Land Change Detection using Multi-Band Raster Data from Sentinel-2 Remote Sensing Images with XGBoost Classifier

Abstract: The growing demand for precise and large-scale means of tracking land use and land cover changes has led to the integration of remote sensing information with sophisticated machine learning algorithms. This study aims to use Sentinel-2 multi-band satellite images combined with the eXtreme Gradient Boosting (XGBoost) algorithm to detect and map land transformations over time. In a supervised classification pipeline, the model is trained against temporal raster data sets to identify high-precision spatial variations. Color-coded output maps are created to visually represent these changes to facilitate interpretability and communication with nontechnical audiences. The methodology provides an efficient and stable alternative to conventional classification techniques, particularly for applications requiring computational feasibility and actionable knowledge. The experimental results demonstrate the potential of this model to effectively detect land changes including urban growth, vegetation loss, and hydrological changes, thus supporting sustainable planning and environmental management.

Keywords: Sentinel-2, XGBoost, Land Change Detection, Remote Sensing, Multi-band Raster Data, Supervised classification.

1 Introduction

Land use/land cover (LULC) classification is a central tool in remote sensing, providing the essential information concerning environmental processes and ecological change. As frequent deforestation, accelerated urban growth, and varying climatic cycles become more predominant, there emerges an urgent necessity for effective systems that can document terrestrial changes economically and precisely. Remote sensing methods—specifically the Sentinel-2 satellite mission—have gained unreplaceability by offering global high-resolution multi-spectral multi-temporal images.

Despite the wealth of data in such datasets, the amount and complexity of satellite imagery create daunting challenges as far as analyzing and interpreting data is concerned. Conventional classification methods tend to falter due to the excessive dimensionality and noise in remote sensing data and thus are inadequate for large-scale real-time situations. This prompted a shift of paradigm towards coupling machine learning algorithms that provide greater performance and scalability.

This article proposes a new method using the extreme Gradient Boosting (XGBoost) algorithm for supervised Sentinel-2 image classification to identify LULC changes in various time periods. XGBoost is specifically well equipped to perform this function because it is highly robust, efficient, and able to manage structured high-dimensional data with less tuning required. The approach prioritizes not only the accuracy of classification but also visual interpretability, producing results in terms of color-coded maps that render spatial transformations easily understandable to analysts, planners, and policymakers. By bringing together open-access satellite data and an easy-to-use but robust machine learning model, this study presents a practical approach to real-world land change monitoring and environmental management.

1.1 Objective

Our primary aim in this study is to develop and evaluate a robust, interpretable, and computationally light system for identifying land cover changes from multi-band Sentinel-2 imagery and the XGBoost classifier. The research seeks to close the gap between data-rich remote sensing technologies and available decision-support tools by allowing stakeholders to visually examine land transformations through well-defined, color-coded output maps. Through the combination of machine learning with open-source satellite imagery, the study also aims to democratize access to sophisticated spatial analysis methods for urban planners, environmental analysts, and policy makers.

1.2 Problem Statement

With the exponential expansion of Earth observation data, one of the essential challenges in environmental and urban analytics is the effective classification and interpretation of high-dimensional raster datasets. Conventional land classification models tend to miss the complexity of landscape changes at various temporal scales. Moreover, they need to be heavily domain-specifically tuned and can produce outputs that are hard to interpret for policymakers and end-users. Even with the existence of powerful algorithms, there is a significant gap in applying these models to real-world applications in a scalable and interpretable way. This research fills the gap in accurately detecting and reporting land cover changes by combining Sentinel-2 data and the XGBoost classifier while reporting results in an understandable visual form.

2 Literature Review

Classifying land use and land cover (LULC) is essential for spatial analysis, especially in urban planning and development, environmental sustainability and monitoring, and disaster management. With the growing availability of satellite data, particularly from the Sentinel-2 mission and computational resources, researchers have increasingly shifted from traditional classification approaches to more advanced machine learning (ML) techniques. These approaches are particularly effective in handling high-dimensional, multi-spectral satellite data and have demonstrated significant improvements in both classification accuracy, temporal analysis, interpretability and processing efficiency. This renders it particularly well-suited for land transformation tracking and cross-year comparison, which closely corresponds to our project's application of Sentinel-2 data for change detection.

2.1 ML for Land change detection and the Role of XGBoost

Traditional classification methods, such as maximum likelihood and minimum distance classifiers, often struggle with complex landscapes and high-dimensional satellite data. To overcome these limitations, machine learning (ML) techniques have been widely adopted. Machine learning and deep learning methods are the prime movers for LULC classification improvement. Random Forest, logistic regression and specifically gradient boosting techniques like XGBoost are popular due to their interpretability and high accuracy on formalized satellite data. Such Algorithms consistently outperform traditional methods due to their robustness, scalability, and ability to handle non-linear relationships in data (5)(8).

XGBoost, in particular, has emerged as a preferred model for structured remote sensing data due to its efficiency and performance in classification operations on various timeframes. In more intricate classification tasks with high-dimensional data or non-linear boundaries between classes, deep learning models like CNNs, R-CNNs, and U-Nets have demonstrated promising performance (1)(3)(7). Yet, in certain environments due to computational limitation and explainability needs, models like XGBoost tend to provide a real-world compromise (5)(6). It gained widespread attention for their accuracy, interpretability, and scalability. XGBoost is particularly well-suited for structured tabular datasets such as multi-spectral remote sensing inputs. Its capability to handle missing data, class imbalance, and high-dimensional features makes it ideal for land cover classification tasks. In comparative assessments, XGBoost often rivals when computational resources or large annotated datasets are limited.

2.2 Visual Interpretation and Color-Mapped Outputs

In depicting classification results, color-mapped LULC maps offer a convenient vehicle for communicating spatial change. Research stresses the need for interpretability and usability of classified maps, particularly where outcomes are to inform policy or assist land-use planning (4). Color-coded visualizations enhance the interpretability of classification results by allowing users to quickly grasp spatial distribution and temporal changes. These visual tools play a crucial role in communicating findings to non-expert stakeholders, including policy makers and urban planners. Studies like those by Nomura and Mitchard (2018) which uses RF classifiers with Sentinel-2 imagery to map plantations in heterogeneous forested regions, showing how visual interpretation can aid in monitoring small-scale changes and emphasized how RGB-based classification maps derived from Sentinel-2 imagery can effectively differentiate land classes such as plantations, wetlands, and built-up areas—even in complex landscapes(2).

Our method addresses this by producing color-mapped results that enable easy comparison over time, accommodating expert analysis as well as stakeholder communication. Change detection maps that use intuitive color schemes (e.g., green for additions, red for losses, and gray for unchanged areas) have proven especially valuable for visual storytelling and impact communication.

In general, the literature reviewed validates our study's methodological decisions: the utilization of Sentinel-2 imagery for temporal land transformation identification, the use of XGBoost for scalable classification, and the creation of interpretable, color-coded visualizations to facilitate end-user interaction. This approach is part of a larger research trend that aims for accessible, accurate, and interpretable LULC mapping.

3 Materials and Research Methods

This study leverages a robust combination of remote-sensing satellite imagery, machine learning classification, and color-coded visualization techniques to assess land transformation over time. This approach relies on Sentinel-2 multi-band raster imagery combined with the powerful XGBoost classifier to perform supervised pixel-wise classification, followed by visual and quantitative analysis of land cover change.

3.1 Data Source and Preprocessing

Specifically, high-resolution Sentinel-2 satellite imagery from two time periods was selected to enable temporal comparison(9). From the full set of Sentinel-2's 13 bands, 11 were retained for analysis—excluding Band 10 due to its low spatial resolution and limited relevance to terrestrial applications. These bands cover a range of spectral domains, including visible lights, near-infrared (NIR), and shortwave infrared (SWIR) bands of the electromagnetic spectrum, all of which play a crucial role for distinguishing between different land cover type and, offering rich spectral signatures for accurate LULC discrimination.

Preprocessing using Python-based geospatial libraries. Each spectral band was loaded and resampled to ensure uniform spatial resolution across bands using bilinear interpolation. These were then stacked into three-dimensional arrays representing the full spectral cube of the study area. The training data—sourced from manually labelled pixels—was divided into two CSV datasets corresponding to the historical and contemporary timeframes. And label encoder maps categorical land cover labels to integers for compatibility with the classifier. Each dataset contained numerical reflectance values for the 11 bands alongside categorical class labels representing LULC types including water, forest, soil and built-up areas.

3.2 Evaluation of Model and Tool Selection

The selection of data sources, machine learning models, and geospatial tools in this research was informed by a deliberate focus on balancing classification accuracy, computational efficiency, and accessibility. Sentinel-2 imagery was chosen due to its free availability, global coverage, and comprehensive high-spectral resolution with bands.

For classification, the XGBoost algorithm was selected based on its strong performance with structured remote sensing data, its tolerance to missing values, and its scalability to large datasets. Compared to other classifiers such as Random Forest or logistic regression, XGBoost offered faster training times and greater interpretability through built-in feature importance metrics. In contrast, XGBoost provided a robust middle ground—delivering high classification accuracy with minimal tuning and moderate training samples.

Separate XGBoost models were trained using supervised learning—one for each temporal snapshot (past and current). Each model was trained using tabular training data that included 11-band spectral values which extracted from each pixel using open-source technology-QGIS and corresponding labeled classes, and predictions were generated for the full satellite image stacks. The output predictions were decoded back to their original class labels and visualized by mapping each class to a unique RGB color for spatial interpretation and class legends. Finally, change detection was performed by comparing the classified outputs from both timeframes on a pixel-by-pixel basis, generating visual difference maps that highlighted spatial shifts in land cover over time.

The software ecosystem used in this study further enhanced its replicability and openness. Python was employed as the primary programming language due to its extensive library support for geospatial analysis (rasterio, numpy, pandas, scikit-learn) and machine learning. Together, these decisions reflect a strategic integration of data, algorithms, and tools aimed at producing scalable, interpretable, and actionable land transformation insights.

3.3 Evaluation of Artifacts

The primary artifacts generated from this research included classified land cover maps for two distinct time periods, RGB-labelled means colour-mapped visualizations for intuitive interpretation, and temporal difference means change detection maps that highlighted zones of land transformation indicating spatial and categorical transitions. These artifacts were evaluated based on both qualitative and quantitative measures:

3.3.1 Qualitative Evaluation

The classified maps were visually assessed to identify meaningful landscape patterns such as urban expansion into agricultural or forested areas, hydrological changes in water bodies, and field-to-soil transitions indicating land clearance. From an analytical perspective, they provided quantitative information on the spatial distribution of land use classes and their transitions over time.

3.3.2 Quantitative Evaluation

To verify classification accuracy and performance by evaluating each model's performance using accuracy, precision, recall, and F1 score 1 and 2. In addition, the comparative performance between XGBoost and other models was assessed. XGBoost achieved high classification performance ($\geq 94\%$) in datasets, with stable recall and precision, especially in dominant land classes like field and forest.

4 Data and Analysis

4.1 Data Description

This study leverages high-resolution multispectral imagery from the Sentinel-2 satellite mission to analyse land transformation over time. Sentinel-2 provides 13 spectral bands, of which 11 were selected for this research—namely, bands B01 to B12, excluding B10. Band B10, a cirrus detection band, was omitted due to its coarse spatial resolution and limited utility in terrestrial land cover classification tasks.

Two temporal images of the same spatial area were utilized: an earlier image of 2018 (corresponding to the condition of the landscape roughly a decade past) and a later image of 2024(corresponding to the contemporary landscape). The temporal combination provides efficient monitoring and evaluation of LULC change.

The chosen 11 bands were used as input features for all machine learning classifiers and were used uniformly across both training datasets and full stacks of images.

4.1.1 Training Data

The pixel-labelled training data were cut and saved in two CSV files: `trainn.csv` for the aging image and `train.csv` for the new image. Each of these files had the following:

- **Feature columns:** Spectral reflectance values for the 11 chosen Sentinel-2 bands, named as `SAMPLE_1`, `SAMPLE_1_2`, ..., `SAMPLE_1_11`.
- **Target column:** A categorical land cover class—`new1` for the old dataset and `n1` for the new dataset, representing LULC classes.

The preprocessing involved:

1. Importing the CSV files using the `pandas` library.
2. Unpacking the feature matrix `X` and respective class labels `y`.
3. Using `LabelEncoder` from the `scikit-learn` library to transform string-based labels into numerical values for model compatibility. Label encoding allowed for consistent class mapping between models and easy decoding for post-classification visualization.

4.2 Workflow Analysis

The below multi-stage pipeline was used to analyse land transformation:

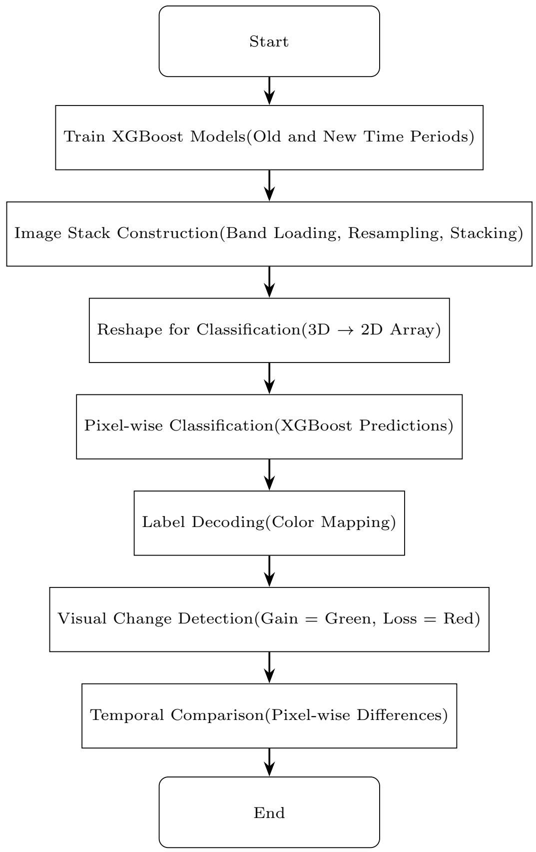

Figure 1: Workflow diagram for land transformation analysis using Sentinel-2 imagery and XGBoost model. Each box represents a key processing stage: model training, image stack creation, reshaping, classification, decoding, visual detection, and temporal comparison. Arrows indicate the sequence of operations

4.2.1 Training of Models

Two independent machine learning models were trained on the XGBoost classifier—each for one time period (old and new images) 1 and 2. XGBoost was utilized for its strength when dealing with high-dimensional tabular data and its strengths in Class imbalance and missing data management, High classification accuracy delivery and Efficient, scalable training performance.

4.2.2 Image Stack Construction

The entire Sentinel-2 image bands were saved as individual `.jp2` files within separate folders. The following preprocessing was performed:

1. **Band Loading:** Each `.jp2` band file was loaded using the `rasterio` library and the corresponding spectral index (e.g., B01 to B12) was matched using keyword filtering.

2. **Resampling:** Bands were resampled through bilinear interpolation to ensure consistent 2D spatial resolution and alignment across all bands.

3. **Stacking:** The 11 bands were stacked together into a 3D array of dimensions `(height, width, 11)`, representing the spectral cube for pixel-wise classification.

4.2.3 Reshaping for Classification

For image stack preparation before model input:

- The 3D stack was remapped into a 2D array of shape `(H` $\times$ `W, 11)`, with one row for each pixel and its spectral signature in the 11 bands.

- The reshaped array was input to the trained XGBoost classifier to produce predictions.

- The output (1D predicted labels) was remapped back to `(H, W)` to yield a spatially referenced classification map.

4.2.4 Label Decoding and Visualization Mapping

After classification, the numeric predictions were mapped back to human-readable class names using the `LabelEncoder` that was saved. The classified image was then color-coded by reference to a legend with each class assigned a unique RGB color: `Blue: Water, Green: Forest, Red: Buildings, Yellow: Field, Brown: Soil, Gray: Road`

4.2.5 Visual Mapping and Change Detection

Post-classification, predictions were mapped to RGB colors corresponding to distinct LULC classes (e.g., green for forest, red for buildings). To highlight transformations and for easy visualization of spatial patterns of distribution of land cover for both temporal snapshots:

- Green indicated land class gain

- Red showed land class loss (e.g., Construction and deforestation)

- Gray represented unchanged areas

These visualizations enabled direct spatial comparison of land cover states across time.

4.2.6 Temporal Comparison and Change Detection

For the purpose of analyzing temporal land changes, a set of binary and multi-class comparison situations were established (e.g., Forest vs. Soil, Buildings vs. Water). For each comparison: Pixel-wise differences were calculated between the new and old classified images. Also, The resulting difference matrix was displayed to show additions and removals of land cover types. These change maps delivered clear, interpretable evidence of landscape change over time.

4.3 Key Observations

Early qualitative analysis of the classified and difference maps indicated the following trends:

- **Urban Expansion:** Substantial increase in the "Buildings" class, specifically in locations previously held by "Field" or "Soil".

- **Vegetation Dynamics:** Deforestation was clear in some zones, while some zones were displaying increased forest cover through afforestation or rewilding projects.

- **Hydrological Alteration:** Water bodies showed small spatial changes, corresponding to potential seasonal fluctuation, floodplain extension, or infrastructural alteration.

These spatial findings accord with established land use patterns and past satellite examination, verifying the validity of the suggested classification and comparison approach. Quantitative assessment through accuracy measures, and class-level data is also addressed in the following Results section.

5 Results

5.1 Comparison of Classification Accuracy

In order to measure classification performance, some supervised learning models were trained on pixel-labeled Sentinel-2 data of both past and recent satellite images. Models were XGBoost, Random Forest (RF), Gradient Boosting (GB), Decision Tree (DT), Logistic Regression (LR), and Naive Bayes (NB). Accuracy, precision, recall, and F1-score performance metrics were evaluated for all.

Table 1: Performance comparison of classification models on Sentinel-2 data (2018). Metrics include Accuracy, Precision, Recall, and F1-Score.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	91.91	92.29	91.91	91.74
XGBoost	94.12	94.29	94.12	94.06
Gradient Boosting	91.91	92.06	91.91	91.63
Decision Tree	91.18	91.46	91.18	91.24
Logistic Regression	93.38	93.75	93.38	93.43
Naive Bayes	90.44	90.55	90.44	90.36

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Table 2: Performance comparison of classification models on Sentinel-2 data (2024). Metrics include Accuracy, Precision, Recall, and F1-Score.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	97.04	96.42	97.04	96.68
XGBoost	97.04	96.63	97.04	96.74
Gradient Boosting	97.04	96.42	97.04	96.70
Decision Tree	92.59	92.03	92.59	92.25
Logistic Regression	96.30	95.75	96.30	95.95
Naive Bayes	94.07	93.64	94.07	93.73

XGBoost was well-balanced between performance and efficiency, reinforcing its value for scalable land classification.

5.2 Visual and Spatial Interpretation of Land Use Transformations

To facilitate interpretability, classification outcomes color mapped for both periods were produced. Temporal changes were indicated on a color-coded difference map: green for additions, red for removals, and gray for unchanged regions. The visual classification results and color-mapped comparisons of the Wormerveer area over an 10-year period complemented the classification-based results which were in close agreement with observations made from the satellite imagery. These visualizations enabled intuitive interpretation of land changes like vegetation loss, urban encroachment, water expansion, and soil exposure.

These results were consistent with visually predicted maps produced through the use of the XGBoost-based classification. Comparative RGB and change maps efficiently emphasized:

- **Water Bodies:** Water courses, like canals and drainage channels, looked broader in the new image. This could be due to flood control structures, dredging activities, or augmented runoff. Though water (class 0) had high classification accuracy. *fig(4)*

- **Field/Forest to Bare Soil:** Vast areas of agricultural, grassland (class 3) and forests(class 1) were substituted by bare soil (class 4), indicating urbanization and land development. Which indicates land clearance for building. *fig(5)* and *fig(6)*
- **Urban Expansion:** The recent images revealed an obvious expansion of built-up area (class 2) replacing former field and forest areas. Land clearing occurring together, frequently triggered by ecological offsets or strategic land planning.*fig(7)*
- **Island Submersion:** Change maps revealed a discernible loss of land area owing to water intrusion. Although Sentinel-2 is not elevation sensitive, the decreased detection of built-up classes on water-impacted areas represents probable submersion. *fig(8)*

These findings confirm that the model not only properly classified the static condition of land cover but also identified dynamic, temporal changes representative of actual urban and environmental growth.

6 Discussion and Implications

Results validate that fusion of Sentinel-2 multispectral data with the XGBoost classification offers an efficient and resilient framework for detecting transformation and land use monitoring. In comparison with conventional methods, this method delivers:

- **High Precision with Limited Training Samples:** XGBoost performed well even when given moderate-sized labeled datasets.
- **Interpretability through RGB Mapping:** Color-coded visualizations gave instant insight into landscape transformations, which aided stakeholder engagement.
- **Scalability:** The model can be scaled to multiple temporal snapshots or other areas with little changes to pipeline architecture.

Hence this framework can be applied to Urban planning and land management, Environmental monitoring and Disaster preparedness (e.g., flood-risk zones).

6.1 Limitations and Future Directions

Although the suggested method worked well, there are a number of limitations:

- **Class imbalance** caused poor performance on infrequently occurring classes (e.g., Class 6) which leads to misclassification. Methods like SMOTE, focal loss, or stratified sampling might reduce the problem. Or we can resort to data augmentation or synthetic sample generation.
- **Pixels with mixed information** in semi-urban or transitional areas might confound pixel-wise classifiers and affect precision and recall. Spatial smoothing or object-based image analysis (OBIA) could be addressed in future work.
- **Seasonal, atmospheric, and light differences** between the two satellite images can introduce temporal comparison noise. Including other correction or normalization methods can help reduce this.
- **Unavailability of supporting data** like elevation, land ownership, soil type or socioeconomic conditions might restrict land use change contextual understanding.

Future studies may investigate the integration of temporal order using deep learning models like LSTM-CNN hybrids, and applying unsupervised change detection methods for real-time observation.

6.2 Socioeconomic and Environmental Developments Reflected in Land Classification Changes

In the past decade, the northern Netherlands more specifically, the provinces of North Holland, Friesland, Overijssel, and Flevoland, have experienced significant changes in land use patterns as a result of climate resilience planning, urban growth, environmental policy change, and ecological restoration. The results are mentioned below.

In the period 2013–2023, there have been measurable changes in the classification of the land in the northern Netherlands driven by water infrastructure development, environmental pressures, and socio-economic transformation. Strategic policy interventions like building artificial islands, reforestation, and town planning have recalibrated the interaction between human settlements and natural habitats.

7 Conclusion

Combining machine learning methods,namely the XGBoost classifier—with multi-spectral, high-resolution remote sensing data from satellites like Sentinel-2 has has significantly enhanced the accuracy and effectiveness of LULC classification. By employing a formal classification pipeline and easy-to-understand color-coded visualizations of raster data, the method facilitates technically correct spatial analysis that is easily understandable by policymakers and urban planners. The results demonstrate the practical applicability of machine learning in enhancing environmental monitoring, urban development assessment, and sustainable resource management. Additionally, the demonstrated flexibility across different time frames and regions provides the generalizability of the proposed approach. With the development of the field, the future research should aim at making models more interpretable, scalable, and multi-temporal dataset applicable for dynamic land change assessment, thereby cementing the employment of AI-enabled remote sensing for tackling global environmental challenges.

Declarations

Use of AI Technology

The authors used AI tools, including ChatGPT by OpenAI, for language editing and refining the structure of the manuscript. No content was generated solely by AI; all research, analysis, and conclusions are original and author-driven.

Conflicts of Interest

All authors declare that they have no conflicts of interest.

Informed Consent

This research did not involve human participants, and therefore, no informed consent was required.

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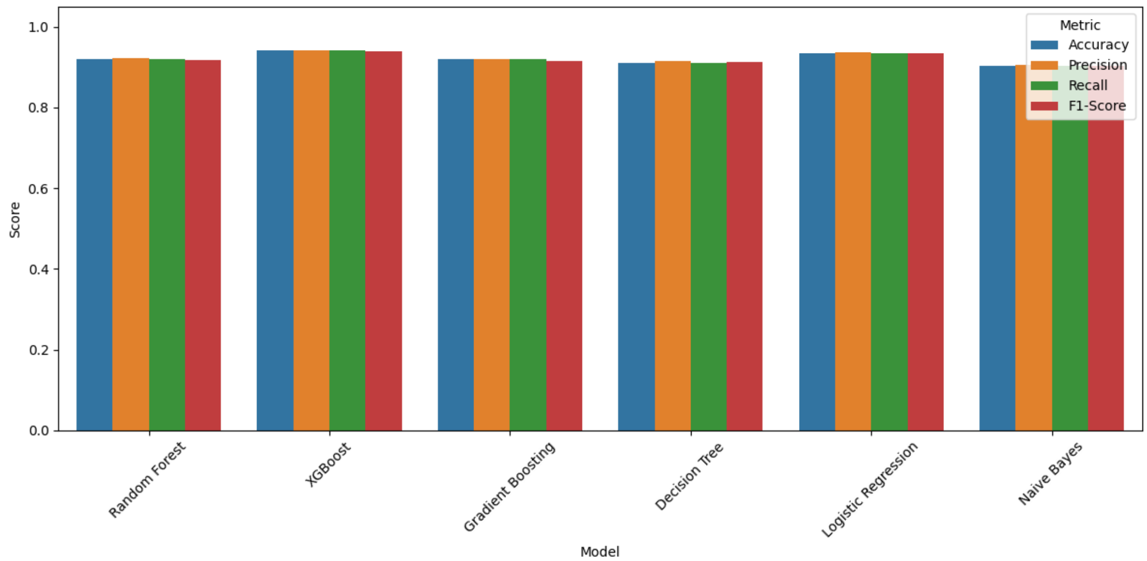


Figure 2: Model performance comparison using 2018 Sentinel-2 data.

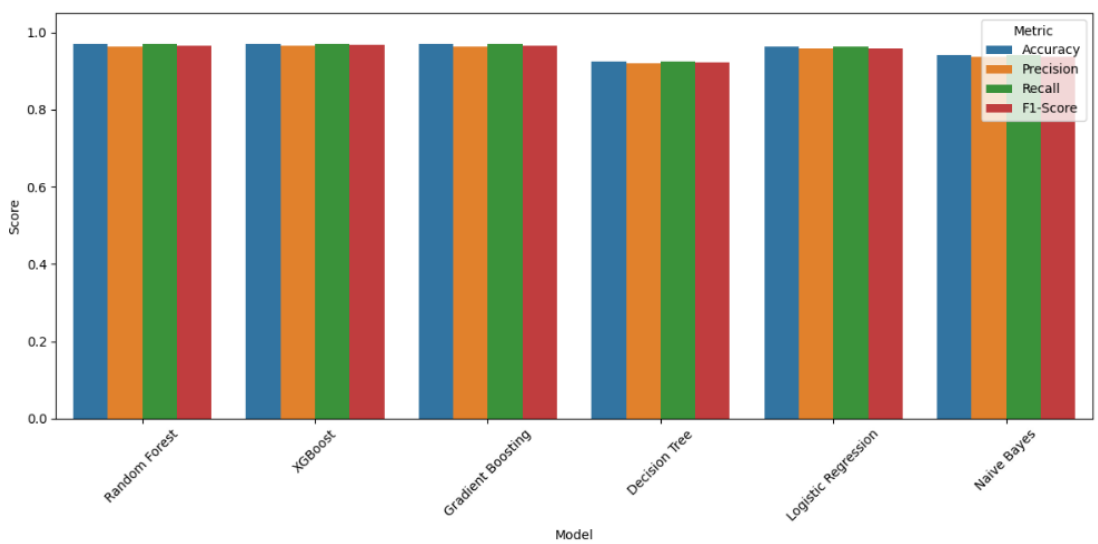
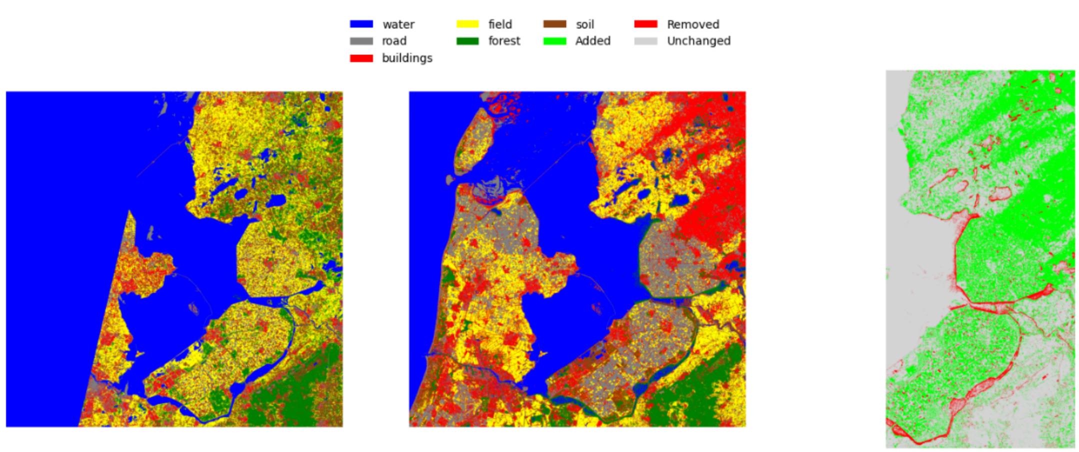
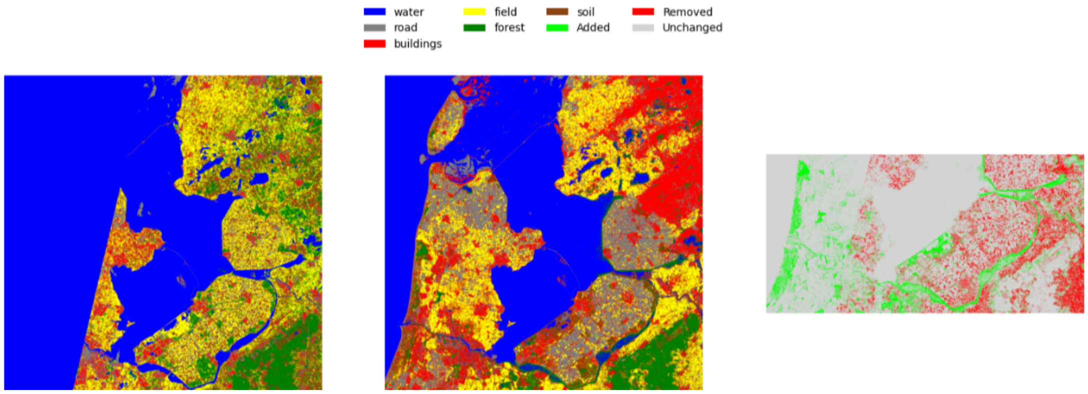


Figure 3: Model performance comparison using 2024 Sentinel-2 data.



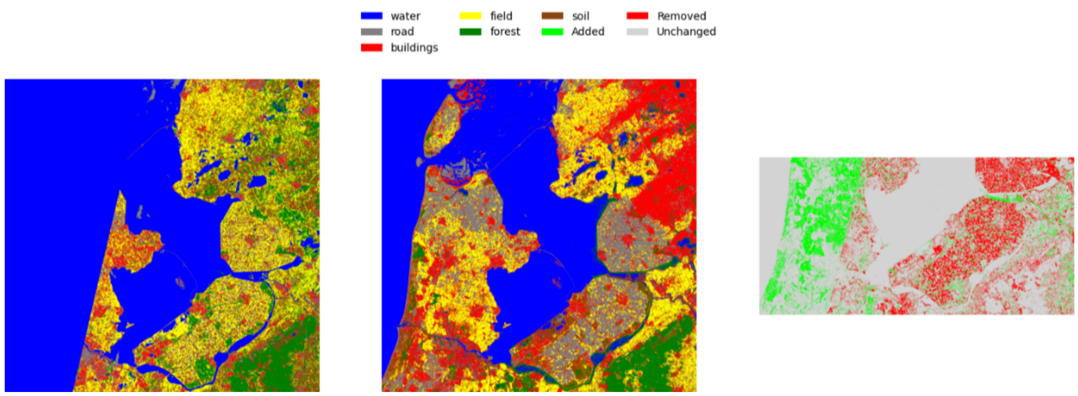
(a) (b) (c)

Figure 4: Expansion of Water Outlets. (2021) Extension of Drinking Water Infrastructure Between IJsselmuiden and Ens. (2020) Strategic Water Balance of Overijssel(10).



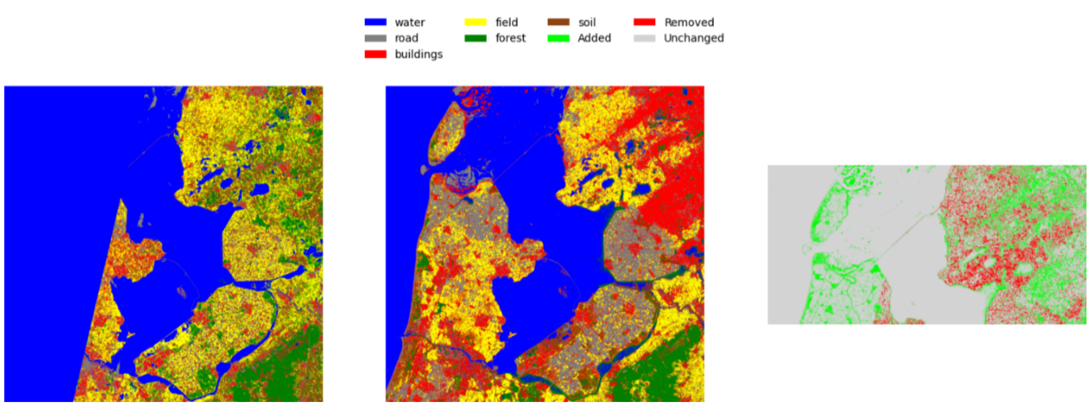
(a) (b) (c)

Figure 5: Reduction in Green Fields and Agricultural Land. (2020–2023) Land-use trends included both deforestation and reforestation(11). (2022) Nitrogen reduction policy led to farmland rezoning in Flevoland and Overijssel(12).



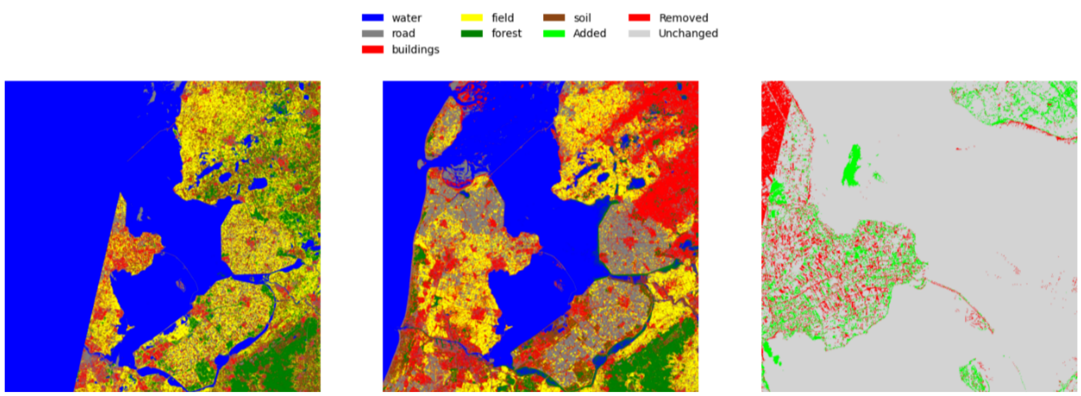
(a) (b) (c)

Figure 6: Transition from Fields and Forests to Barren Land. (2017) Soil subsidence in Friesland reduced productivity(13). (2021–2022) Zeewolde data center was halted, leaving land undeveloped(14).



(a) (b) (c)

Figure 7: Deforestation Trends. (2013–2022) Urban development replaced 178 km² of farmland(11). (2015–2023) Urban growth caused tree loss; 92,000 trees planted in Friesland(12)(15).



(a) (b) (c)

Figure 8: Island Submergence and Creation. (2016–2023) Marker Wadden islands built using nature-based methods(16)(17). (2018) Nieuw Land National Park showcased land reclamation with conservation(18).