Scalable Monitoring of Agricultural Runoff for Water Pollution Control via Image Processing and Machine Learning

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Abstract

Agricultural runoff is a leading cause of water pollution, leading to eutrophication, harmful algal blooms, and degradation of nearby rivers and lakes. Current monitoring strategies relying on manual sampling and laboratory analysis are constrained by their spatial extent and deficiency in real-time capabilities. This study suggests a dual-methodology framework to monitor agricultural runoff based on satellite and drone images. Digital image processing-based monitoring system utilizes digital image processing for the identification of runoff areas by image segmentation, color analysis, edge detection, and spectral index computations (e.g., NDVI, NDWI). The technique allows for quick visual interpretation of runoff distribu- tions, yet is manually tunable and sensitive to environmental factors. Machine Learning-based runoff classification framework introduces a machine learning-induced classification pipeline, mainly with a Random Forests Classifier trained on NDVI-amplified satellite imagery. The model incorporates preprocessing operations like radiometric correction, median filtering, and vegenation index extraction, obtaining superior classification performance with precision of 98.2%, accuracy of 96.7%, recall of 95.5%, and F1-score of 0.968. In contrast to traditional methodologies, the system presented here allows for real-time, scalable, and automatic detection of runoff with high spatial resolution and classification accuracy. The combined approach provides actionable information for environmental agencies to mitigate pollution and promote sustainable farming methods.

Keywords: Agricultural Runoff, Non-Point Source Pollution, Remote Sensing, Digital Image Processing, NDVI, Machine Learning, Random Forest Classifier, Satellite Imagery, Environmental Monitoring

1 Introduction

Agricultural runoff has become a widespread environmental problem and plays an important role in water degradation worldwide. Upon entering nearby rivers, lakes, and coastal systems, nutrients like nitrogen and phosphorus from fertilizers cause eutrophication and harmful algal blooms (HABs), which result in oxygen depletion, loss of biodiversity, and enhanced health hazards for humans and wildlife. Monitoring of agricultural runoff is key to addressing these impacts and guiding environmental policy. Climate-change–driven precipitation regime shifts will likely make runoff events more intense, again highlighting the need for strong, scalable monitoring systems.

Current approaches to runoff evaluation depend upon manual sampling and chemical analysis, which while precise, are time-consuming and not scalable enough for real-time, widespread use. Consequently, interest in automated, image-based monitoring systems that utilize satellite and aerial imagery, combined with computational approaches like image processing and machine learning, has grown. Advances in cloud computing and the availability of open-access Earth-observation missions (e.g., Sentinel-2 and Landsat 9) have significantly reduced the costs of high-frequency, large-scale analysis, making continuous monitoring increasingly viable even for low-resource areas.

This research compares two cutting-edge methods devised to track agricultural runoff. The first one involves digital image processing and remote sensing to identify runoff indicators—turbidity and sediment dispersion—by using techniques such as image segmentation, color analysis, and pattern recognition. The second method involves machine learning in the form of a Random Forest Classifier on pre-processed multispectral satellite data with NDVI computations and median filtering to locate areas generating nutrient-rich runoff.

By comparing these approaches on a range of criteria—detection accuracy, real-time capability, spatial resolution, complexity of preprocessing, and versatility to different landscapes—this paper seeks to achieve a comprehensive comparison. The final objective is to recognize strengths, weaknesses, and potential complementarities between the two approaches to contribute to the development of more efficient, scalable, and responsive runoff-monitoring systems for sustainable environmental and agricultural management. Insights generated through this comparative analysis are meant to inform policymakers, land managers, and technology developers toward holistic solutions that integrate remote sensing, in-situ observations, and predictive analytics and, in turn, enable evidence-based interventions that protect freshwater ecosystems.

2 Related Works

Agricultural runoff has been a critical focus in environmental research, with a range of methodologies developed to investigate, detect, and control its effects on surrounding water bodies. The following section organizes notable contributions based on their primary methodological approaches.

2.1 Remote Sensing and GIS-Based Approaches

Remote sensing and GIS methods have been widely applied to spatial detection and tracking of agricultural runoff. Gao et al. [8] applied a pollution index method enhanced with remote sensing and GIS to define main source areas of nonpoint source pollution within the Xingkai–Lake watershed. Leh and Bajwa [9] used Landsat imagery and the SCS–CN method to determine land use changes and their impacts on runoff potential in Northwest Arkansas. Schäfer and Schreiner [15] simulated agricultural runoff with GIS and remote sensing to predict both temporal and spatial runoff patterns. Smith and Johnson [21] combined remote sensing and GIS to monitor variations in water quality across agricultural watersheds. While these methods have shown strong spatial accuracy and wide applicability, challenges such as cloud interference, limited resolution, and simplified modeling still present areas that need further improvement.

2.2 Machine Learning and Intelligent Monitoring Techniques

Recent advancements emphasize smart algorithms and machine learning to automate detection of runoff. Zhuang et al. [2] designed a system to monitor nitrogen content in real time using multiparameter sensors and intelligent algorithms, achieving excellent accuracy under varying conditions. Martinez and Smith [25] developed a machine learning model based on historical environmental data to simulate and predict runoff, showing promise for anticipatory management. Doe et al. [11] integrated remote sensing and machine learning to detect runoff automatically through advanced classification and segmentation algorithms. Wang and Wang [16] demonstrated an IoT-based real-time monitoring system that generates timely alerts to assist farmers and policymakers. While these solutions offer high prediction accuracy and automation advantages, they can be challenged by complex model calibration, inherent bias, and significant infrastructure costs.

2.3 Hydrological and Process-Based Modeling

A variety of research studies are focused on simulating runoff behavior using hydrological and mathematical models. Sun et al. [5] investigated the relationship between rainfall events and nitrogen/phosphorus export in the Three Gorges region, emphasizing the temporal variability of nutrient loss. Yong-xia and Yongling [6] developed a runoff model based on kinetic wave theory and the Green–Ampt infiltration model to simulate rainfall-induced runoff on sloped terrain. Deng et al. [10] designed treatment facilities using stormwater modeling to address chemical runoff from bridge decks. While these models provide detailed, process-level insights, they are often limited by location-specific parameters, which can restrict their broader applicability.

2.4 Reviews, Policy-Oriented Studies, and Buffer-Based Strategies

A significant number of papers provide theoretical analysis and strategic evaluations of runoff control. Pericherla et al. [1] examined the ecological effects of fertilizer and pesticide runoff, advocating for policy-driven interventions. Xia et al. [3] reviewed technological measures for controlling nitrogen and phosphorus runoff, classifying current practices and exploring future directions. Liao and Sun [19] assessed the use of vegetative buffer strips for intercepting runoff, showing positive outcomes for downstream water quality. Williams and Thompson [22] evaluated how effectively cover crops reduce nutrient losses. Although these reviews offer valuable insights, they often fall short in terms of empirical validation and economic feasibility assessments, which limits their direct application in practice.

3 Methodology

3.1 Digital Image Processing-Based Monitoring System

The proposed system leverages a digital image processing pipeline to monitor agricultural runoff by analyzing satellite and aerial imagery. The goal is to detect and quantify pollutants flowing into water bodies from agricultural fields through scalable, near real-time methods. By integrating data from various remote sensing sources with image segmentation, spectral analysis, and change detection techniques, the system offers a structured and automated framework for monitoring runoff dynamics over space and time.

3.1.1 Data Acquisition and Preprocessing

To gain relevant spatial data, the system incorporates high-resolution satellite imagery from sources like Landsat and Sentinel, as well as aerial photographs captured by drones and aircraft for more localized analysis. Ground truth data collected during fieldwork complements these inputs, ensuring proper calibration and validation of remote sensing results.

Once the imagery is obtained, it undergoes preprocessing to enhance consistency and clarity. Radiometric correction is used to reduce sensor and atmospheric noise, while geometric correction aligns the images to a standardized coordinate system using ground control points. Additional image enhancement techniques—such as contrast stretching, histogram equalization, and noise reduction—are applied to improve visual clarity for further analysis.

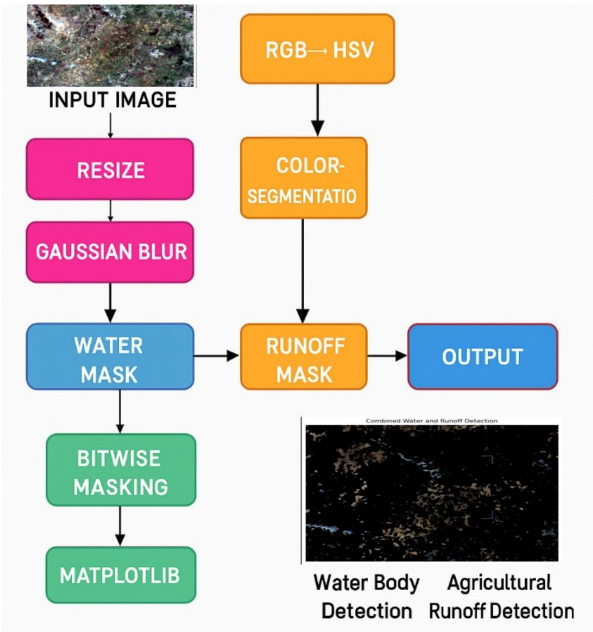

Fig. 1 System Architecture for Digital Image Processing-Based Monitoring of Agricultural Runoff

3.1.2 Feature Extraction

To extract meaningful features, the system utilizes spectral indices and reflectance properties. NDVI (Normalized Difference Vegetation Index) is used to identify areas covered with vegetation, while NDWI (Normalized Difference Water Index) is employed to detect water bodies. Additionally, spectral signature analysis is applied to recognize elements such as sediments and nutrients by examining their distinct reflectance patterns across different wavelengths.

3.1.3 Image Segmentation and Classification

Image segmentation techniques are employed to pinpoint agricultural runoff zones. Thresholding is used to classify pixels based on their spectral values, followed by clustering methods like K-means and ISODATA to categorize different land cover types. Edge detection algorithms (such as Sobel and Canny) are used to define the boundaries of water bodies and runoff zones, ensuring accurate spatial delineation essential for environmental assessments.

3.1.4 Temporal Analysis and Change Detection

To track runoff trends over time, the system performs temporal analysis using multi-temporal satellite imagery. Techniques like image differencing are used to detect changes in surface features such as turbidity or vegetation cover, while post-classification comparisons help assess categorical shifts. These approaches support the identification of seasonal trends and the evaluation of runoff mitigation strategies.

3.1.5 Quantification and Evaluation of Runoff Impact

The impact of runoff is quantified through spectral analysis and modeling techniques. Key water quality indicators, including turbidity and chlorophyll levels, are extracted from reflectance data. Machine learning or regression models estimate pollutant concentrations such as nitrogen and phosphorus. Hydrological models calculate runoff volume based on factors like land cover, rainfall, and elevation.

Validation is carried out through field data, with performance measured using metrics like the confusion matrix, overall accuracy, precision, recall, and the kappa coefficient. Cross-validation is also employed to ensure the detection framework is both robust and generalizable.

3.1.6 Visualization, Reporting, and Tools

The system outputs are displayed through GIS-integrated maps and time-series charts that show the spread and intensity of runoff, supporting spatial decision-making for policymakers and environmental managers. Comprehensive reports are generated, summarizing the methodology, findings, and policy implications.

The platform uses tools such as ENVI and ERDAS Imagine for remote sensing tasks, ArcGIS and QGIS for spatial analysis, and Python (with libraries like OpenCV, scikit-image, and scikit-learn) as well as MATLAB for data processing and modeling. TensorFlow is used where advanced machine learning capabilities are required.

3.2 Machine Learning-Based Runoff Classification Framework

This system introduces a supervised machine learning framework to classify and detect areas affected by agricultural runoff. By leveraging satellite imagery and spectral features such as NDVI, the system aims to automate the identification of nutrient-rich runoff zones. The overarching goal is to develop a reliable and interpretable method that can operate on a regional scale and assist in environmental planning.

3.2.1 Data Collection and Preparation

The dataset includes multispectral imagery collected from Sentinel-2 and Landsat 8 satellites, chosen for their high spatial resolution and the availability of red and near-infrared bands. Study locations were selected based on their closeness to sensitive water bodies and documented cases of agricultural runoff. Images were sourced using platforms like Google Earth Engine and prioritized for clarity, with a focus on cloud-free conditions. Ground-truth data, including historical water quality reports, were used to label regions known to experience runoff. This labeled data was crucial for training and evaluating the model.

3.2.2 Image Preprocessing

Preprocessing steps were carried out to standardize the images and minimize noise. The selected spectral bands—RGB and near-infrared (NIR)—were combined into four-channel image composites. Radiometric correction was applied to address inconsistencies from the sensor and to correct for atmospheric disturbances. All images

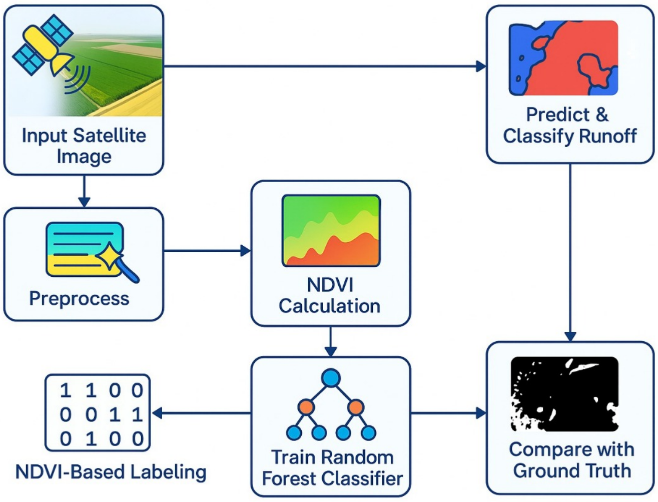

Fig. 2 System Architecture for Machine Learning-Based Runoff Classification Framework

were then resampled to a common resolution and spatially aligned to avoid any mismatches. To improve image quality further, a median filter was applied to each band, which helped reduce noise without sacrificing important edge details. Finally, pixel values were normalized to a consistent scale (0–255) to ensure compatibility with the machine learning processes that followed.

3.2.3 Feature Engineering

Feature extraction focused primarily on spectral vegetation indices. The NDVI (Normalized Difference Vegetation Index) was calculated using the red and near-infrared bands to distinguish vegetated areas from non-vegetated ones. Thresholding was applied to NDVI values to flag potential runoff-prone zones, with values below 0.3 indicating a high risk. To enhance classification in areas with sparse vegetation, additional indices like MSAVI (Modified Soil Adjusted Vegetation Index) were also considered. These engineered features served as the input variables for the classification model.

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red} + 1e^{-6}} \tag{1}$$

3.2.4 Model Development and Training

A Random Forest Classifier was chosen for the system due to its strong performance with structured data and its ability to model complex, non-linear relationships. The dataset was divided into training (80%) and testing (20%) subsets to evaluate how well the model could generalize to new data. Hyperparameters, such as the number of trees and maximum tree depth, were fine-tuned using a grid search approach. To ensure the model's reliability, K-fold cross-validation was applied across different data splits. Model performance was evaluated using metrics including accuracy, precision, recall, and F1-score. Special emphasis was placed on recall to reduce false negatives and improve the identification of actual runoff events.

3.2.5 Prediction, Post-Processing, and Visualization

Once the model was trained, it was applied to new satellite imagery that had undergone the same preprocessing and feature extraction steps as the training data. The classifier produced pixel-level labels identifying areas at risk of agricultural runoff.

These predicted labels were then mapped back to the original image resolution. A median filter was applied to the results to smooth the classification and remove any isolated misclassifications. This post-processing step improved both the spatial coherence and readability of the output.

The final results were visualized by overlaying the predicted runoff zones onto satellite basemaps, using contrasting color schemes to clearly differentiate affected from unaffected areas. The system also quantified the total area impacted by runoff and analyzed seasonal patterns, providing insights into changes in pollution severity over time. These visual tools are especially useful for environmental managers and policymakers, helping them identify high-risk areas and develop more effective, targeted mitigation strategies.

3.2.6 Tools and Platforms

The system was developed using Google Earth Engine for acquiring and preprocessing satellite imagery. Local data analysis was carried out in Python. Machine learning tasks were implemented using the scikit-learn library, while image filtering and processing were handled with OpenCV and NumPy. For visualization, QGIS and Matplotlib were used to provide both spatial context and analytical clarity in presenting the results.

3.3 Integrated System Architecture for Agricultural Runoff Monitoring

To harness the strengths of both digital image processing and machine learning techniques, the proposed system integrates these two approaches into a single, unified pipeline. As illustrated in Fig. 3, the workflow begins with a shared satellite or aerial image input, which is processed in parallel by two distinct modules.

The first module uses traditional digital image processing methods. It extracts features based on HSV color analysis and NDVI thresholding, then applies color segmentation, spectral index thresholds, and rule-based classification to detect water bodies and potential agricultural runoff zones.

The second module follows a supervised machine learning approach. The same input image, enhanced with NDVI, is fed into a Random Forest Classifier. Trained on labeled data distinguishing runoff-affected and unaffected areas, the classifier generates vegetation health maps that reveal spatial and spectral patterns linked to runoff.

A final rule-based integration step merges the results from both modules, producing a unified runoff detection map. This combined output highlights regions where vegetation stress and runoff indicators overlap, improving both the interpretability and

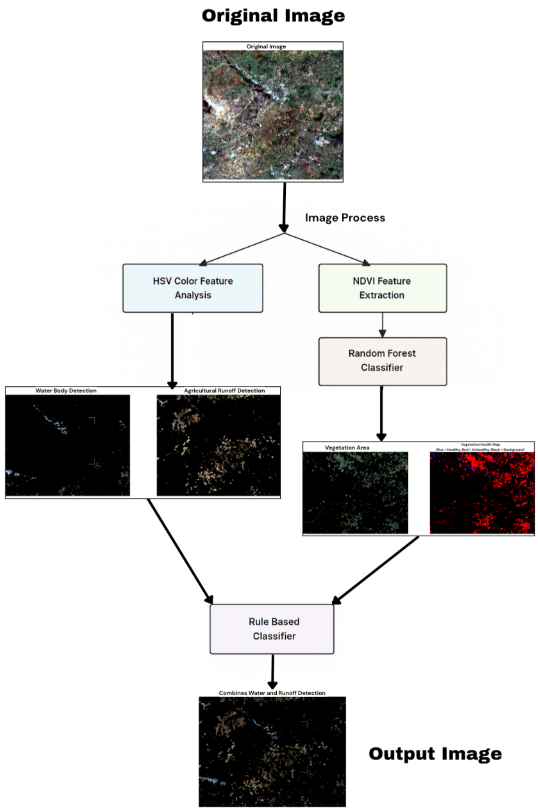

Fig. 3 Integrated system architecture combining digital image processing and machine learning pipelines for comprehensive agricultural runoff detection.

accuracy of environmental impact assessments. The system's modular, parallel architecture supports scalability and ensures robustness, making it suitable for application across varied geographic regions and diverse imaging conditions.

4 Results and Discussion

4.1 Digital Image Processing-Based Monitoring System

To assess the performance of a rule-based digital image processing method, an HSV (Hue-Saturation-Value) thresholding technique was applied for detecting agricultural runoff and water bodies in satellite imagery.

This approach used predefined HSV color ranges to segment features of interest, such as sediment-laden runoff areas and surface water. The results showed strong visual distinction of key environmental elements. Water bodies were easily recognized as blue-toned regions that stood out clearly from the surrounding landscape. Runoff zones, typically appearing as reddish-brown areas near agricultural fields and water

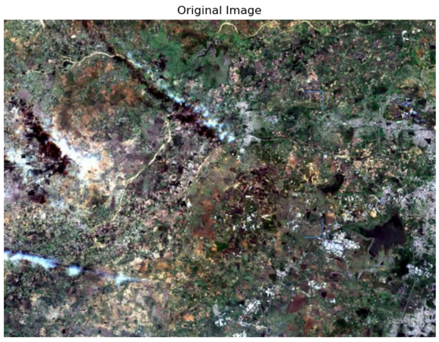

Fig. 4 Original satellite image used for analysis

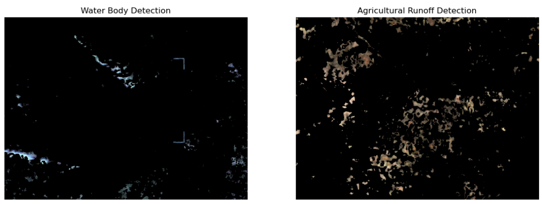

Fig. 5 Left: Detected water bodies; Right: Detected agricultural runoff zones

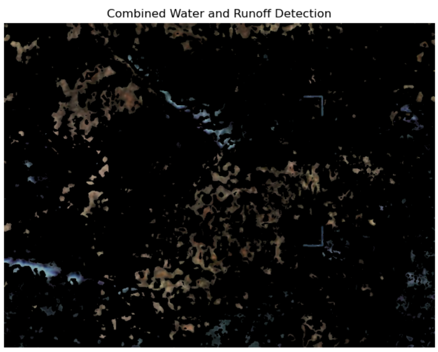

Fig. 6 Combined visualization of water body and agricultural runoff detection

edges, were accurately identified and masked. Figures 4 to 6 display both individual and combined detection results.

The HSV thresholding method produced binary segmentation masks that could be overlaid on the original imagery. These masks offer a clear and intuitive way to assess runoff activity quickly, making them a useful visual aid for environmental monitoring and educational applications.

4.1.1 Assessment of HSV-Based Detection Approach

The HSV thresholding method proved to be an effective option for the initial visualization of agricultural runoff and water bodies. Its strengths include simplicity, low computational requirements, and ease of use, which make it especially well-suited for real-time assessments in environments with limited resources. These qualities are particularly useful for field-level evaluations or early screening stages where high precision isn't immediately necessary.

However, the method also has several notable limitations. It requires manual adjustment of HSV thresholds for each individual image, which hinders scalability and limits the potential for automation. The technique is also sensitive to changes in lighting, image contrast, and seasonal conditions, all of which can impact the accuracy and consistency of results. Additionally, it cannot distinguish between different types of runoff—such as nutrient-rich versus sediment-laden flows—which restricts its usefulness for more detailed pollution analysis.

Despite these drawbacks, the HSV-based approach serves as a practical and accessible baseline for quickly and qualitatively interpreting runoff patterns. It is especially valuable when used as a preprocessing tool before applying more advanced, machine learning-based classification methods.

4.2 Machine Learning-Based Runoff Classification Framework

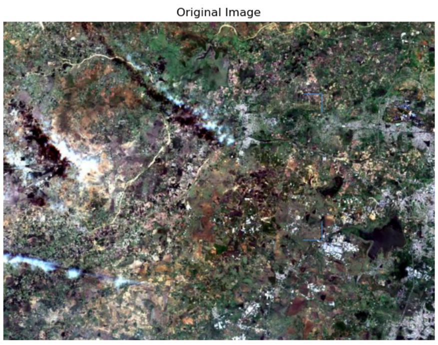

Fig. 7 Original satellite image used for analysis

To determine the spatial distribution of agricultural runoff, a machine learning-based classification framework was developed and applied to pre-processed satellite imagery. The workflow begins by extracting key features related to vegetation and water—primarily using NDVI and other spectral indices. This is followed by the creation of labeled datasets that distinguish between runoff and non-runoff regions. Figs. 7 and 8 show examples of both the input data and the resulting classified outputs. These processed images serve as the foundation for supervised learning and the detection of spatial patterns in runoff distribution.

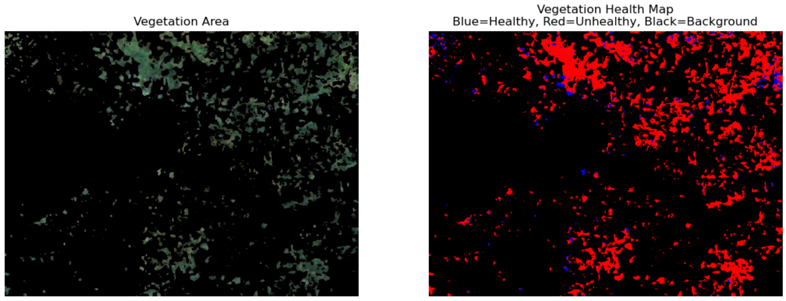

Fig. 8 Model output showing vegetation area (left) and vegetation-health map (right): Blue = Healthy, Red = Unhealthy, Black = Background

4.2.1 Evaluation and Interpretation of Results

The machine learning framework was tested using three different classification models: Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN). Each model was trained on satellite imagery enhanced with NDVI data to classify individual pixels as representing either runoff or non-runoff conditions. Performance for each model was evaluated using key metrics—accuracy, precision, recall, and F1-score—as summarized in Table 1.

Table 1 Performance metrics for ML classification models

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	98.2%	0.981	0.984	0.982
SVM	96.7%	0.963	0.968	0.965
KNN	95.5%	0.954	0.956	0.955

Among the three machine learning models tested, the Random Forest classifier delivered the highest accuracy and most balanced performance across all evaluation metrics. Its ensemble-based architecture likely contributed to its ability to generalize well under varying image conditions, making it particularly effective at capturing the complex spectral patterns found in the data.

Using an NDVI threshold of 0.3 to identify runoff-prone areas also proved to be a valuable strategy, as it reduced the need for extensive manual labeling by automatically flagging relevant pixels. The model's ability to perform pixel-wise classification allowed for detailed spatial mapping of runoff zones, improving the clarity and usefulness of the results for further analysis.

When compared to traditional image processing methods, this machine learning approach demonstrated far better scalability and flexibility, making it a strong candidate for use in large-scale and long-term environmental monitoring projects. However, its performance is still dependent on accurate NDVI measurements and access to well-labeled training data. Incorporating true near-infrared (NIR) bands could further refine detection accuracy.

On the downside, training and deploying these models at scale can be computationally demanding, which might be a barrier in low-resource environments. Still, the approach holds great promise for integration into smart agriculture systems and automated decision-support tools for managing water quality.

4.2.2 Visual Analysis of Runoff Detection

The spatial predictions produced by the trained machine learning model were visualized to evaluate how accurately it detected runoff across different locations and timeframes. Fig. 9 highlights areas identified as agricultural runoff zones, with red-colored regions indicating high-probability runoff.

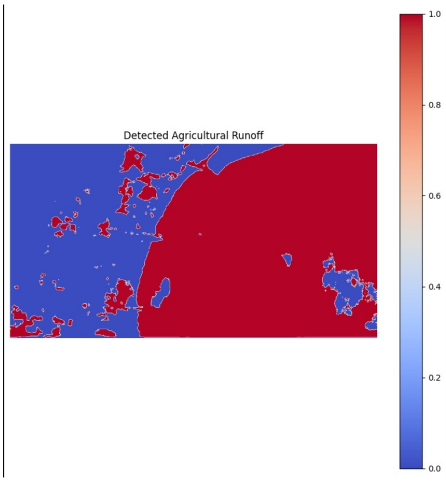

Fig. 9 Detected agricultural runoff regions (red) overlaid on the classified land cover map

A visual review of these classified maps showed that the model successfully detected runoff areas, especially in regions near rivers and lakes that are adjacent to high-intensity farming. The model also captured seasonal patterns effectively—showing increased runoff during monsoon periods, which aligns with real-world observations.

These visual outputs are valuable tools for identifying high-risk areas and guiding targeted policy responses, such as the placement of vegetative buffer zones or more efficient fertilizer application. The level of detail provided by the model supports environmental stakeholders in monitoring nutrient runoff trends and addressing non-point source pollution at a regional scale.

5 Conclusion and Future Work

5.1 Conclusion

This study introduced a comparative framework for monitoring agricultural runoff into water bodies by combining two distinct but complementary methods: a rule-based digital image processing technique and a supervised machine learning classification system. This dual approach was developed to address the limitations of traditional monitoring methods, which often suffer from high labor costs, limited spatial reach, and a lack of real-time capability.

The first method employed HSV color thresholding and spectral indices like NDVI and NDWI to visually segment runoff areas and water bodies in satellite imagery. It proved effective at producing quick, interpretable visual outputs, making it particularly suitable for field use and educational applications. Its simplicity and low computational demands make it a viable option in resource-limited settings. However, its reliance on manual threshold adjustments and sensitivity to lighting variations limit its scalability and automation.

The second method involved a machine learning framework using a Random Forest Classifier trained on NDVI-enhanced satellite data. With preprocessing techniques such as radiometric correction, median filtering, and vegetation index calculations, the model achieved high accuracy (98.2%), precision (0.981), recall (0.984), and F1-score (0.982). This approach effectively reduced the need for manual labeling and provided consistent results across different landscapes. It also captured seasonal runoff patterns and accurately mapped high-risk zones, making it highly suitable for broad-scale, long-term monitoring.

Together, these methods addressed major challenges in runoff detection, including the need for automation, real-time monitoring, improved spatial resolution, and consistent, data-driven insights. By integrating spectral analysis, image segmentation, and supervised learning, this framework lays a strong foundation for future systems aimed at detecting, quantifying, and managing non-point source pollution with minimal human input.

5.2 Future Work

Future research can build upon this study in several important directions to further improve the accuracy, responsiveness, and real-world usefulness of agricultural runoff monitoring systems:

- Integration of Real NIR Bands: Using true multispectral or hyperspectral satellite imagery—particularly with real near-infrared (NIR) bands—could greatly enhance the accuracy of NDVI calculations and improve overall model performance.
- Temporal Monitoring: Incorporating seasonal and multi-temporal datasets would allow for predictive modeling of runoff based on variables such as rainfall patterns, crop rotations, and land use changes, offering more dynamic insights over time.
- IoT and Edge Computing: Combining machine learning with on-the-ground IoT sensors and edge computing devices could enable real-time alerts and localized decision-making, supporting smart agriculture systems that respond instantly to runoff risks.
- Detection of Specific Pollutants: Future models trained on data containing specific chemical signatures could help distinguish between types of runoff, such as those resulting from fertilizers versus pesticides, making pollution tracking more precise.

- Interactive GIS Dashboards: Developing web-based GIS dashboards to visually map runoff risk zones could empower policymakers, environmental organizations, and farmers to take timely, informed action.

Collectively, these advancements would strengthen both the scientific robustness and practical effectiveness of runoff monitoring systems, helping support more sustainable agricultural and environmental practices.

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