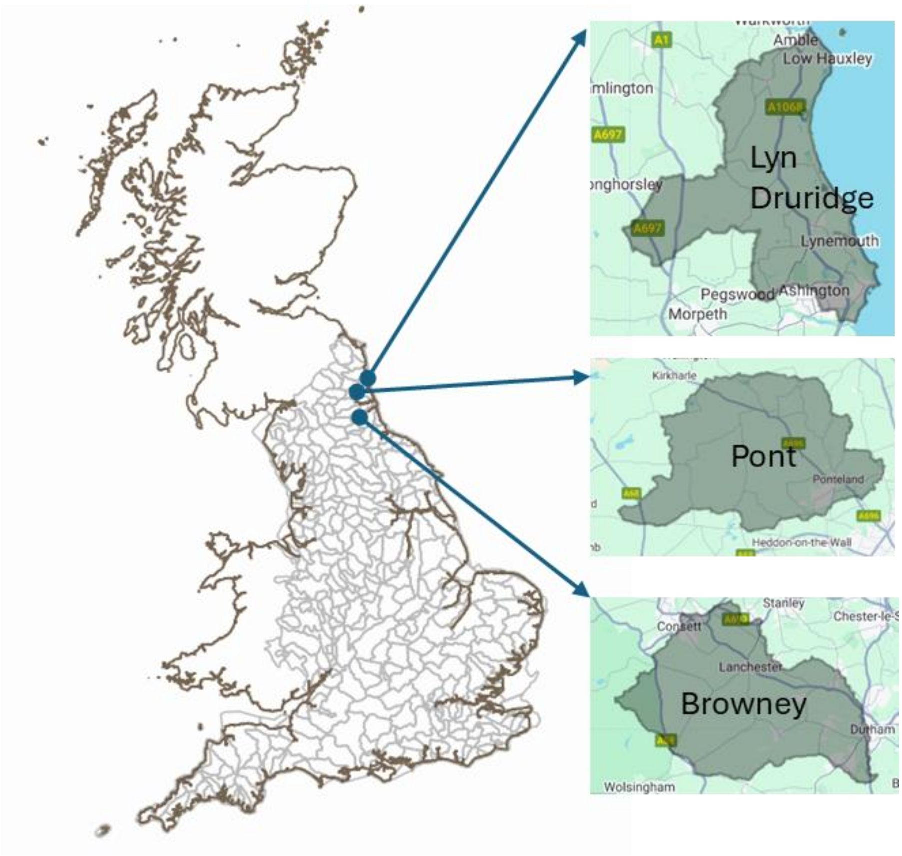


Figure 1. Catchment boundaries used in this study

- **Cloud Masking**: Scenes were filtered using the cloud mask layer provided by Sentinel to remove cloud pixels, ensuring reliable index calculations. The present method has considered less than 20% cloudy pixels while selecting the Sentinel 2 satellite images.

- **Image Extent:** Image Coverage: The example below illustrates the spatial coverage of Sentinel imagery available on Google Earth Engine (GEE). It provides insight into the availability of satellite images for a specific Area of Interest (AOI).

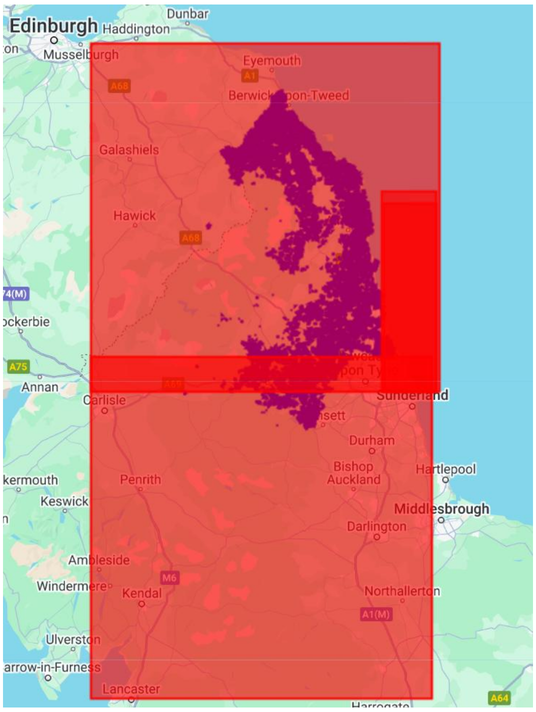


Figure 2. Sentinel 2 image extent for Northumberland, UK

Satellite images with cloud cover ranging from 1% to 90% were explored to assess their availability. This helps to determine how many scenes are needed to generate an optimal composite image for model input. Accordingly, the cloud cover threshold can be adjusted to balance image quality and temporal coverage. The tables below illustrate how image availability varies with cloud cover percentage across different seasons.

Table 2. Year 2020-21 (Cloud cover and image availability)

Cloud %	**1%**	**5%**	**10%**	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**
Summer (Jun-Aug)	3	4	4	6	7	11	16	21	30	42	59
Autumn (Sep-Nov)	0	1	4	9	12	16	28	37	41	53	65
Winter (Dec-Feb)	0	0	4	10	13	21	27	31	41	49	60
Spring (Mar-May)	3	6	9	12	17	21	27	33	50	62	69

Table 3. Year 2023-24 (Cloud cover and image availability)

Cloud %	**1%**	**5%**	**10%**	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**
Summer (Jun-Aug)	1	2	4	7	7	8	8	17	28	39	53
Autumn (Sep-Nov)	1	3	5	6	9	12	17	23	28	35	48
Winter (Dec-Feb)	0	1	2	4	5	10	14	18	25	27	33
Spring (Mar-May)	0	0	1	3	7	11	14	17	24	28	37

Table 4. Year 2024-25 (Cloud cover and image availability)

Cloud %	**1%**	**5%**	**10%**	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**
Summer (Jun-Aug)	0	0	1	4	7	13	15	20	29	39	54
Autumn (Sep-Nov)	1	4	5	6	12	17	22	24	33	36	50
Winter (Dec-Feb)	1	4	4	8	10	15	17	21	31	36	46
Spring (Mar-May)	11	14	15	18	20	25	30	37	46	49	56

2.2. Input data preparation and GEE Asset creation

- Download Catchment data from https://environment.data.gov.uk/catchment-planning/ and add into GEE asset.
- Add the crop mask asset containing Crop Map of England (CROME) information into GEE (to be prepared in below manner).
    - Extract farmland (fclass = 'farmland') from OpenStreetMap (OSM) land use repository using QGIS/ArcGIS/programmatically.
    - Clip the farmland layer for targeted catchment.
    - Clip CROME crop type data for targeted catchment.
    - Dissolve CROME crop classes spatially based on crop type and create centroid geometry from each class. This can be done using geospatial tool like QGIS/ArcGIS/programmatically.
    - Intersect the farmland and crop point dataset together to create a new Crop mask includes crop type. Add this layer as an crop mask asset in GEE.

2.2.1. Crop mask

This model requires a crop mask to run effectively and avoid misclassification of other land use classes. In this work, we have opted to use the openly available farmland boundary data from OSM land cover data to isolate agricultural areas for analysis. This data, which includes polygons tagged as fclass = farmland, is extracted and converted into a vector layer (e.g., shapefile). In GEE, it is imported as a FeatureCollection and used to clip satellite imagery or mask out non-agricultural land, ensuring that remote sensing models focus only on cropland.

Figure 3. OSM crop layer used as crop mask

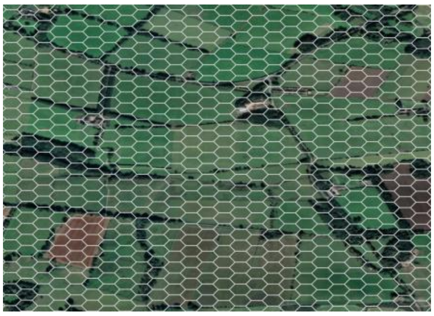
Limitations:

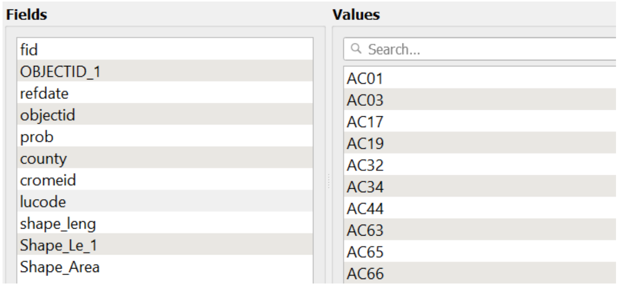
While OSM is a valuable open-source platform maintained by a global community of contributors, it is important to acknowledge the following limitations, such as:

- Data Completeness: OSM coverage is generally more comprehensive in urban and semi-urban areas. In rural regions, including agricultural zones, the completeness of farmland boundaries may vary depending on contributor activity.
- Positional Accuracy: Studies have shown that OSM features in the UK typically have good positional accuracy (within a few meters), but this can vary locally.
- Update Frequency: OSM data is updated continuously by volunteers, but there is no guaranteed schedule for updates or quality control.

2.2.2. Ingesting Crome crop type data in GEE

The CROME dataset uses a hexagonal grid system to divide the landscape into uniform cells. This data has been enhanced by adding crop description. This layer has been combined with crop mask layer to enhance the mask information.





category (String)	county (String)	cromeid (String)	lu_type (String)	lucode (String)	objectid (Float)	prob (Float)	refdate (String)	shape_leng (Float)
Cereal Crops	DUR	RPA41860654638 1	Spring Barley	AC01	359312.9999999994	0.328	20220401	239.94452163
Cereal Crops	DUR	RPA41656654610 3	Spring Barley	AC01	360176	0.532	20220401	239.94452163
Cereal Crops	DUR	RPA41278654302 0	Spring Barley	AC01	360543.00000000006	0.412	20220401	239.94452163

Figure 4. CROME dataset and its attributes

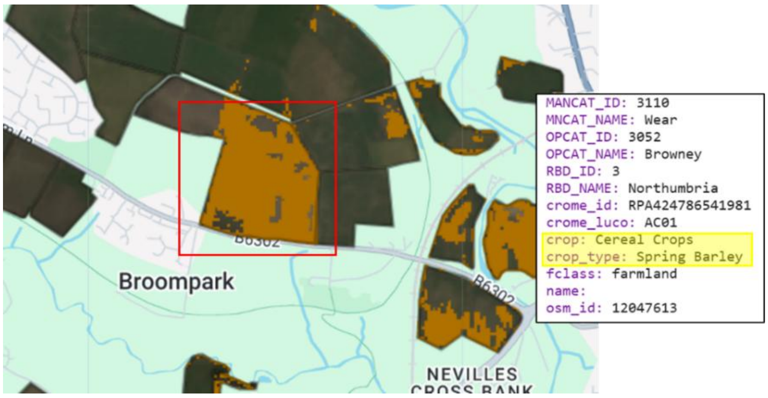


Figure 5. CROME dataset integrated with OSM farmland layer

2.2.3. Ingesting Rainfall Data in GEE

Historical rainfall data was downloaded from DEFRA's Hydrology Explorer for gauge stations located within each catchment. This ground-based data was then used in Google Earth Engine to compare with satellite-derived moisture indices like NDMI, enabling a more robust assessment of soil moisture variability and hydrological conditions. The current method applicable to integrate any other rainfall data as well.

Example:

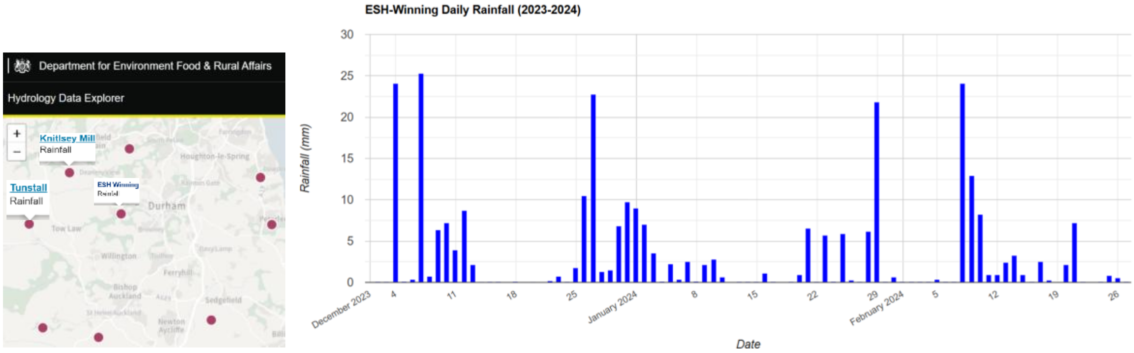


Figure 6. Rainfall data visualization in GEE

2.3. Exploring Sentinel 2 Imagery in GEE

The purpose of this initial analysis is to understand the variability and distribution of spectral information in satellite imagery over the Area of Interest (AOI). Specifically, we examined:

Raw Sentinel-2 data (without atmospheric correction or surface reflectance adjustments), Surface Reflectance data and Harmonized data products (processed to ensure consistency across time and sensors). Surface reflectance data is a pre-processed to correct for atmospheric effects, whereas harmonized data is also atmospherically corrected and offset adjusted to reduce sensor inconsistencies, making it more suitable for time-series analysis and comparison across dates.

This comparison helps us assess how different spectral bands behave and how they can be used to distinguish between land cover types such as vegetation, bare soil, and water.

Sentinel-2 is a satellite mission from the European Space Agency that provides high-resolution optical imagery. Each image contains multiple spectral bands, including:

- Red (R)
- Green (G)
- Blue (B)
- Near-Infrared (NIR)
- Short-Wave Infrared 1 (SWIR1)
- Short-Wave Infrared 2 (SWIR2)

These bands capture different wavelengths of light, which are useful for identifying various surface features. For example, vegetation reflects strongly in the NIR band, while bare soil and built-up areas show distinct patterns in the SWIR bands.

We conducted a histogram-based analysis of the spectral bands to evaluate the spread and variation of pixel values in both raw, surface reflectance and harmonized datasets.

Histograms provide a visual summary of how pixel intensities are distributed across an image.

Key Insights

- **Variation in Raw Data**: The raw data showed a wider spread in pixel values, especially in the visible bands (R, G, B), due to atmospheric interference such as haze or cloud cover.
- **Surface Reflectance and Harmonized Data**: These products exhibited more consistent and narrower distributions, indicating improved reliability for downstream analysis like crop classification or land cover mapping.
- Spectral Band Behaviour:
    - **NIR**: Strongly peaked in vegetated areas, useful for identifying crop health.
    - **SWIR1 & SWIR2**: Help differentiate between soil moisture levels and bare land.

The below histograms represent the distribution of surface reflectance pixel values across different seasons for the Browney catchment area. These distributions are derived from three satellite data products: TOA (Top of Atmosphere), BOA (Bottom of Atmosphere), and BOA Harmonized. The TOA data, which includes atmospheric effects such as scattering and absorption, exhibits a noisier and less uniform distribution, indicating the presence of radiometric distortions. In contrast, the BOA and BOA Harmonized products—corrected for atmospheric interference—show well-stretched histograms, reflecting improved radiometric quality and enhanced contrast, which are more suitable for quantitative remote sensing analyses. To investigate surface dynamics in relation to bare cropland detection, the distribution of pixel values across various spectral bands were analysed.

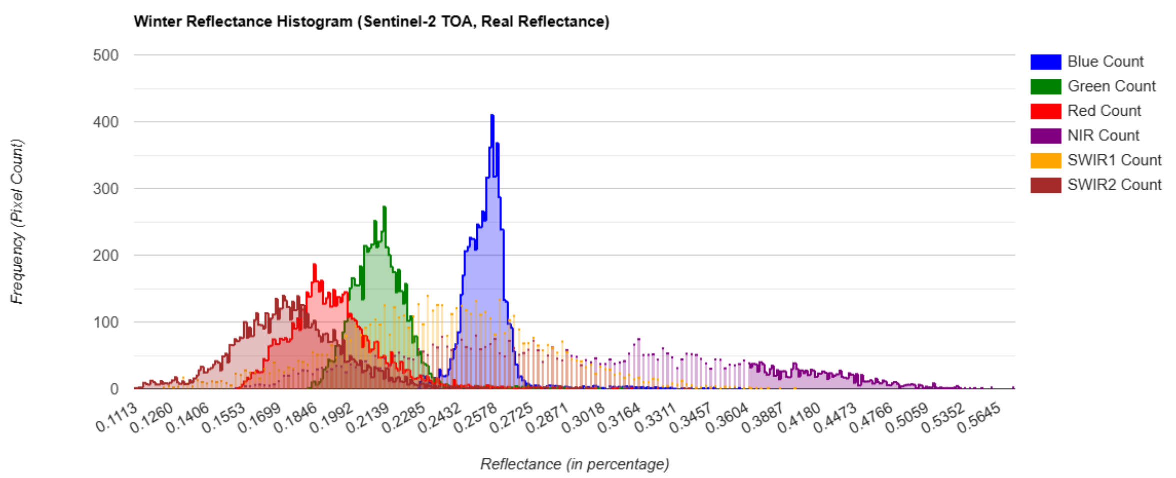


Figure 7. TOA image reflectance - Winter

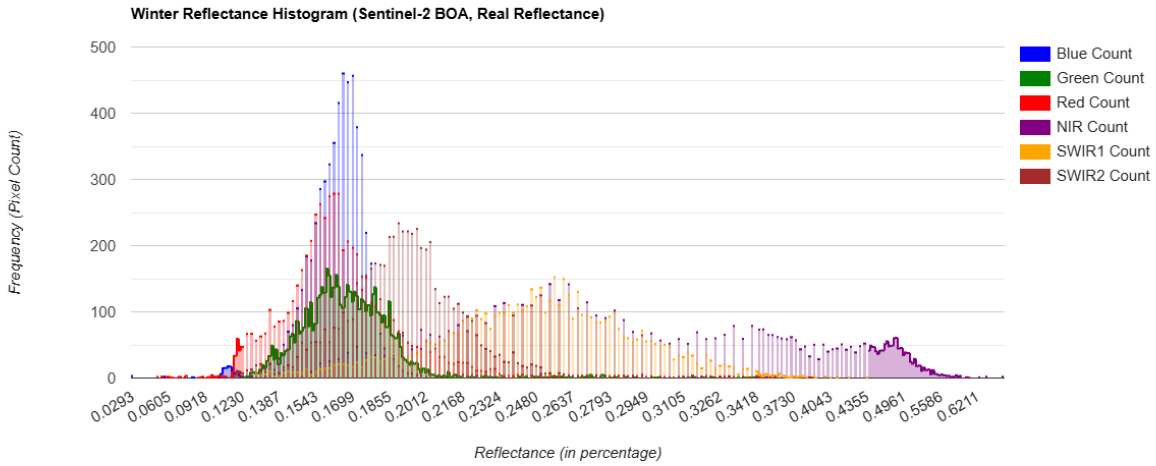


Figure 8. BOA image reflectance – Winter

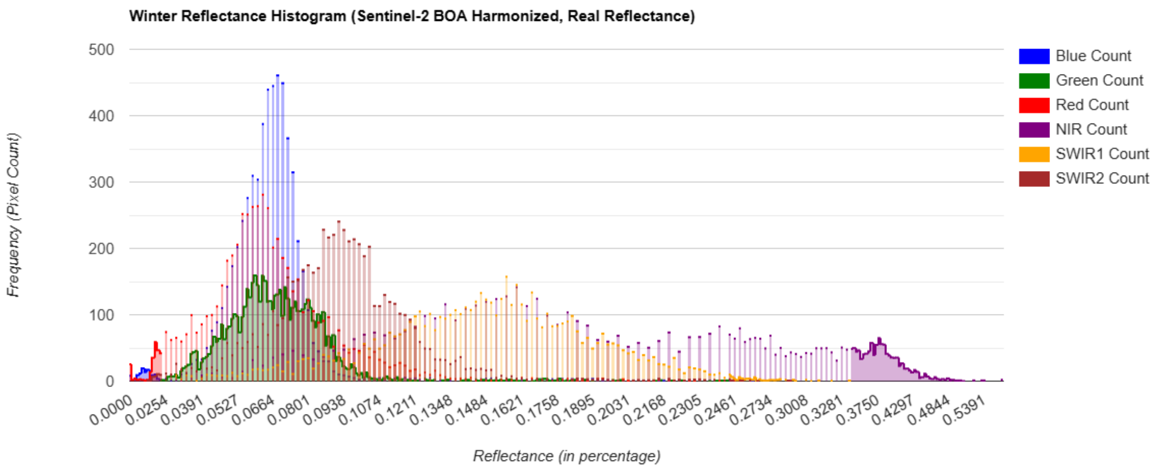


Figure 9. BOA harmonized image reflectance - Winter

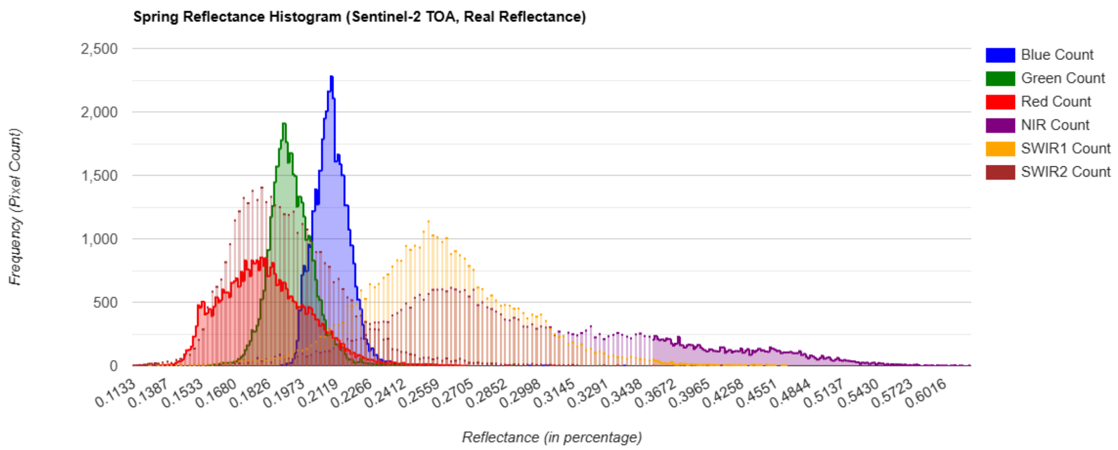


Figure 10. TOA image reflectance - Spring

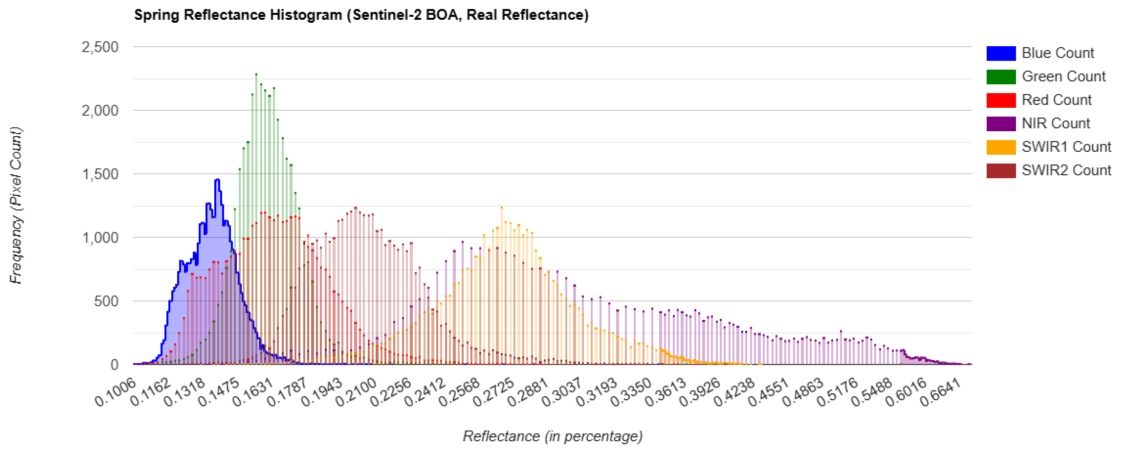


Figure 11. BOA image reflectance - Spring

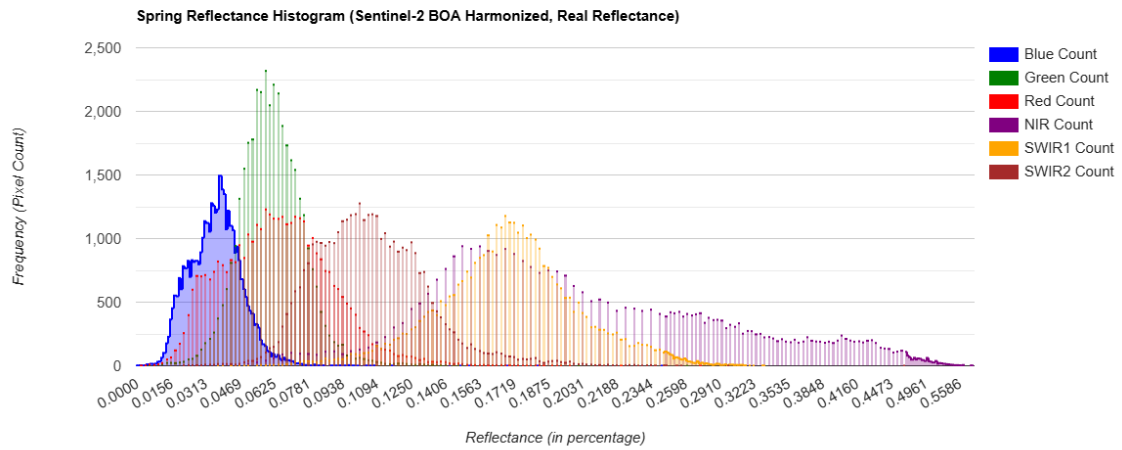


Figure 12. BOA harmonized image reflectance - Spring

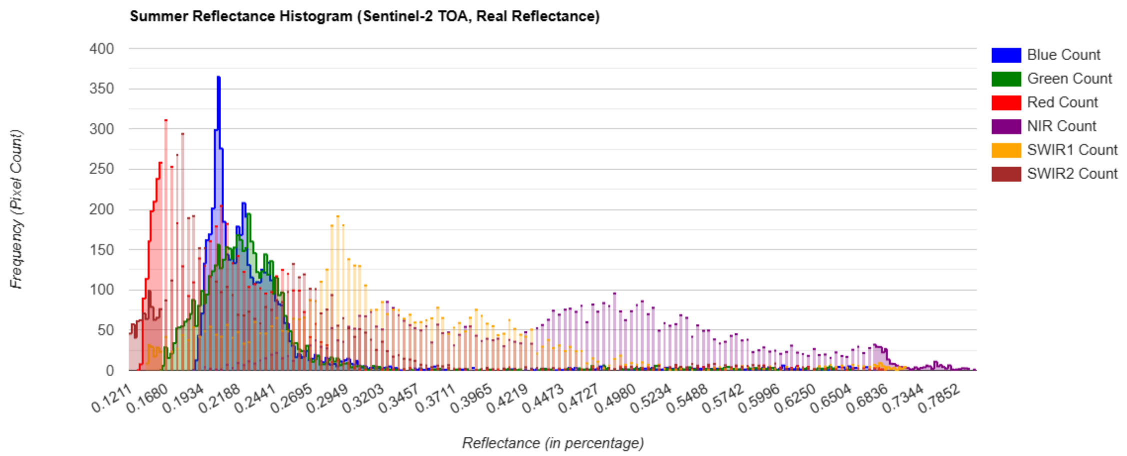


Figure 13. TOA image reflectance - Summer

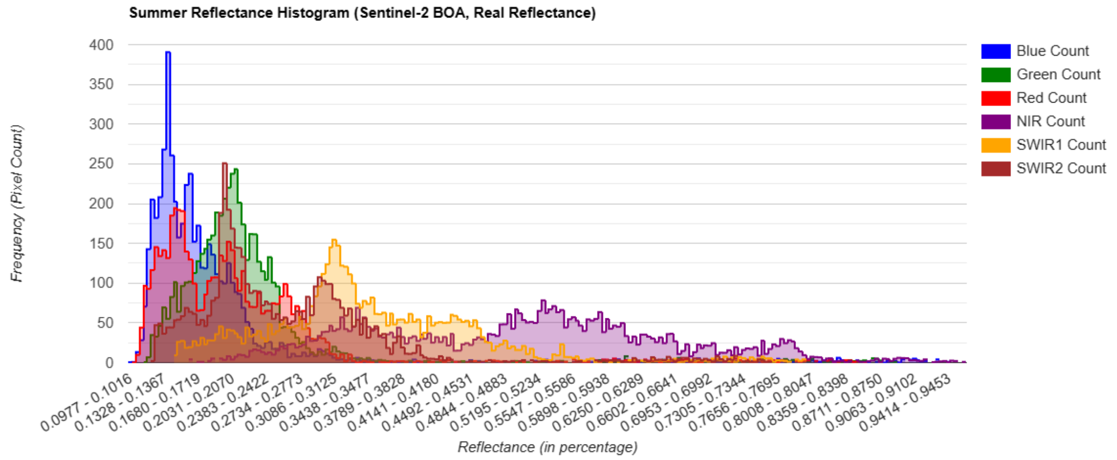


Figure 14. BOA image reflectance - Summer

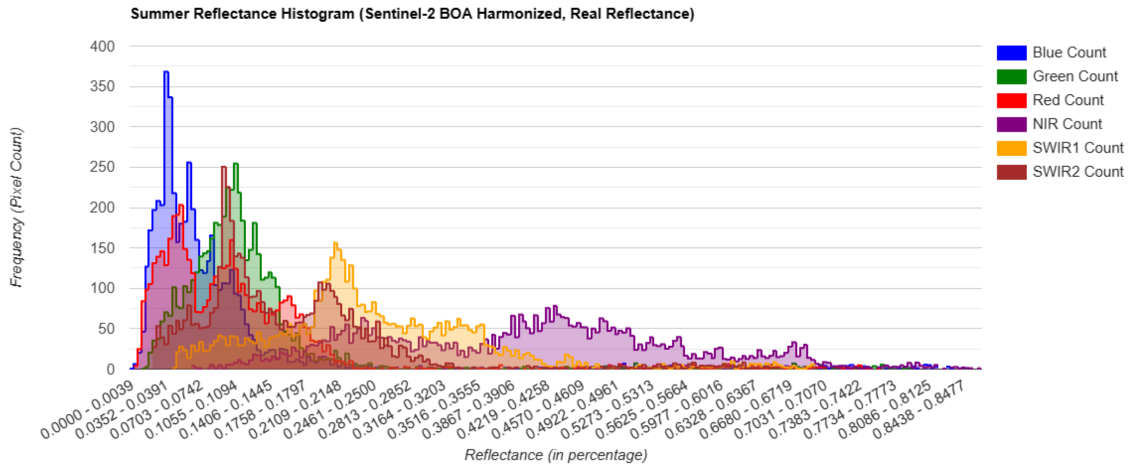


Figure 15. BOA harmonized image reflectance - Summer

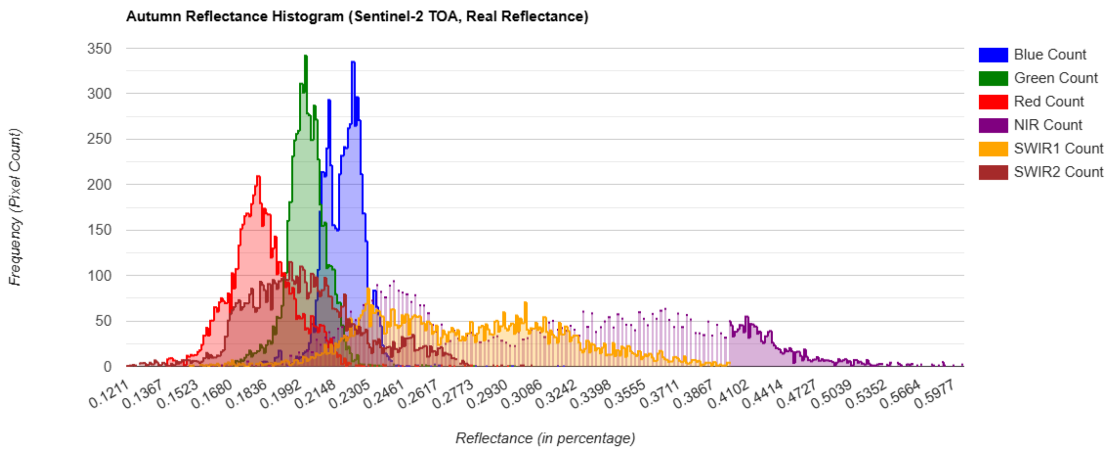


Figure 16. TOA image reflectance - Autumn

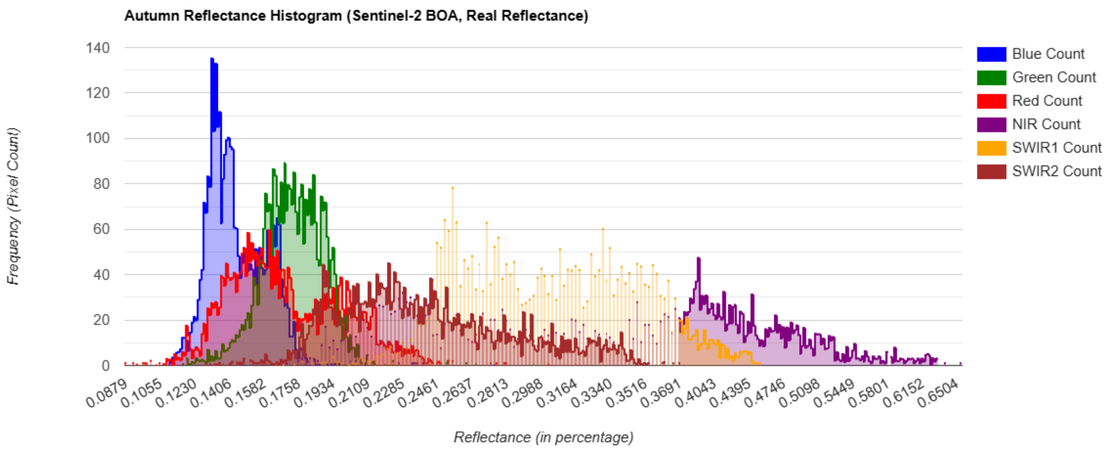


Figure 17. BOA image reflectance - Autumn

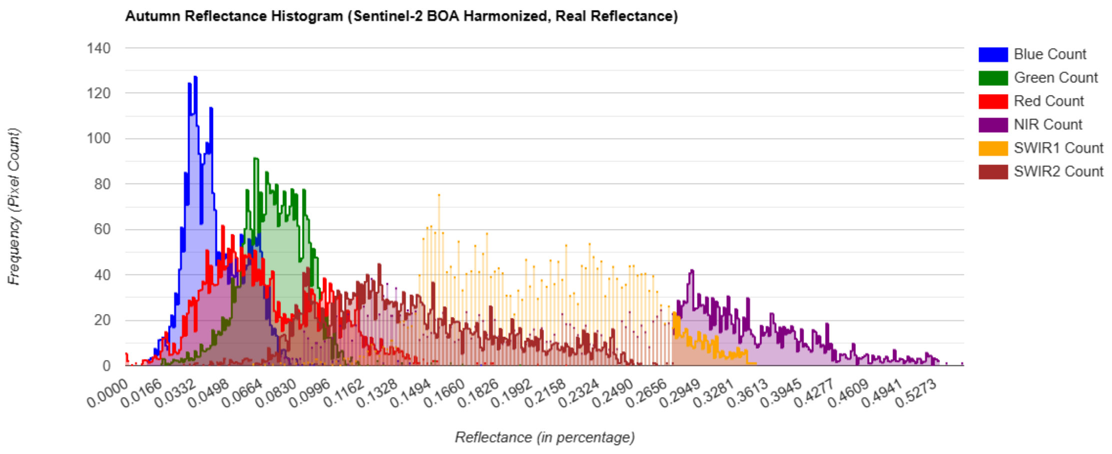


Figure 18. BOA harmonized image reflectance - Autumn

While model building, we quantitatively analysed the surface reflectance data for both summer and winter seasons to evaluate surface conditions, complementing the insights obtained from spectral index assessments (see Table 5)

Table 5. Seasonal Reflectance Distribution Comparison

Band	Summer Reflectance Range	Winter Reflectance Range	Interpretation
Blue	0.02 – 0.20	0.03 – 0.09	Summer shows more variation; winter is more uniform.
Green	0.02 – 0.24	0.03 – 0.11	Higher and broader in summer due to active vegetation.
Red	0.012 – 0.22	0.02 – 0.14	Summer reflects more, indicating diverse surfaces.
NIR	0.12 – 0.74	0.06 – 0.48	Much higher in summer, showing dense vegetation.
SWIR1	0.04 – 0.68	0.03 – 0.26	Summer indicates more moisture; winter is drier.
SWIR2	0.2852 – 0.32	0.02 – 0.16	Summer is more reflective; winter suggests bare or dry surfaces.

2.3.1. Composite Image vs RAW Image

A composite image using the median function in Google Earth Engine (GEE) is a common technique for reducing noise (like clouds) in satellite imagery by combining multiple images over a period. Raw image generally has issues with cloud and shadow, sensor noise etc. which generally bring uncertainties in surface reflectance.

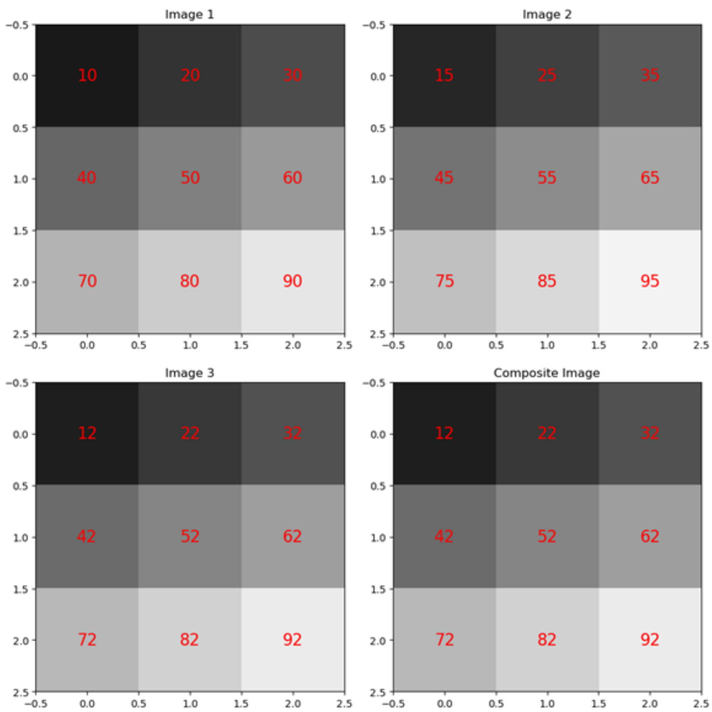


Figure 19. Illustration of creating satellite image composite based on median value

Table 6. Visual Comparison

Feature	Raw Image	Median Composite
Cloud Coverage	Often present	Mostly removed
Temporal Accuracy	Exact date	Time-averaged
Noise Level	Higher	Lower

3. Model Selection

This model leverages quantitative spectral indices like Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), and Bare Soil Index (BSI) providing quantitative, standardized metrics that remove ambiguity and interpretable outputs for land surface analysis. Spectral characteristics of BSI, NDVI, and SAVI provide a powerful way to understand the biophysical characteristics of the Earth's surface, especially in agricultural or semi-natural landscapes.

Table 7. Remote Sensing Indices

Index	Formula	Threshold	Purpose	Reference
BSI	((SWIR + RED) - (NIR + BLUE)) / ((SWIR + RED) + (NIR + BLUE))	> 0 (Bare soil)	Exposed soil detection	Mzid et al., 2021
NDVI	(NIR - RED) / (NIR + RED)	> 0.4 (Vegetation)	Vegetation health	Rouse et al., 1974
SAVI	((NIR - RED) / (NIR + RED + L)) × (1 + L)	> 0.4 (Vegetation)	Soil-adjusted vegetation	Huete, 1988
NDMI	(NIR - SWIR) / (NIR + SWIR)	> 0.4 (No stress)	Moisture in vegetation	Gao, 1996
NDSI	(GREEN - SWIR1) / (GREEN + SWIR1)	> 0.4 (Snow)	Snow detection	Hall & Riggs, 2011

- GREEN = Reflectance in the green band
- RED = Reflectance in the red band
- NIR (Near Infra-Red) = Reflectance in the near-infrared band
- SWIR (Short Wave Infra-Red) Reflectance in the short wave-infrared band.
- L = Soil brightness correction factor (commonly L = 0.5)

Below is the histogram distributions generated from Sentinel 2 Surface Reflectance and Harmonized composite imagery for winter season of 2024.

For example, in case of NDVI and SAVI

- A peak near 0 or slightly above: indicating bare soil or sparse vegetation
- A second peak or tail toward higher values: indicating moderate to dense vegetation

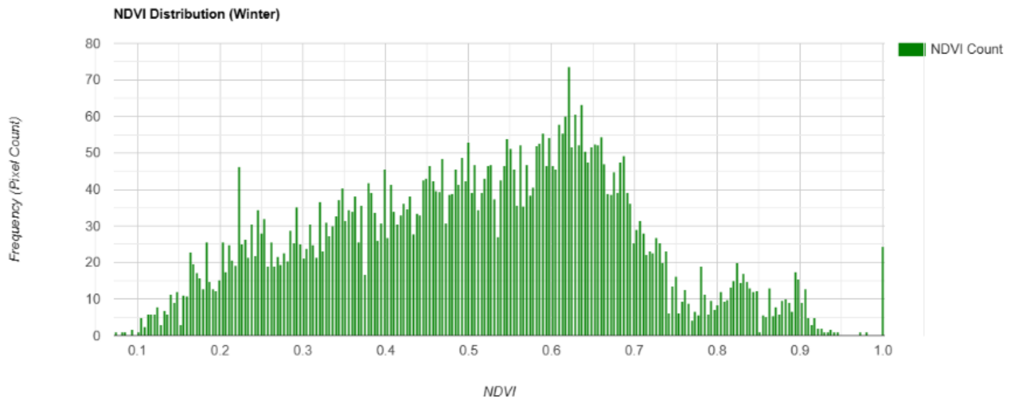


Figure 20. Distribution of NDVI values during winter (2024) in Browney

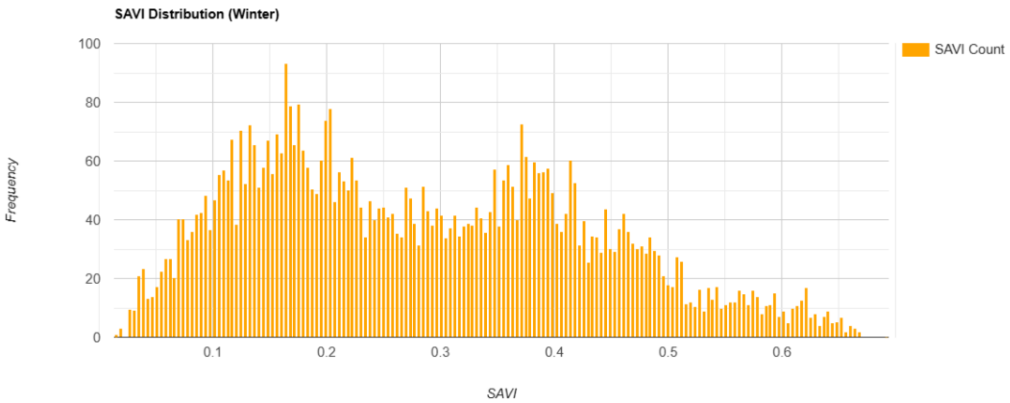


Figure 21. Distribution of SAVI values during winter (2024) in Browney

Whereas for BSI, a peak above 0 indicating bare soil which includes transition zones as well.

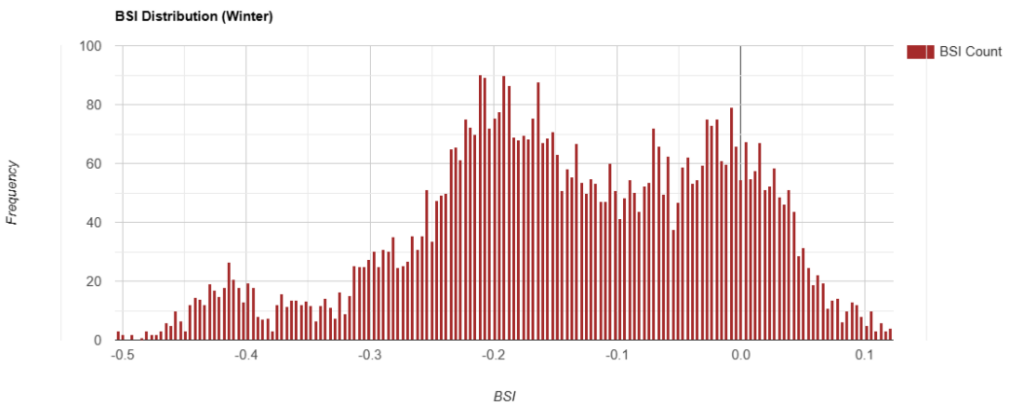


Figure 22. Distribution of BSI values during winter (2024) in Browney

Normalized Difference Vegetation Index (NDVI)

- High NDVI values (>0.6): Dense, healthy vegetation (e.g., forests, crops in peak growth).
- Moderate values (0.3 to 0.5): Sparse or stressed vegetation.
- Low or negative values (< 0.3): Bare soil, built-up areas, or water bodies.

Soil Adjusted Vegetation Index (SAVI)

- SAVI values follow a similar pattern to NDVI but are less sensitive to soil reflectance.
- In semi-arid or bare areas, SAVI provides a more stable vegetation signal than NDVI.

Table 8. Interpreting SAVI values

SAVI Range	Interpretation
< 0.2	Likely bare soil or very sparse vegetation
0.2 – 0.3	Transitional zone (sparse vegetation)
> 0.3	Increasing vegetation density

Why NDVI and SAVI alone are not enough?

Both NDVI and SAVI are Near Infra-Red (NIR) based vegetation indices, meaning they primarily measure the presence and vigor of vegetation by comparing the reflectance in the NIR and Red bands. However, bare soil can sometimes reflect moderate NIR, especially if it's dry or has light-coloured minerals.

Sparse vegetation or crop residues can confuse NDVI/SAVI, leading to false positives for vegetation. These indices are less sensitive to soil characteristics, such as moisture, texture, or organic content.

Bare Soil Index (BSI) as Key Index

With respect to some studies related to bare land mapping using multispectral images, Bare Soil Index (BSI) has achieved better accuracy. The Bare Soil Index was developed to better isolate bare soil by incorporating multiple spectral bands, not just NIR and Red.

Table 9. Understanding SWIR pattern for different land cover

Property	SWIR Response
Dry bare soil	High reflectance
Moist soil	Lower reflectance
Vegetation	Low reflectance (due to water content)
Water	Very low reflectance

Based on image interpretation and spectral characteristics, BSI threshold has been decided (Table 10).

Table 10. Interpreting BSI thresholds

BSI Value	Likely Surface Type
> 0	Bare soil, built-up, dry land
< 0	Vegetation, water, moist soil

This threshold is also useful because:

- A binary classification (bare vs. non-bare).
- Building a mask for bare soil detection.
- It is a simple rule that works with large-scale monitoring.

These indices are often used as inputs for machine learning models, classification algorithms, or threshold-based decision systems.

BSI outputs

A demonstration is shown in the figure below, where the top image represents farmlands in the Browney catchment (UK) using a False Colour Composite (FCC) of Sentinel-2 Surface Reflectance and Harmonized bands (near-infrared, red, and green) to enhance land cover visibility. The image below to FCC shows the extracted bare cropland areas, with amber indicating winter exposure and blue representing summer, highlighting seasonal variation in soil exposure.

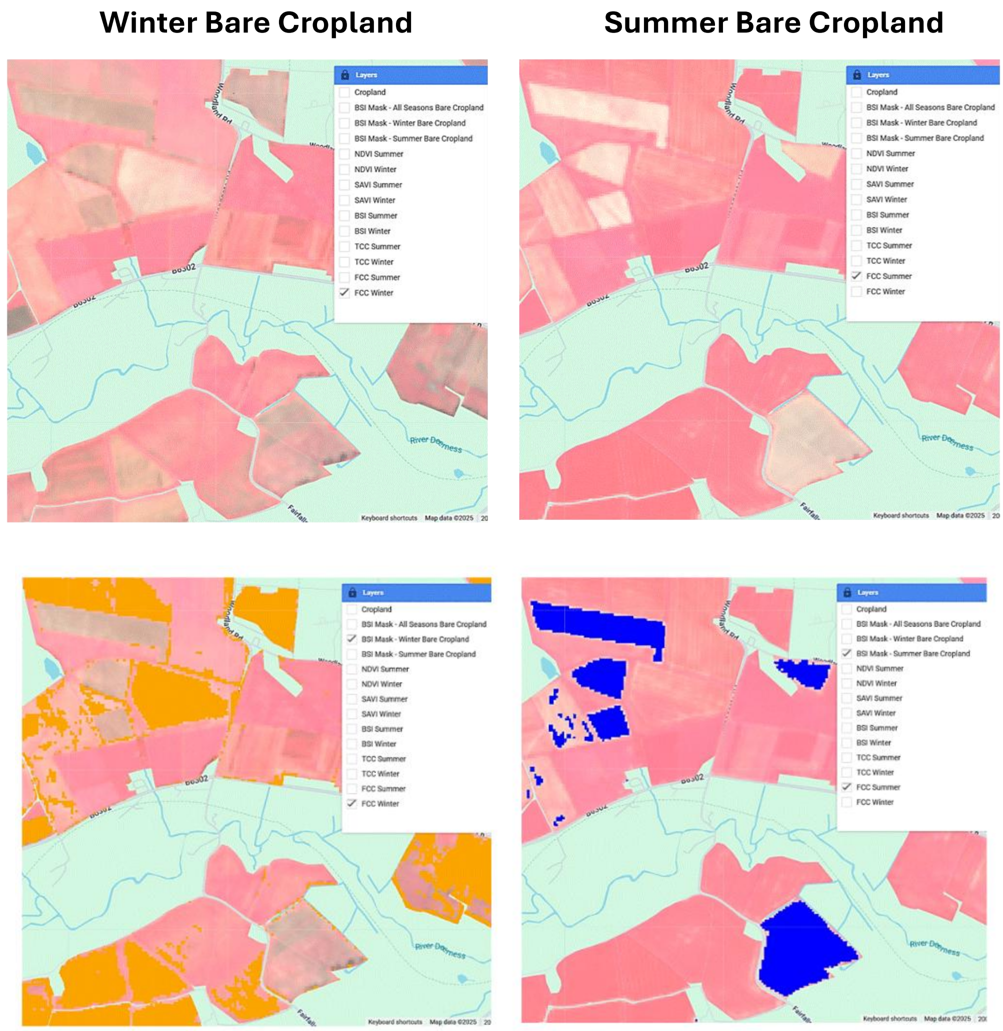


Figure 23. BSI based winter and summer bare cropland detection

3.1. Challenges and alternatives

Weather events (snow and rainfall) in the United Kingdom, can significantly alter surface reflectance captured by satellite sensors, often introducing anomalies or biases in spectral indices used for vegetation and soil analysis. To address this, the model incorporates a robust feature that utilizes spectral index time series to differentiate between bare soil and surfaces influenced by weather conditions. By examining the temporal patterns of multiple indices—NDVI, SAVI, BSI, NDMI, and NDSI—the model can accurately infer surface conditions with high sensitivity over time, ensuring more reliable analysis even under variable environmental conditions.

Snow

- High reflectance in visible and NIR bands: Snow is highly reflective, especially in the visible spectrum, which can artificially inflate NDVI values.
- NDVI (Normalized Difference Vegetation Index): Snow cover can mimic vegetation signals due to its brightness in NIR, leading to false positives in vegetation detection.
- SAVI (Soil Adjusted Vegetation Index): Snow can obscure soil and vegetation, reducing the reliability of SAVI, especially in sparse vegetation areas.
- BSI (Bare Soil Index): Snow cover reduces the visibility of bare soil, leading to underestimation of soil exposure.

Rain and Wet Surfaces

- Lower reflectance in NIR and SWIR bands: Wet surfaces absorb more NIR and SWIR radiation, which can depress NDVI and SAVI values.
- NDVI: Rain-soaked vegetation and soil reduce NIR reflectance, potentially underestimating vegetation health.
- SAVI: Similarly affected, especially in low vegetation cover areas where soil moisture dominates the signal.
- BSI: Wet soil appears darker, reducing the contrast between soil and vegetation, which can skew BSI values.

3.1.1. Weather Effects on Detection Accuracy

The January 2023 image (left) shows snow-covered terrain in the Browney catchment, which disrupted model output. A clearer image from February (right) resulted in more accurate detections.

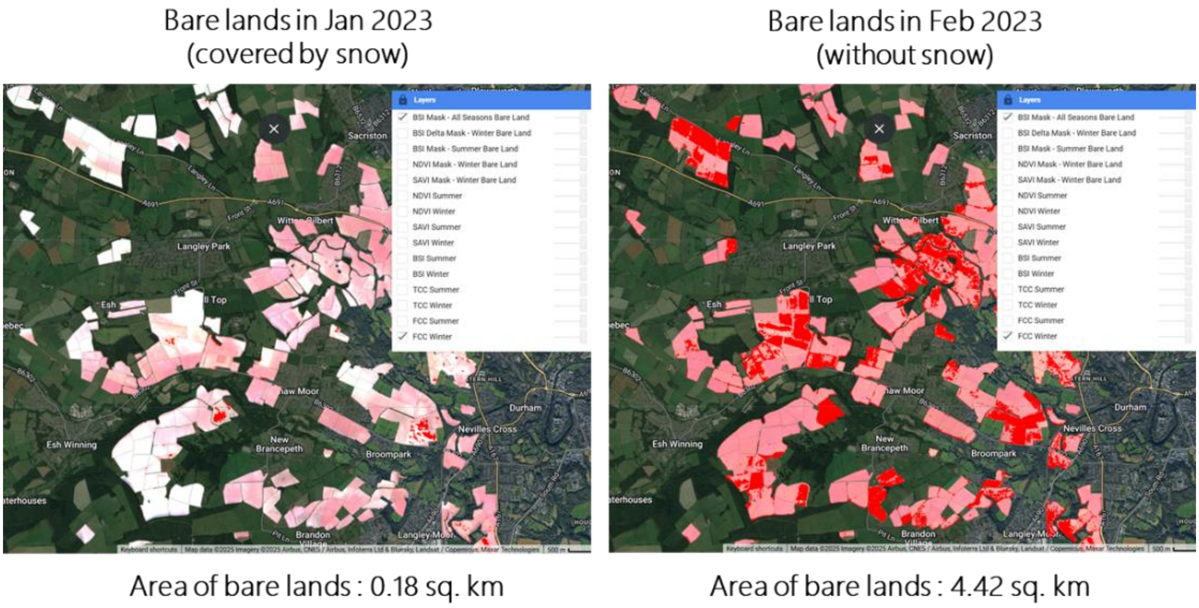


Figure 24. Weather effects on detection accuracy

3.1.2. Boosting Model Capability through Time Series Integration

Weather-related challenges are often unavoidable during satellite imaging, which can hinder the effective performance of index-based analysis. To address this, the current model incorporates a time series chart as an alternative method for accurately assessing surface conditions and selecting the optimal timeframe for model execution. In addition to supporting analysis during challenging weather conditions, this time series capability also enables continuous monitoring of cropland throughout the year. This year-round insight can significantly enhance crop monitoring by capturing seasonal trends, detecting anomalies, and supporting timely agricultural decision-making.

Additionally, the model integrates historical rainfall data from gauge stations. This helps identify rain events and supports the model when satellite imagery is unavailable or compromised for specific dates.

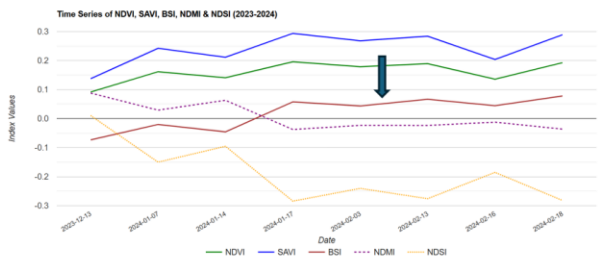
This model operates at the OpenStreetMap (OSM) land parcel level, enabling:

- Geospatial analysis of cropland across various timescales—annually, quarterly, monthly, or within custom date ranges.
- Independent CSV generation of all indices for different satellite image dates.
- Direct reference to actual osm_id values, allowing:
    - Monitoring crop rotation patterns
    - Precise geolocation tracking
    - Repeatable and consistent analysis
    - Seamless integration with other geospatial datasets

Examples

The graphs and tables below illustrate how weather conditions can significantly impact the model's performance. In ideal scenarios—such as clear, dry days—the model yields strong results, as indicated by positive BSI values alongside low NDVI and SAVI, and negative NDSI and NDMI, all of which suggest minimal vegetation and no snow or excess moisture. However, during or after adverse weather events like rain or snow, the model's accuracy can decline. This is reflected by a drop in BSI to negative values and spikes in NDSI and NDMI, signalling surface conditions that obscure accurate interpretation. These examples highlight the importance of selecting appropriate imagery windows to ensure reliable model outputs.

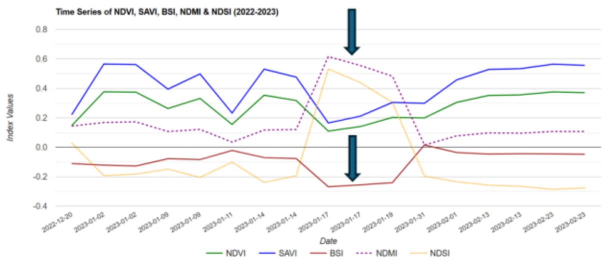
Baseline Surface Reflectance in Absence of Weather Interference



OPCAT_NAME	osm_id	Date	BSI	NDVI	SAVI	NDMI	NDSI
Browney	266300258	01-01-2024	0.029	0.172	0.258	-0.003	-0.25
Browney	424935308	01-01-2024	0.004	0.213	0.319	0.01	-0.24
Browney	424935345	01-01-2024	0.003	0.165	0.247	0.018	-0.2
Browney	910061571	01-01-2024	0.019	0.146	0.219	-0.027	-0.203
Browney	13654783	01-01-2024	0.001	0.142	0.213	0.006	-0.161

Figure 25. Baseline surface reflectance in absence of weather Interference

Surface Reflectance Under Weather Influence



OPCAT_NAME	osm_id	Date	BSI	NDVI	SAVI	NDMI	NDSI
Browney	537033729	17-01-2023	-0.29	0.234	0.351	0.564	0.407
Browney	537033731	17-01-2023	-0.156	-0.097	-0.146	0.453	0.498
Browney	424730741	19-01-2023	-0.255	0.107	0.161	0.498	0.431
Browney	424730832	19-01-2023	-0.26	0.136	0.204	0.53	0.432
Browney	424730843	19-01-2023	-0.226	0.178	0.267	0.423	0.273

Figure 26. Surface reflectance under weather Interference

To better understand the interrelationships among spectral indices under optimal atmospheric conditions, a correlation analysis was performed between the Bare Soil Index (BSI) and other commonly used indices e.g. NDVI, SAVI, NDSI and NDMI. Under ideal weather conditions, the Bare Soil Index (BSI) exhibits a strong negative correlation with other vegetation and moisture-related indices such as NDVI (Normalized Difference Vegetation Index), SAVI (Soil-Adjusted Vegetation Index), NDSI (Normalized Difference Snow Index), and NDMI (Normalized Difference Moisture Index). This inverse relationship suggests that as BSI values increase—indicating more exposed or bare soil—the values of the other indices tend to decrease, reflecting reduced vegetation cover, moisture content, or snow presence. This behaviour aligns with the physical interpretation of these indices: areas with high BSI typically lack vegetation and moisture, which are the primary contributors to higher values in NDVI, SAVI, NDSI, and NDMI.

Example

Table 11. Correlation between BSI and other remote sensing indices

Dec,23 – Feb,24	BSI vs NDMI	BSI vs NDVI	BSI vs SAVI	BSI vs NDSI
Pearson's Correlation	-0.9779	-0.9391	-0.9591	-0.9792
P-value	0.0413	0.0270	0.0270	0.0256

3.2. Validation (Phase 1)

To validate the accuracy of bare cropland detection using remote sensing, high-resolution historical imagery from Google Earth Pro was utilized as a ground truth reference. The validation process involved the following steps:

3.2.1. Reference Image Selection

Cloud-free, high-resolution satellite images for the Browney catchment were identified from Google Earth Pro's historical archive. Suitable imagery was found for March 2020 and March 2022, representing the winter season when bare cropland is most visible.

3.2.2. Ground Truth Point Identification

Previously clipped OpenStreetMap (OSM) farmland boundaries in KML format were imported into Google Earth Pro. Using these boundaries as a guide, 26 bare cropland locations were manually identified from the March 2022 imagery, and 16 locations from the March 2020 imagery.

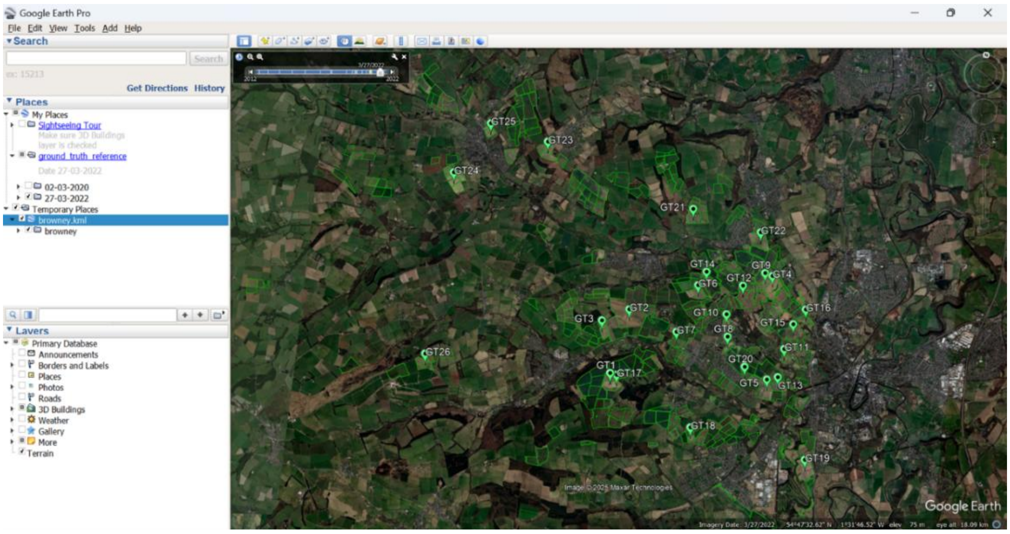


Figure 27. Ground Truth Reference Taken from Google Earth Pro (27-03-2022) (Source: Imagery © Google, Map data © 2022 Google. Source: Google Earth Pro, accessed [Mar, 2022])

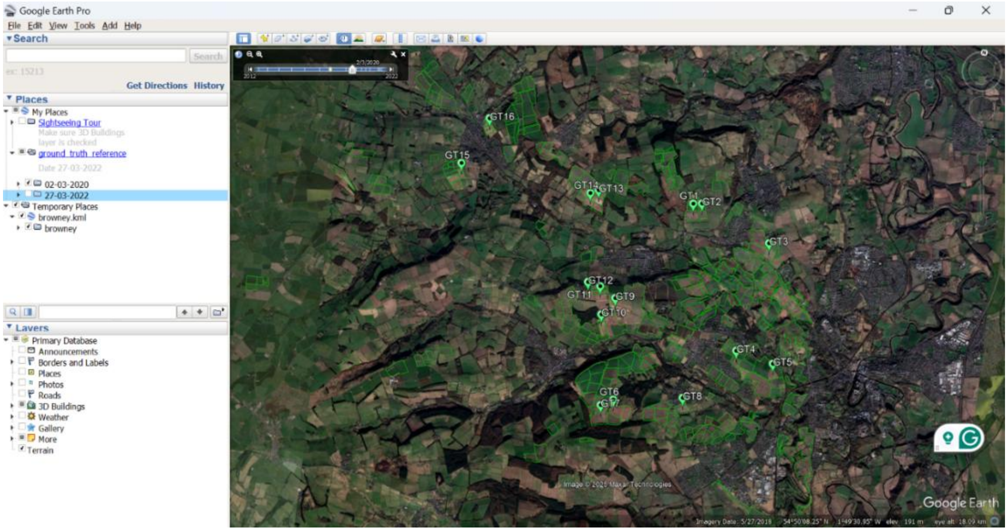


Figure 28. Ground Truth Reference Taken from Google Earth Pro (02-03-2020) (Source: Imagery © Google, Map data © 2020 Google. Source: Google Earth Pro, accessed [Mar, 2020])

3.2.3. Data Preparation and Import

The identified reference points were exported as CSV files and imported into Google Earth Engine (GEE). These points served as ground truth data for validation.

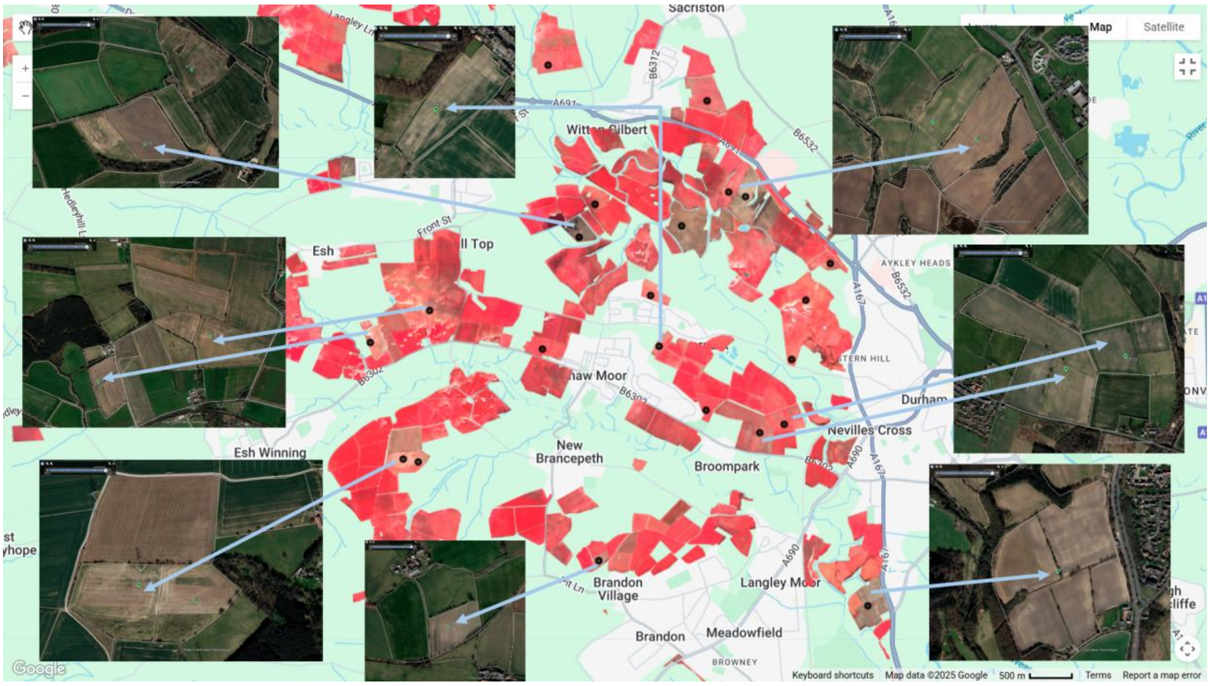


Figure 29. Ground truth (black points) are overlayed on GEE Sentinel 2 FCC imagery for same period (March 2022) (Source: Imagery © Google, Map data © 2022 Google. Source: Google Earth Pro, accessed [Mar, 2022])

Figure 30. Ground truth (black points) are overlayed on GEE Sentinel 2 FCC imagery for same period (March 2020) (Source: Imagery © Google, Map data © 2022 Google. Source: Google Earth Pro, accessed [Mar, 2020])

3.2.4. Overlay and Comparison

The reference points were overlaid on the corresponding bare cropland detection layers generated in GEE for both 2020 and 2022. A spatial comparison was performed to determine how many reference points fell within the detected bare cropland areas.

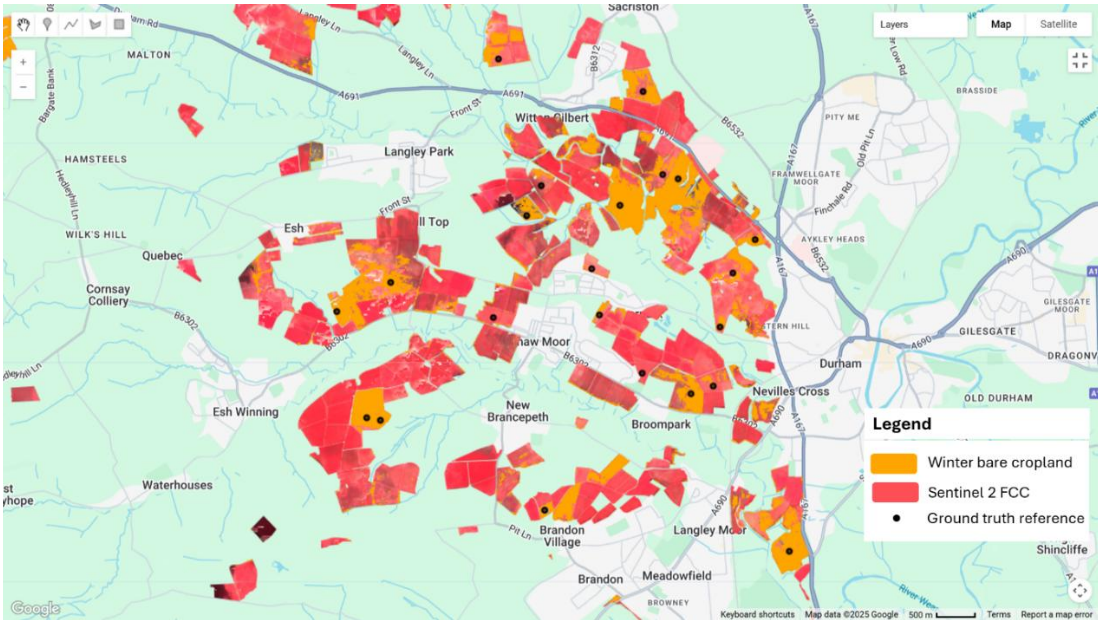


Figure 31. Overlaying ground truth data on bare cropland detection layer (2022)

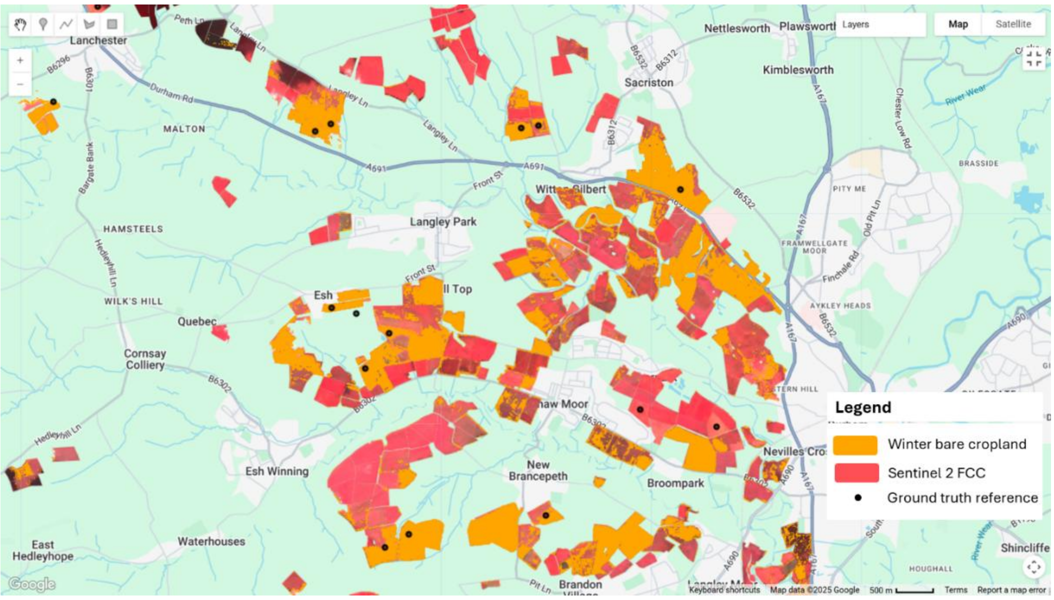


Figure 32. Overlaying ground truth data on bare cropland detection layer (2020)

3.2.5. Accuracy Assessment

Validation was conducted by calculating the proportion of reference points that correctly intersected with the detected bare cropland polygons. This provided a direct measure of the detection model's spatial accuracy.

Table 12. Accuracy assessment

	Bare land	**Non-bare land**	**Total**	**Overall Accuracy**
Winter Bare land	37	5	42	88.1%

3.3. Overall Model Workflow

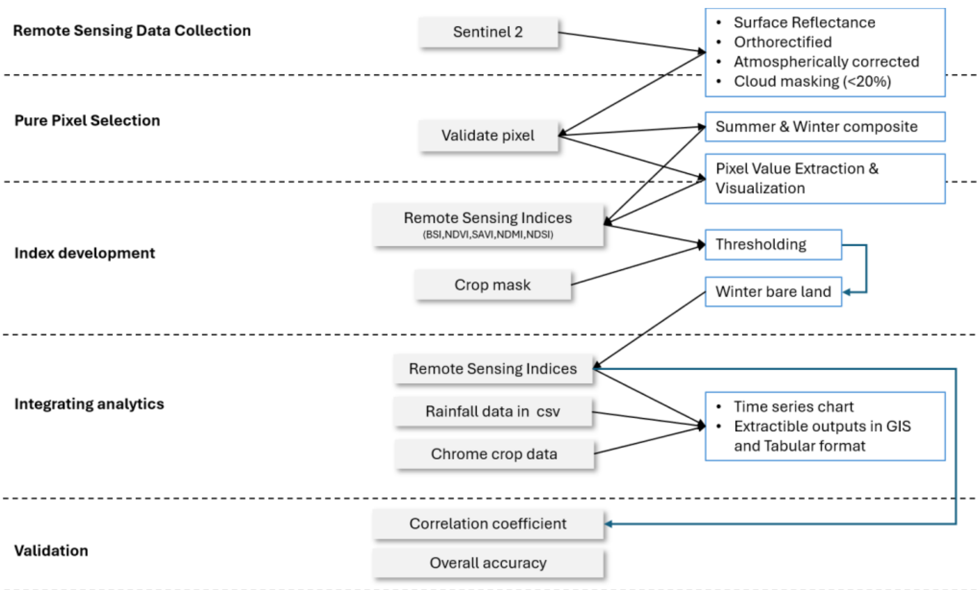


Figure 33. Overall methodology of the work

4. Validation using out-of-sample dataset (Phase 2)

To ensure the reliability of the bare cropland model, a carefully selected out-of-sample dataset was used for validation. This means the data chosen for testing was not part of the original dataset used to develop or train the model, allowing for an unbiased assessment of its performance on new, unseen conditions.

The validation dataset was specifically designed to test the model sensitivity to satellite sensor reflectance across different soil conditions. To achieve this, four major soil types - Chalky, Clayey, Peat, and Sandy were selected based on classifications from the British Geological Survey, ensuring geopedological diversity. To maintain agricultural relevance, farmland areas were extracted using OpenStreetMap (OSM) land use data, focusing on the farmland tag. A total of 19 UK catchments were chosen to represent a wide range of spatial and environmental variability, supporting robust validation of the model output across diverse landscapes.

Best practice to validate remote sensing outputs is using ground truth reference data for specific mapping periods - and sometimes calibration using ground spectroscopy. However, in the absence of *in-situ* ground reference data, we have leveraged Google Earth Pro's historical high-resolution imagery for validation. Visual clues were used to detect bare cropland and non-bare cropland in these images (see two examples in Figure 34), and corresponding coordinates were recorded. The manually identified areas of bare cropland and non-bare cropland were then compared to the result of the model analysis on the Google Earth Engine (GEE) images (Sentinel 2 images) for the same sites and for the same timeframe (varies between ~3 days to ~2 weeks) to assess consistency and accuracy of the model (Figure 35). This multi-layered validation approach ensures that the model is both reliable and adaptable across different soil textures and geographic contexts.

Figure 34. Examples of bare and non-bare cropland manually identified from Google Earth Pro's historical high-resolution imagery (Imagery © Google, Map data © 2022 Google. Source: Google Earth Pro, accessed [Mar, 2022])

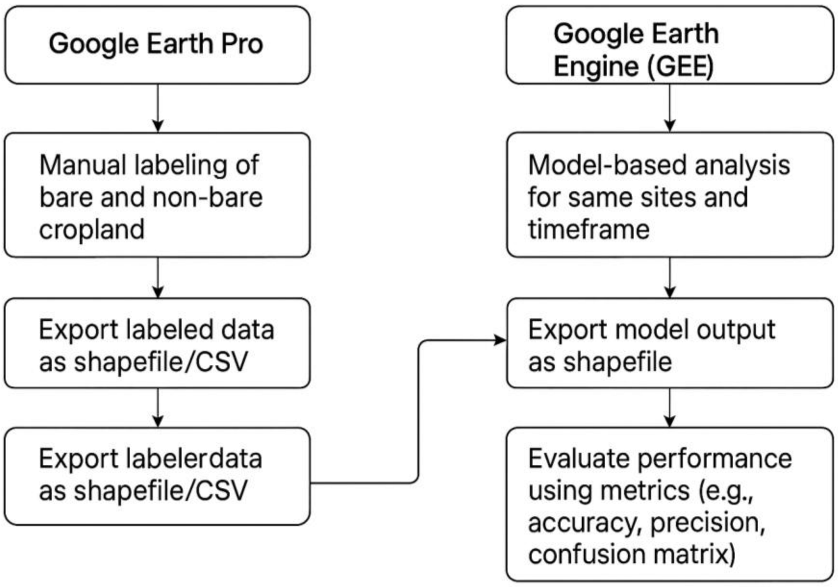


Figure 35. Flowchart illustration the steps taken in the validation methodology using the out-of-sample dataset

4.1. Catchment Selection Criteria

- **Soil Types Included**: Chalky, Clayey, Peat, Sandy (Figure 36)

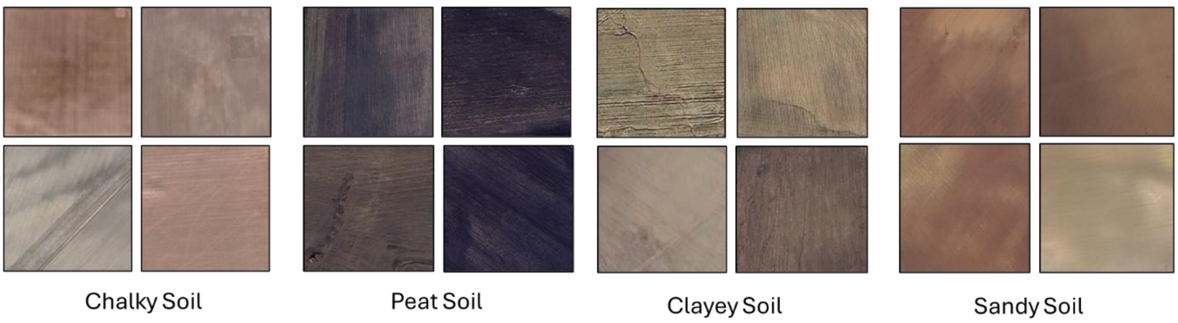


Figure 36. Example visual signatures of distinct bare soil categories in high-resolution imagery (Imagery © Google, Map data © 2022, 2023, 2024, 2025 Google. Source: Google Earth Pro, accessed [Mar, 2022, 2023, 2024, 2025])

- **Farmland Availability Criteria**: OSM land use data (tag: farmland)
- **Number of Catchments Selected**: 19
- **Catchment with major soil types:** British Geological Survey (BGS) soil type data is used for analysis (Figure 37).

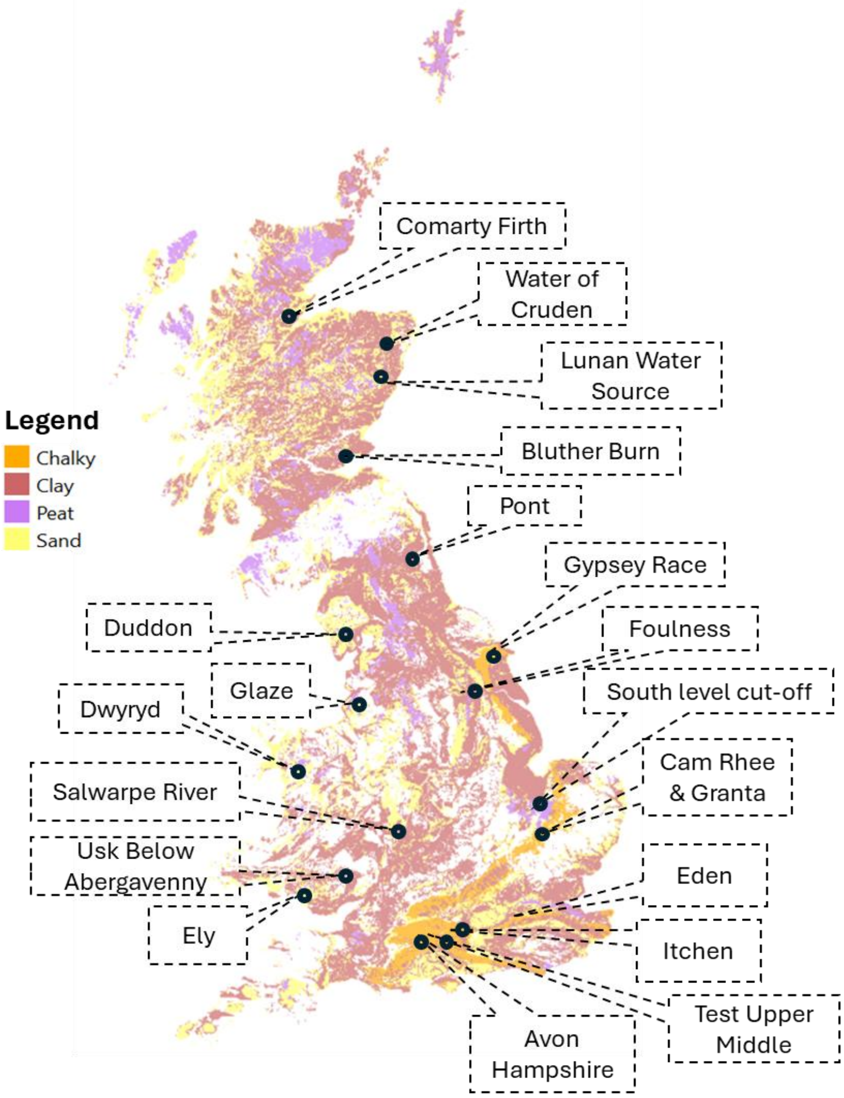
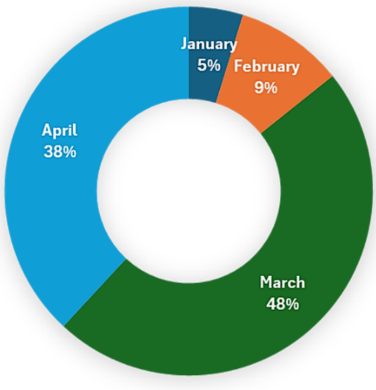


Figure 37. 38 Selected catchments of different soil types (source: BGS)

4.2. Ground Truth Reference Data Preparation

- **Source**: Google Earth Pro HR images and Sentinel-2 10m Multi Spectral Optical images.
- **Timeframe Alignment:** The validation dataset was developed based on the availability of high-resolution historical imagery in Google Earth Pro, ensuring adequate coverage across all selected catchments (and soil types). To align with typical periods of bare soil exposure, we focused on the UK winter season (December to February) between 2019 and 2025. However, due to limited image availability during winter months in certain catchments, we extended the validation period to include March and April where necessary (Figure 38).



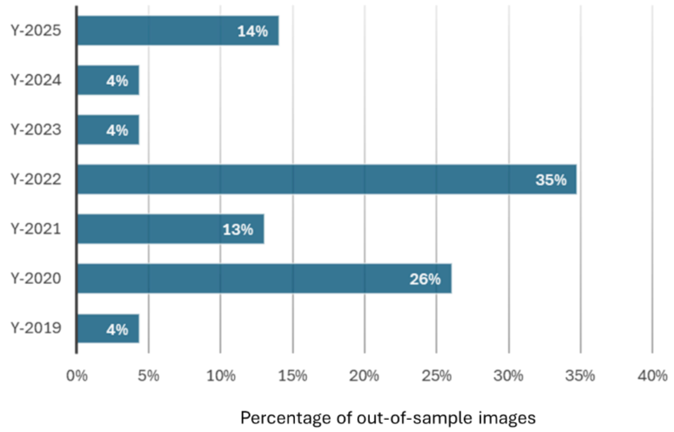


Figure 39. Selected timeframes for out of sample data validation

Sample Size: In the 19 selected catchments encompassing 36,479 farmland fields, 2,094 fields were manually labelled as bare cropland or non-bare cropland. The labelled fields represent 6% of total farmland fields (Table 13), with the majority of the samples from England (~58%) followed by Scotland (~30%) and Wales (~12%) (Table 14).

Table 13. Distribution of manually labelled farm fields across catchments

Name of the Catchments	No of Farmland Fields	No of samples	% of sample
AvonHampshire	1693	89	5%
Duddon	2162	150	7%
CamRheeandGranta	1950	241	12%
Foulness	4648	81	2%
Glaze	1739	52	3%
Itchen	1680	206	12%
GypseyRace	2083	127	6%
SalwarpeRiver	516	64	12%
Southlevelandcutoff	3460	111	3%
TestUpperandMiddle	2057	60	3%
Pont	710	42	6%
Eden	495	140	28%
BlutherBurn	2591	168	6%
CromartyFirth	1947	180	9%
LunanWaterSource	923	89	10%
WaterofCruden	1140	51	4%
Ely	725	65	9%
Dwyryd	930	80	9%
UskbelowAbergavenny	5030	98	2%
	36479	2094	6%

Table 14. Distribution of manually labelled farmland fields across countries in Britain

Sample Locations	No of catchments	Bare cropland	Non-bare cropland	TOTAL	Data Availability (GT reference and sentinel 2)
England	11	648	575	1223	Jan, Feb, Mar, Apr
Wales	3	88	155	243	Feb, Mar, Apr
Scotland	5	338	290	628	Mar, Apr
TOTAL	19	1074	1020	2094	

Reference Classes: These are the categories used to label the dataset:

- **Bare Cropland**: Agricultural fields that are not covered by vegetation — typically after harvest or during land preparation.
- **Non-Bare Cropland**: Fields that have visible vegetation cover — crops growing or residue left after harvest.

Performance Metrics Computed:

1. Confusion Matrix A table showing the counts of
   - True Positives (TP): Correctly predicted bare cropland
   - True Negatives (TN): Correctly predicted non-bare cropland
   - False Positives (FP): Non-bare cropland predicted as bare
   - False Negatives (FN): Bare cropland predicted as non-bare cropland
2. Overall Accuracy: Measures the proportion of correct predictions out of all predictions.
3. Precision: Indicates how many predicted bare cropland pixels were actually bare.
4. Recall: Measures how many actual bare cropland pixels were correctly identified
5. F1 Score: A harmonic mean of precision and recall — useful to show balance between classes

4.3. Performance Metrics at Catchment level

Table 15. Confusion matrix across selected catchments in Great Britain

Sl No.	Catchment	Country	Soil type		BSI Threshold >0		BSI Threshold >0.1	
					Predicted Bare	Predicted Non-Bare	Predicted Bare	Predicted Non-Bare
1	Avon Hampshire	England	Chalky	Actual Bare	32	1	30	3
				Actual Non-Bare	14	42	1	55
2	Cam Rhee and Granta	England	Chalky	Actual Bare	127	2	119	10
				Actual Non-Bare	14	98	3	109
3	Duddon	England	Sandy	Actual Bare	39	5	33	11
				Actual Non-Bare	3	103	0	106
4	Foulness	England	Sandy	Actual Bare	33	2	33	2
				Actual Non-Bare	9	37	3	43
5	Glaze	England	Peat	Actual Bare	11	8	8	11
				Actual Non-Bare	2	31	1	32
6	Gypsey Race	England	Chalky	Actual Bare	103	2	98	7
				Actual Non-Bare	0	22	0	22
7	Itchen	England	Chalky	Actual Bare	140	3	131	12
				Actual Non-Bare	1	62	0	63
8	Salwarpe River	England	Clay	Actual Bare	20	6	12	14
				Actual Non-Bare	2	36	1	37
9	South level cutoff	England	Peat	Actual Bare	58	1	56	3
				Actual Non-Bare	0	52	0	52
10	Test Upper Middle	England	Chalky	Actual Bare	24	3	20	7
				Actual Non-Bare	2	31	1	32
11	Pont	England	Clay	Actual Bare	25	3	25	3
				Actual Non-Bare	4	10	1	13
12	Dwyryd	Wales	Sandy	Actual Bare	12	6	9	9
				Actual Non-Bare	0	62	0	62
13	Usk Below Abergavenny	Wales	Clay	Actual Bare	34	5	29	10
				Actual Non-Bare	1	58	0	59
14	Ely	Wales	Clay	Actual Bare	26	5	18	13
				Actual Non-Bare	2	32	0	34
15	Eden	Scotland	Sandy	Actual Bare	56	3	51	8
				Actual Non-Bare	3	78	0	81
16	Bluther burn	Scotland	Clay	Actual Bare	75	6	68	13
				Actual Non-Bare	2	85	0	87
17	Water of Cruden	Scotland	Sandy	Actual Bare	34	0	33	1
				Actual Non-Bare	0	17	0	17
18	Lulnan Water Source	Scotland	Clay	Actual Bare	55	4	52	7
				Actual Non-Bare	1	29	0	30
19	Cromarty Firth	Scotland	Clay	Actual Bare	105	0	100	5
				Actual Non-Bare	4	71	0	75

Table 16. Performance metrics across selected catchments in UK

Sl. No	Catchement	Country	Soil type	BSI Threshold > 0				BSI Threshold > 0.1			
				Accuracy	Precision	Recall	F1 Score	Accuracy	Precision	Recall	F1 Score
1	Avon Hampshire	England	Chaky Soil	0.83	0.97	0.7	0.81	0.96	0.91	0.97	0.94
2	Cam Rhee and Granta	England	Chaky Soil	0.93	0.9	0.98	0.94	0.95	0.98	0.92	0.95
3	Duddon	England	Sandy Soil	0.95	0.93	0.89	0.91	0.93	1	0.75	0.86
4	Foulness	England	Sandy Soil	0.86	0.94	0.79	0.86	0.94	0.94	0.92	0.93
5	Glaze	England	Peat Soil	0.81	0.85	0.58	0.69	0.77	0.89	0.42	0.57
6	Gypsey Race	England	Chaky Soil	0.98	1	0.98	0.99	0.94	1	0.93	0.97
7	Itchen	England	Chaky Soil	0.98	0.99	0.98	0.99	0.94	1	0.92	0.96
8	Salwarpe River	England	Clay Soil	0.88	0.91	0.77	0.83	0.77	0.92	0.46	0.62
9	South level cutoff	England	Peat Soil	0.99	1	0.98	0.99	0.97	1	0.95	0.97
10	Test Upper Middle	England	Chaky Soil	0.92	0.92	0.89	0.91	0.87	0.95	0.74	0.83
11	Pont	England	Clay Soil	0.83	0.86	0.89	0.88	0.9	0.96	0.89	0.93
12	Eden	Scotland	Sandy Soil	0.96	0.95	0.95	0.95	0.94	0.86	1	0.93
13	Bluther burn	Scotland	Clay Soil	0.95	0.97	0.93	0.95	0.92	0.87	1	0.93
14	Water of Cruden	Scotland	Sandy Soil	1	1	1	1	0.75	0.66	1	0.8
15	Lulnan Water Source	Scotland	Clay Soil	0.94	0.98	0.93	0.96	0.92	1	0.88	0.94
16	Cromarty Firth	Scotland	Clay Soil	0.98	0.96	1	0.98	0.97	1	0.95	0.98
17	Dwyryd	Wales	Sandy Soil	0.93	1	0.67	0.8	0.89	1	0.5	0.67
18	Usk Below Abergavenny	Wales	Clay Soil	0.94	0.97	0.87	0.92	0.9	1	0.74	0.85
19	Ely	Wales	Clay Soil	0.89	0.93	0.84	0.88	0.8	1	0.58	0.73

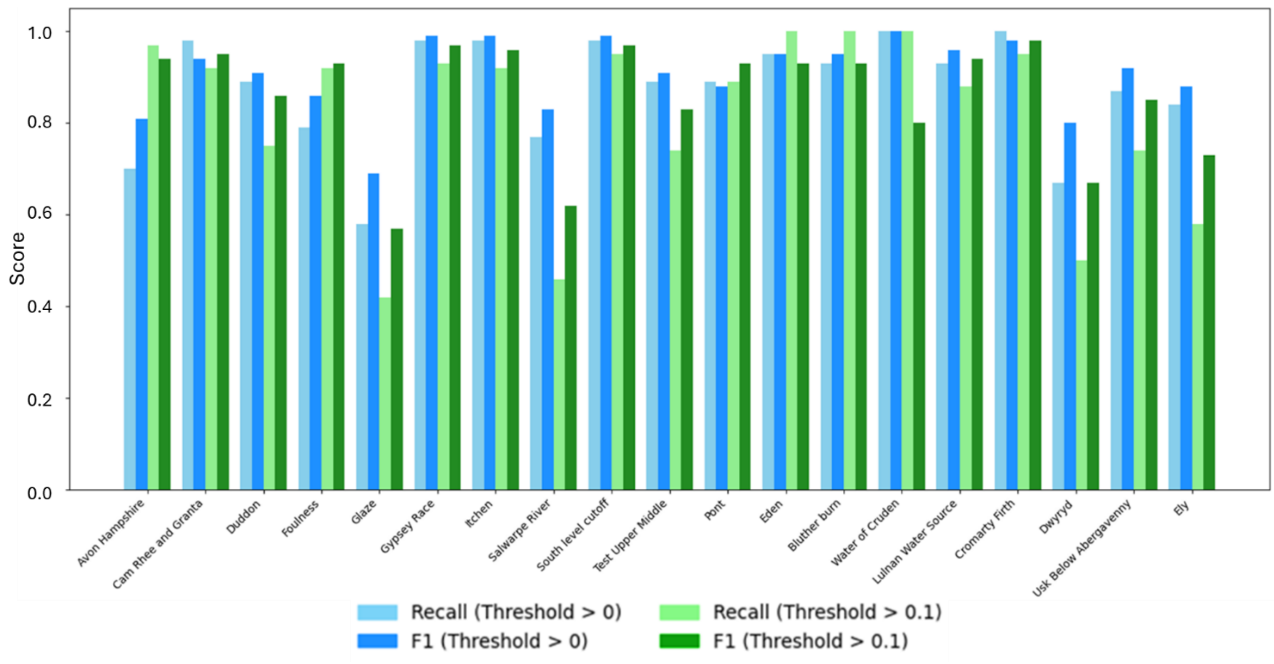


Figure 40. Recall and F1 score comparison across catchments

4.3.1. Catchment-Level Insights

High Performing Catchments (Consistent Across Thresholds)

As per the table 15, Table 16 and Figure 39

- Gypsey Race, Itchen, and South Level Cutoff show high recall and F1 scores across both BSI thresholds (>0 & >0.1), suggesting strong model confidence and balance.
- Cam Rhee and Granta also maintains high performance, with minimal drop in recall at the higher threshold.

Catchments Sensitive to Threshold Change

- Glaze and Dwyryd show a significant drop in recall at Threshold > 0.1, indicating that the model becomes more conservative and misses more true positives.
- Salwarpe River and Ely also show reduced recall and F1 scores at the higher threshold, suggesting these areas may require threshold tuning or additional features.
- However, we cannot conclusively determine why certain catchments perform less effectively, as model sensitivity may be influenced by complex interactions between land cover, soil type, topography, and seasonal variability.

4.4. Performance Metrics and Threshold Sensitivity to Soil Category

Table 17. Confusion matrix across selected BGS Soil types in UK

Soil type		BSI Threshold >0			BSI Threshold >0.1		
		Predicted Bare	Predicted Non-Bare	Total	Predicted Bare	Predicted Non-Bare	Total
Chalky	Actual Bare	97%	3%	437	91%	9%	437
	Actual Non-Bare	11%	89%	286	2%	98%	286
Clayey	Actual Bare	92%	8%	369	82%	18%	369
	Actual Non-Bare	5%	95%	337	1%	99%	337
Peat	Actual Bare	88%	12%	78	82%	18%	78
	Actual Non-Bare	2%	98%	85	1%	99%	85
Sandy	Actual Bare	92%	8%	190	84%	16%	190
	Actual Non-Bare	5%	95%	312	1%	99%	312

Table 18. Performance metrics across selected BGS Soil types in UK

Soil type	BSI Threshold > 0				BSI Threshold > 0.1			
	Accuracy	Precision	Recall	F1 Score	Accuracy	Precision	Recall	F1 Score
Chalky	0.94	0.93	0.97	0.95	0.94	0.99	0.91	0.95
Clayey	0.94	0.96	0.92	0.94	0.91	0.99	0.82	0.9
Peat	0.93	0.97	0.88	0.93	0.91	0.86	0.99	0.92
Sandy	0.94	0.92	0.92	0.92	0.87	0.98	0.71	0.83

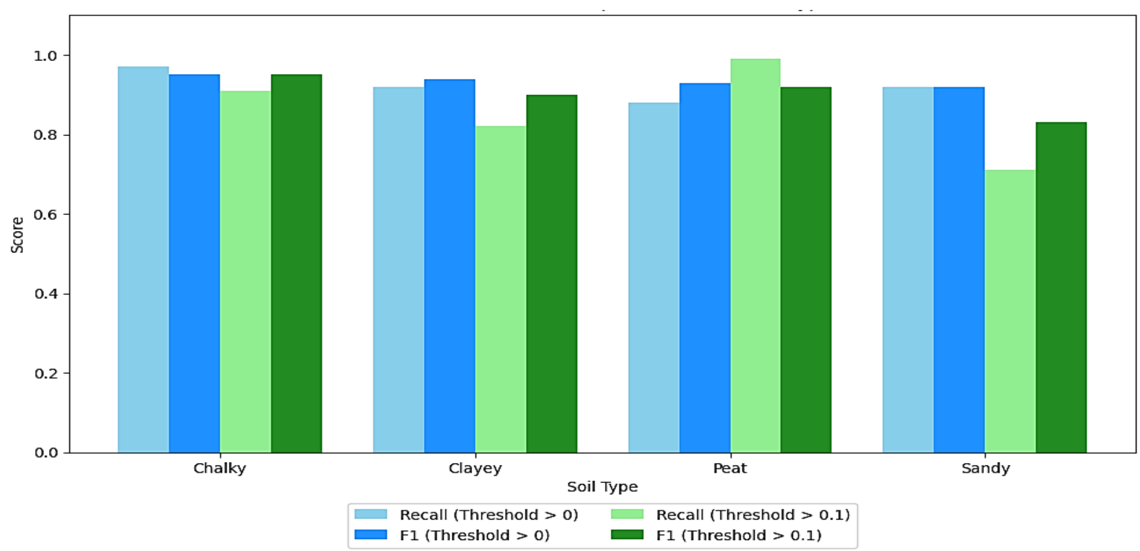


Figure 41. Recall and F1 score comparison across different soil types

4.4.1. Key Insights

As per the Table 15, Table 16 and Figure 40

Chalky Soil

- Accuracy consistently high across all metrics and thresholds.
- Minimal change between thresholds, indicating stable model performance.

Clayey Soil

- Slight drop in recall and F1 score at Threshold > 0.1.
- Precision remains very high, suggesting fewer false positives.

Peat Soil

- Recall improves significantly at Threshold > 0.1 (from 0.88 to 0.99).
- Precision drops, indicating more false positives at the higher threshold.

Sandy Soil

- Most sensitive to BSI threshold change.
- Recall drops from 0.92 to 0.71, and F1 score from 0.92 to 0.83.
- Indicates potential need for threshold tuning or additional features.

4.5. Overall Performance Summary

The Bare cropland model demonstrated strong and consistent performance across different regions and soil types. Validation was conducted using two BSI threshold levels greater than 0 and greater than 0.1 to assess sensitivity and robustness.

At threshold greater than 0, the model achieved:

High overall accuracy, precision and recall (0.94), indicating reliable detection of bare soil areas with minimal false positives or negatives (Table 19).

Table 19. Overall Performance metrics and threshold sensitivity

BSI Threshold>0

Metric	Overall	Chalky Soil	Clayey Soil	Peat Soil	Sandy Soil
Accuracy	0.94	0.94	0.94	0.93	0.94
Precision	0.94	0.93	0.96	0.97	0.92
Recall	0.94	0.97	0.92	0.88	0.92
F1-Score	0.94	0.95	0.94	0.93	0.92

BSI Threshold>0.1

Metric	Overall	Chalky Soil	Clayey Soil	Peat Soil	Sandy Soil
Accuracy	0.91	0.94	0.91	0.91	0.87
Precision	0.99	0.99	0.99	0.86	0.98
Recall	0.84	0.91	0.82	0.99	0.71
F1-Score	0.91	0.95	0.9	0.92	0.83

F1-Score remained balanced across all soil types, with Chalky Soil showing the highest recall (0.97).

At threshold greater than 0.1, the model maintained high precision (0.99 overall), but recall dropped to 0.84, reflecting a more conservative detection approach. This trade-off resulted in slightly lower F1-Scores, especially in Sandy Soil (0.83) areas, where image availability and seasonal variability may have influenced performance.

The model's sensitivity to surface moisture and snow cover, as documented in the model specification, is an important consideration. These environmental factors can influence spectral reflectance and may lead to misclassification, particularly during winter months or in areas with persistent cloud cover or snow.

Soil specific considerations:

Chalky Soil consistently showed strong performance across all metrics.

Peat Soil had the highest recall at threshold >0.1 (0.99), suggesting good model sensitivity in organic-rich areas.

Sandy Soil showed slightly lower recall and F1-scores, indicating potential challenges in spectral differentiation.

5. Conclusions

5.1. Key Findings

- Effective Discrimination: BSI effectively distinguishes bare cropland from vegetated and non-agricultural surfaces due to its sensitivity to soil reflectance in visible and shortwave infrared bands; a well-calibrated threshold of BSI enables automated detection of bare cropland areas from satellite imagery across seasons.
- An additional benefit of the model is the ability to generate timeseries data of bare and non-bare cropland across years at OSM land parcel level.
- Identifying bare cropland can enhance understanding of erosion risk within a catchment, especially when combined with factors like soil type, slope, and rainfall intensity.

5.2. Strengths

- Simplicity: BSI is computationally simple and can be applied to a wide range of satellite data (e.g., Landsat, Sentinel-2 etc.).
- High Sensitivity to Bare Soil: It captures soil brightness and dryness effectively, making it ideal for detecting exposed soil surfaces.
- Scalability: Suitable for large-scale monitoring by regulators like the Environment Agency. Google Earth Engine (GEE) incurs low computational cost as well because it leverages cloud-based parallel processing and free access to global datasets, eliminating the need for expensive hardware, software licenses, or data

storage — making it highly cost-effective for both individuals and commercial users.

- Temporal monitoring enables time-series analysis of bare soil across multiple land parcels, which can be compared over time and correlated with runoff, erosion, or nutrient leaching. This approach helps improve understanding of erosion risk during bare soil periods.
- Flexibility: The model offers a highly adaptable approach—thresholds can be adjusted, new indices can be integrated, and existing ones can be modified. This flexibility makes the model suitable for reuse and enhances its applicability across broader scales.

5.3. Limitations

- Soil Moisture and Snow Influence: Wet soils can alter reflectance, leading to underestimation of bare areas.
- Threshold Sensitivity: Fixed thresholds may not generalise well across regions with different soil types or land management practices.
- OSM farmland data coverage varies across regions in UK, but alternative parcel level datasets can be integrated to support model execution.
- The CROME crop type dataset is available only for England and may not be available for the most recent years, which may limit its applicability for current assessments. However, alternative crop classification datasets can be integrated to support model execution.
- Model inputs consist of multiple GIS datasets that must be uploaded as Google Earth Engine (GEE) assets in a valid and consistent coordinate reference system (CRS). GEE does not automatically convert coordinate systems, so users must ensure all layers are correctly aligned before analysis to avoid spatial mismatches and ensure accurate results.

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