Optimized Wetland Classification in Arid Coastal Environments: Integrating Sentinel-2 Imagery with Hyperparameter-Tuned Machine Learning Algorithms

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Abstract

Coastal wetlands play a vital role in maintaining ecological balance by providing essential ecosystem services such as carbon sequestration, biodiversity conservation, and water regulation. However, these sensitive environments are increasingly threatened by human pressures and climate change, underscoring the need for accurate, scalable, and efficient monitoring approaches. Remote sensing offers cost-effective alternatives to traditional wetland monitoring methods. In this study, we developed an advanced machine learning framework for classifying and analyzing the Miankaleh coastal wetland an internationally recognized Ramsar site located along the southeastern coast of the Caspian Sea using Sentinel-2 data processed on the Google Earth Engine (GEE) platform. In this context, four machine learning algorithms Support Vector Machine (SVM), Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Ensemble Learning—were systematically evaluated for wetland classification after extracting diverse spectral, spatial, and textural features, including vegetation and water indices. The findings revealed that among the tested classifiers, XGBoost achieved the highest accuracy (OA = 0.86, Kappa = 0.835) with the shortest computation time (49 seconds), outperforming traditional methods. Furthermore, hyperparameter optimization using Grid Search, Random Search, Bayesian Optimization, and SHAP-based tuning showed that although Grid Search produced the highest Kappa (0.839), its computational cost was more than eight times greater than the default configuration. These results demonstrate that XGBoost, even with minimal tuning, provides an optimal balance between classification accuracy and computational efficiency for coastal wetland environments. The proposed framework highlights the potential of integrating open-access satellite data, cloud-based processing, and optimized machine learning models for large-scale, operational wetland monitoring and management.

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1. Introduction

Wetlands, as one of the key components of the Earth's ecosystems, cover approximately 3–7% of the planet's surface (Gibbs, 2000) and are often referred to as the "kidneys of the Earth" (Kool et al., 2022). These dynamic environments are characterized by complex spatial and temporal interactions among vegetation, water, and soil, and provide essential ecosystem services such as water purification, flood regulation, carbon sequestration, and biodiversity conservation (Arij et al., 2025). However, in recent decades, wetlands have undergone significant transformations due to climate change, urban expansion, agricultural development, and other human-induced activities. These pressures have resulted in the degradation of more than 50% of global wetlands, leading to reduced water levels, the spread of invasive species, and declining water quality (Davidson, 2014). Accurate understanding of the current status of wetlands, identification of vulnerable areas, and analysis of land cover changes are critical steps for their effective conservation. Accordingly, developing precise, efficient, and scalable methods for classifying wetland components and analyzing their temporal dynamics has become increasingly important (Tiner, 2016).

Wetland classification involves the systematic identification of various components to distinguish between different land cover types within these complex ecosystems (Ozesmi and Bauer, 2002; Adam et al., 2010). One of the key challenges in this process is the accurate separation of spectrally similar features, particularly submerged aquatic vegetation and open water, which often exhibit comparable reflectance characteristics in specific spectral bands (Luo et al., 2015). These challenges are compounded by the inherent heterogeneity of wetland environments, where subtle spectral differences among vegetation types—such as trees, shrubs, and emergent plants—require advanced analytical approaches for reliable classification (Rebelo et al., 2017). In addition, variable soil conditions, including bare and saline soils, further increase the complexity of accurate class discrimination. In this regard, traditional classification methods are often costly, time-consuming, and limited in their capacity to monitor dynamic changes over time. In contrast, remote sensing enables multi-scale classification (Ozesmi and Bauer, 2002) and serves as a complementary or alternative approach that effectively addresses the operational and scalability limitations of conventional methods (Silva et al., 2008).

Remote sensing technologies, particularly those developed through European Space Agency (ESA) initiatives, have played a vital role in monitoring and managing wetlands. Among them, the Sentinel-2 sensor—with its high spatial resolution, broad spectral range, and frequent revisit capabilities—has become a key data source in land cover classification and environmental monitoring (Mahdavi et al., 2018). Its open-access policy and robust performance make it a valuable alternative to traditional methods, especially in studies requiring continuous and cost-effective observation In line with the growing potential of remote sensing for wetland classification, numerous studies have explored the effectiveness of various machine learning algorithms and classification techniques for land cover mapping. (Mahdianpari et al., 2018) conducted a comprehensive study to develop the first detailed provincial-scale wetland inventory map of Newfoundland, Canada, using multi-year Sentinel-1 SAR and Sentinel-2 optical data on the Google Earth Engine (GEE) platform. They compared pixel-based and object-based Random Forest classification approaches for mapping five wetland and three non-wetland classes. The results demonstrated the superiority of the object-based method, which achieved a Kappa coefficient of 0.85, confirming its effectiveness for large-scale wetland mapping. This finding aligns with the results of (Belgiu and Drăguţ, 2016), who identified Random Forest as a suitable option for complex wetland environments due to its effective management of high-dimensional data and resistance to overfitting. Building upon this approach, (Wen and Hughes, 2020) investigated the performance of several ensemble learning (EL) algorithms for mapping coastal wetlands in the Manning River Estuary, Australia. They compared three main ensemble approaches—bagging, boosting, and stacking—including Random Forest (RF), Gradient Boosting Machine (GBM), XGBoost, and bagged trees. The results showed that ensemble classifiers, particularly RF and weighted subspace RF, achieved high predictive accuracy in distinguishing coastal wetland types. However, ensemble models exhibited limitations in classifying minority wetland classes, and the stacking method produced inconclusive outcomes. The study highlighted the importance of incorporating hydro-geomorphic variables and suggested that vegetation indices derived from long-term remote sensing data could further improve wetland discrimination. Additionally, The importance of spectral indices in improving wetland classification was emphasized by (Pena-Regueiro et al., 2020). They demonstrated that combining various vegetation indices and water indices such as NDWI plays a key role in accurate wetland component discrimination.

The introduction of Sentinel-2 data has further enhanced the use of these spectral indices in wetland research (Mahdianpari et al., 2018), as its Red-Edge bands have been shown to improve vegetation classification accuracy by up to 12% (Immitzer et al., 2016).

Despite significant advances in wetland classification through remote sensing and machine learning, several research gaps persist. Previous studies have primarily focused on individual algorithms rather than comprehensive comparative analyses of multiple machine learning methods on identical datasets. Most research has concentrated on temperate systems, leaving coastal wetlands in arid and semi-arid regions understudied despite their unique spectral characteristics. Additionally, systematic optimization of feature combinations and algorithm parameters for enhanced accuracy and computational efficiency remains inadequately addressed.

1.1 Research Innovation and Contribution

This study addresses these critical gaps by introducing a comprehensive machine learning framework that advances wetland classification methodology through several key innovations. First, we implement and rigorously evaluate multiple machine learning algorithms—including Random Forest (RF), Support Vector Machine (SVM), Ensemble Learning, and XGBoost—specifically for coastal wetland environments, providing a systematic performance comparison across these approaches. Through comprehensive evaluation, we identify the best-performing algorithm and subsequently apply advanced hyperparameter optimization techniques using various methods to enhance classification performance and processing speed, offering practical insights for model selection and tuning in wetland remote sensing applications

2. Material and methods

2.1 Study area

Miankaleh wetland, located in northern Iran along the southeastern coast of the Caspian Sea, is a Ramsar site of international importance covering approximately 68,800 hectares (Fig. 1). This UNESCO Biosphere Reserve comprises two distinct components: The Gorgan Bay aquatic ecosystem (44,800 ha) with semi-enclosed brackish waters, and the terrestrial

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Miankaleh Peninsula (24,000 ha) supporting diverse vegetation communities including tree and bushland formations (Arij et al., 2025). The Miankaleh Wetland receives hydrological inputs from multiple sources, including inflow from the Caspian Sea via the Chopoghli channel, annual precipitation averaging 60 cm, and freshwater discharge from the Qareh Sou River system. The elevation across the wetland ranges between 15 and 30 meters below mean sea level (Seifi and Ghobadi, 2017).

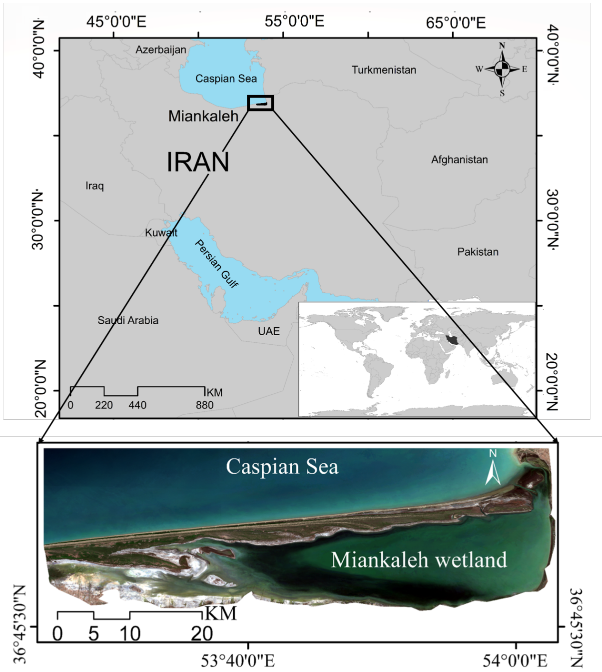

Figure 1. The geographical map displays the location of the Miankaleh wetland in northern Iran, situated along the southeastern coast of the Caspian Sea, the world's largest inland water body.
The left panel illustrates the regional context of the Miankaleh wetland within Iran and neighboring countries, while the right panel represents a detailed Sentinel-2 true-color composite image. This figure demonstrates the spatial extent and complex landscape configuration of the Miankaleh wetland as designated under the Ramsar Convention for internationally important wetlands.

2.2 Materials

2.2.1 Reference and Satellite data

Freely available Sentinel-2 multispectral images from the ESA/European Commission Copernicus Mission were used for wetland classification and change detection analysis (Bhatnagar et al., 2020). The image was acquired in June 2019 with cloud coverage limited to 30%, ensuring consistent phenological conditions for accurate temporal comparison. Surface reflectance data (Level-2A) were utilized for analysis to minimize atmospheric effects and enhance classification accuracy. All necessary image processing procedures were conducted within the Google Earth Engine (GEE) platform using JavaScript programming environment.

Reference data for training and validation were collected 2019, ground truth data were systematically collected through field surveys using Global Navigation Satellite System (GNSS) positioning within a 10×10-meter grid framework to ensure spatial accuracy and comprehensive coverage of wetland classes.

2.3 Classification Methodology and Performance Evaluation

2.3.1 Support Vector Machines (SVM)

SVM introduced by (Cortes and Vapnik, 1995), constructs optimal hyperplanes that maximize margins between classes in high-dimensional feature space. The Radial Basis Function (RBF) kernel was employed to handle non-linear class boundaries: $K(x_i,x_j) = \exp(-\gamma||x_i-x_j||^2)$. Key parameters optimized included C (regularization parameter controlling bias-variance trade-off) and γ (kernel coefficient determining decision boundary flexibility).

2.3.2 Random Forest (RF)

proposed by (Breiman, 2001), combines multiple decision trees trained on bootstrap samples using bagging ensemble technique. Classification decisions are made through majority voting across trees. The algorithm's robustness stems from feature randomization at each split and out-of-bag error estimation. Parameters optimized included n_estimators (250), max_depth, min_samples_split, and max_features to balance accuracy and computational efficiency.

2.3.3 Extreme Gradient Boosting (XGBoost)

XGBoost, developed by (Chen and Guestrin, 2016), implements gradient boosting with advanced regularization and optimization techniques. The objective function combines prediction loss and regularization terms: $Obj = \Sigma l(y_i,\hat{y}_i) + \Sigma[\gamma T + \frac{1}{2}\lambda||w||^2]$, where l represents loss function, T is number of leaves, and λ controls L2 regularization. Key optimized parameters included learning_rate (0.01-0.3), max_depth (3-10), n_estimators (100-1000), and subsample ratio.

2.3.4 Ensemble Learning

A weighted ensemble approach combined predictions from SVM, RF, and XGBoost using (Chen and Guestrin, 2016): $\hat{y}(\text{ensemble}) = \Sigma(w_i \times \hat{y}_i)$, where wi represents weights determined by individual model cross-validation performance and $\hat{y}_i$ denotes predictions from each classifier.

2.3.5 Hyperparameters Optimization

To enhance the performance of each classifier, comprehensive hyperparameter optimization was carried out using three widely adopted techniques: Grid Search, Bayesian Optimization, and SHAP-based tuning. Grid Search exhaustively evaluates predefined parameter combinations (Syarif et al., 2016), while Bayesian Optimization efficiently navigates the search space using probabilistic modeling of the objective function (Frazier, 2018). Additionally, SHAP (SHapley Additive exPlanations) values were employed to identify feature importance and interpret model behavior. These optimization strategies were applied using stratified cross-validation to ensure generalizability of the models (Gebreyesus et al., 2023).

2.3.6 Accuracy Assessment

Classification performance was evaluated using Overall Accuracy (OA), Kappa coefficient, Precision, Recall, and F-score. OA represents the proportion of correctly classified samples among all reference data, indicating the general reliability of the model. However, since OA may be affected by class imbalance, the Kappa coefficient was also calculated to account for agreement occurring by chance. κ values range from −1 to +1, with values above 0.8 indicating strong agreement (Landis and Koch, 1977). Class-specific performance was further assessed using Precision (TP/(TP+FP) and Recall (TP/(TP+FN), representing the user's and producer's accuracy, respectively. Precision reflects the model's ability to avoid false positives, while Recall indicates its capacity to capture all true instances. The F-score, computed as the harmonic mean of Precision and Recall, provides a balanced indicator of classification quality, especially in heterogeneous wetland environments (Powers, 2020). All metrics were derived from confusion matrices obtained through stratified cross-validation to ensure reliable and unbiased performance assessment.

2.4 Methodology

As depicted in the methodological workflow (Figure 2), the analytical framework began with the systematic acquisition and preprocessing of Sentinel-2 multispectral imagery within the Google Earth Engine (GEE) cloud-based geospatial processing environment. In the initial phase, an extensive feature extraction procedure was carried out to derive a diverse set of spectral and spatial attributes, including original spectral bands, vegetation and water indices (e.g., Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), etc), Gray-Level Co-occurrence Matrix (GLCM) texture features, and various differential index combinations. To address potential redundancy and enhance model efficiency, a correlation analysis was subsequently performed to quantify multicollinearity among the extracted variables. This analysis facilitated the selection of an optimal subset of features, characterized by strong discriminatory capacity and low inter-feature correlation.

The refined feature set was then utilized to conduct supervised classifications using four advanced machine learning algorithms: Support Vector Machine (SVM), Random Forest (RF), Extreme Gradient Boosting (XGBoost), and an Ensemble Learning approach. Classification outcomes were rigorously evaluated using the 2019 reference dataset, with accuracy assessments based on established statistical metrics including Overall Accuracy (OA), and the Kappa coefficient. Additionally, confusion matrix analysis was employed to determine the most robust classifier. The best-performing algorithm was subsequently fine-tuned through comprehensive hyperparameters optimization, employing advanced techniques such as Bayesian Optimization, Grid Search, SHAP analysis, and Stratified Cross-Validation, to enhance model robustness and generalization performance.

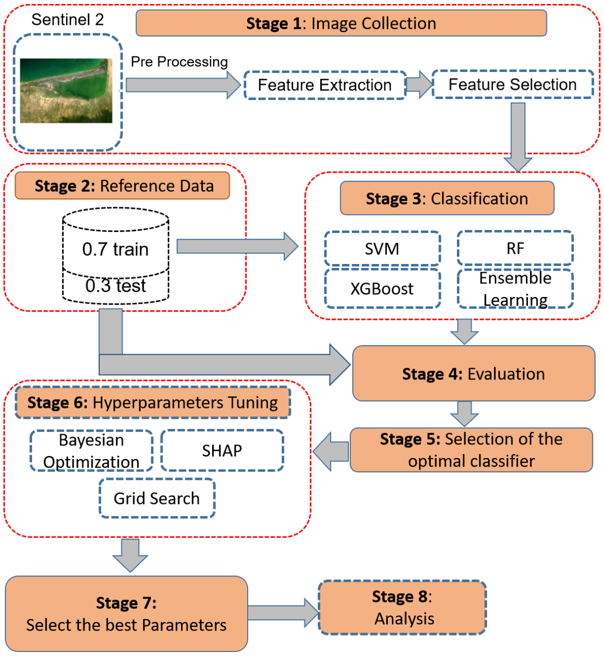

Figure 2. The overall workflow of the study

3. Result

Comprehensive machine learning-based wetland classification performance was quantified using advanced analytical approaches across temporal and spatial dimensions. For performance evaluation, we employed confusion matrix-derived metrics to precisely determine classification accuracy and class discrimination capabilities. This enabled consistent performance evaluation across multi-class wetland environments with heterogeneous spectral characteristics and temporal variations.

Feature correlation analysis revealed significant multicollinearity among the initial 45 extracted features (see Appendix A). Strong positive correlations ($r > 0.8$) were observed between vegetation indices (NDVI-EVI: $r = 0.89$, SAVI-GNDVI: $r = 0.85$), while negative correlations existed between water and vegetation indices (NDWI-NDVI: $r = -0.76$). Following correlation-based filtering (threshold $r > 0.8$), 28 features were retained, reducing computational complexity while preserving discriminatory capability (see Appendix A).

Feature importance analysis showed that advanced spectral indices outperformed conventional indices in coastal wetland classification, with GNDVI, water-related indices, and NIR band being most effective, while textural features contributed moderately (see Appendix A).

Following the completion of feature extraction and selection workflows, multi-class wetland classification was implemented using the four specified machine learning algorithms, as visualized in Figure 3. Comprehensive accuracy assessment and comparative performance evaluation are presented in Table 1 and Figure 4 (for more details, see appendix A)

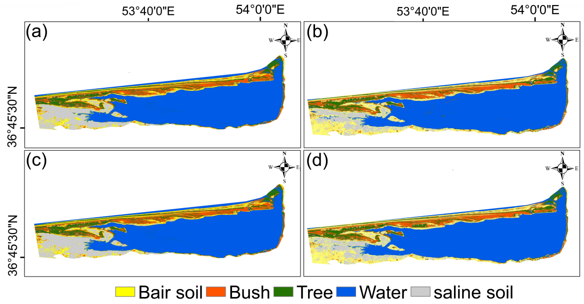

Figure 3. Wetland classification maps for 2019 derived from machine learning algorithms: (a) Random Forest (RF), (b) Support Vector Machine (SVM), (c) Ensemble Learning, and (d) XGBoost.

Each map illustrates the spatial distribution of wetland classes across the study area, demonstrating varying classification performance and spatial consistency among different algorithmic approaches.

Method	OA	Kappa	Time (sec)
SVM	0.76	0.7	196
RF	0.77	0.71	267
Ensemble learning	0.77	0.71	250
XGBoost	0.86	0.835	49

Table 1. Performance comparison of classification methods based on Overall Accuracy (OA), Kappa coefficient, and execution time.

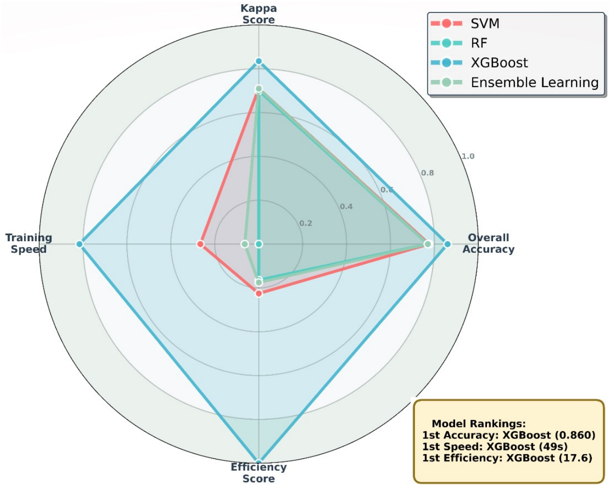

Figure 4. Radar chart comparison of machine learning model performance.

This graphical representation enables simultaneous comparison of four machine learning algorithms across different performance dimensions. The evaluation metrics include Overall Accuracy, Training Speed, Efficiency, F1-Score, and Model Ranking.

According to Figure 5, the classification results indicated that XGBoost outperformed other algorithms across all land cover classes, achieving particularly high precision and recall in the Tree and Bare soil classes. Moderate yet consistent performance was observed for Bush areas, with RF and Ensemble Learning showing comparable F1-scores. SVM demonstrated the lowest accuracy in several classes, including a noticeable decline in recall for the Water class.

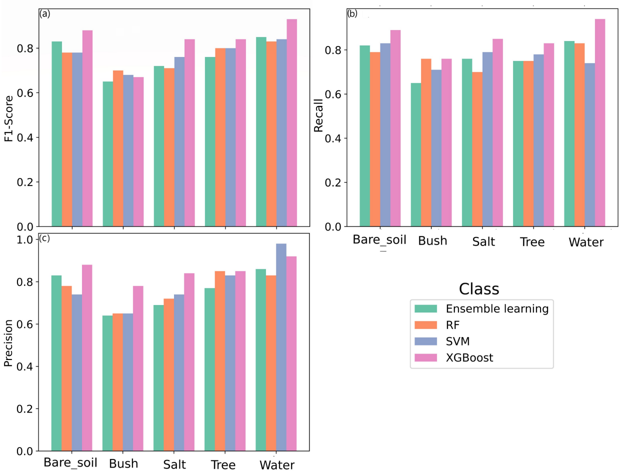

Figure 5. Performance comparison of four classifiers across land cover types using F1-score, Recall, and Precision.

Based on the obtained results and the selection of XGBoost as the optimal classifier, the model was subsequently optimized using various hyperparameter tuning methodologies to evaluate and compare their respective performance characteristics.

The KAPPA-time trade-off analysis presented in Figure 5 demonstrates distinct performance patterns across hyperparameter optimization strategies. Grid Search achieved the highest classification accuracy (KAPPA = 0.839) at the expense of computational efficiency (420 seconds), while baseline XGBoost configuration delivered competitive performance (KAPPA = 0.835) with superior efficiency (49 seconds). Random Search and SHAP-based optimization exhibited intermediate performance with KAPPA coefficients of 0.824 and 0.821, respectively, requiring 250 and 360 seconds execution time.

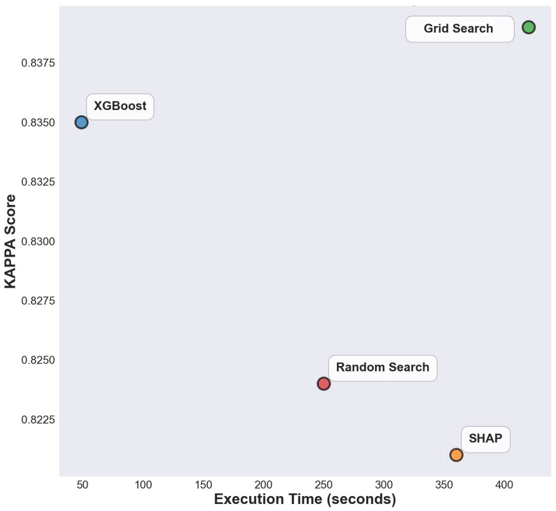

Figure 6. Performance trade-off analysis of XGBoost optimization strategies showing KAPPA coefficient versus execution time.

4. Discussion

4.1 Feature Selection and Importance Analysis

Correlation analysis reduced the feature space from 45 to 28 variables by eliminating highly correlated features. Strong inter-correlations between vegetation indices (NDVI-EVI: r = 0.89, SAVI-GNDVI: r = 0.85) revealed significant redundancy among spectral indices, consistent with Silva et al. (2008).

Feature importance analysis revealed contrasting patterns in wetland spectral discrimination. GNDVI and water-related indices outperformed conventional NDVI in coastal wetland classification, supporting findings from Pena-Regueiro et al. (2020) yet contradicting studies where NDVI achieved 88.12% accuracy in seasonal wetland mapping Xu et al. (2018). Our findings align with Stratoulias et al., (2015) regarding enhanced discrimination in Mediterranean coastal systems. The The weak tidal regime of the Caspian Sea limits periodic inundation, and vegetation reflectance in Miankaleh is primarily influenced by variations in soil moisture, salinity, and plant density. Under these conditions, GNDVI yields more consistent results than NDVI, particularly in sparsely vegetated or mixed soil–vegetation pixels.

GLCM textural features showed moderate contribution to classification performance, partially supporting Zhou et al., (2021) who reported 8% enhancement, yet contradicting studies where textural features provided minimal improvement Zhang et al., (2024). This suggests that while texture discriminates wetland vegetation types (emergent vs. submerged), its contribution is overshadowed by the inherent spectral complexity of wetland plant communities and water-vegetation boundaries, unlike terrestrial vegetation where texture becomes more critical for species discrimination.

4.2 Performance Comparison of Machine Learning Algorithms

The comparative evaluation of machine learning algorithms revealed significant variations in their effectiveness for coastal wetland classification. XGBoost demonstrated superior performance as shown in Table 1, substantially outperforming traditional algorithms including Random Forest, Support Vector Machine, and Ensemble Learning. This finding challenges the widely reported superiority of Random Forest in wetland classification studies Belgiu and Drăguţ, (2016) and Mahdianpari et al., (2018), suggesting that gradient boosting methods may be more suitable for complex coastal wetland environments.

Our findings indicate that the exceptional performance of XGBoost can be attributed to its sophisticated gradient boosting framework, which iteratively optimizes prediction errors through sequential tree construction and advanced regularization techniques. The results demonstrate that unlike Random Forest's parallel tree construction, XGBoost's sequential learning approach enables more effective handling of the spectral complexity inherent in coastal wetlands, where subtle differences between land cover classes require advanced discriminatory capabilities. The analysis reveals that XGBoost's built-in regularization mechanisms effectively prevent overfitting, which proves particularly crucial when dealing with the high-dimensional feature space typical of multispectral remote sensing data.

The computational efficiency analysis revealed another significant advantage of XGBoost, requiring only 49 seconds of execution time (Figure. 5), while RF and SVM required 267 and 196 seconds, respectively. According to findings by Yimer et al., (2024), the RF algorithm benefits from temporal advantages over SVM due to its parallelization nature and resistance to overfitting. Similarly, results from Salas et al., (2024) confirm this observation. However, while Chen and Guestrin, (2016) addressed execution speed optimization in the initial design of XGBoost, this evaluation had not been conducted in the context of wetland classification until now.

In this study, we demonstrate for the first time that XGBoost not only exhibits superiority in coastal wetland classification accuracy but also delivers significantly more optimal performance in terms of execution time compared to other algorithms. Our analysis revealed that this temporal advantage stems from the sequential boosting structure, utilization of pre-sorting mechanisms, and regularization techniques within the XGBoost architecture, which collectively reduce computational complexity and enable faster model convergence.

4.3 Hyperparameter Optimization Trade-offs

The hyperparameter optimization analysis revealed a clear trade-off between classification accuracy and computational efficiency. As shown in Figure 5, the Grid Search approach achieved the highest accuracy; however, its computational cost (420 s) was considerably higher than that of the baseline XGBoost configuration (49 s), which already yielded a nearly equivalent accuracy (Kappa = 0.835). This indicates that the default parameter settings of XGBoost are sufficiently robust for coastal wetland classification, where timely model execution can be as crucial as absolute accuracy. Such a balance between performance and efficiency is essential for large-scale operational monitoring.

These findings are consistent with several previous studies emphasizing that hyperparameter tuning enhances accuracy but at the expense of computational demand. For example, Park et al., (2021), in Sentinel-2 land-cover mapping, reported that Grid Search achieved the highest overall accuracy, whereas Random Search was significantly faster. They also found that XGBoost consistently outperformed RF and LightGBM. Similarly, Shao et al., (2024) demonstrated that XGBoost achieved 81% accuracy compared to 77% for RF in multisensor urban mapping. These studies collectively support our observation that XGBoost attains strong baseline accuracy even with limited parameter tuning.

However, our results contrast with studies suggesting that the default XGBoost configuration is insufficient for optimal performance. For instance, Samat et al., (2020) found that fine-tuning was essential to achieve optimal results in hyperspectral image classification. Similarly, Byun et al. (2021) concluded that high accuracy could only be achieved through comprehensive hyperparameter optimization, identifying Grid Search as the most effective though computationally intensive method. In addition, Ma et al., (2025) reported that Bayesian optimization achieved the best accuracy, while Grid Search slightly outperformed Random Search for wetland mapping. Along the same lines, Khan et al., (2025) emphasized the necessity of Grid Search for improving the accuracy of XGBoost models in wetland-related applications.

The divergence between our results and these studies can be attributed to differences in data complexity, target classes, and application context. Unlike the aforementioned works that addressed heterogeneous multi-class environments or hyperspectral data, our dataset represents a spectrally homogeneous coastal wetland system with a limited number of broad classes. Such spectral separability reduces XGBoost's sensitivity to parameter variations, allowing the default configuration to perform near-optimally. Moreover, our study prioritizes operational efficiency—rapid and repeatable wetland mapping for monitoring purposes—over maximizing marginal accuracy gains. In this context, the minimal accuracy improvement obtained through Grid Search (<0.5% Kappa) does not justify its eightfold increase in computational time.

In summary, while extensive hyperparameter optimization has proven valuable for complex and heterogeneous remote-sensing tasks, our findings suggest that for spectrally distinct and structurally stable coastal wetland systems, the default XGBoost configuration offers an optimal balance between accuracy and efficiency. This highlights that the value of exhaustive tuning is context-dependent, and in operational wetland monitoring, computational efficiency may reasonably take precedence over marginal accuracy improvements.

4.4 Limitations and Future Research Directions

In interpreting these results, several limitations must be considered. This study focused on a single coastal wetland ecosystem, and the generalizability of the findings to other wetland types and geographic regions requires further investigation. Reliance on Sentinel-2 optical data, while cost-effective and readily accessible, constrains the analysis to cloud-free conditions and may not capture the full spectral information needed for detailed wetland differentiation. Future research directions should include: (1) evaluating the developed framework across diverse wetland types and geographic settings, (2) integrating multi-sensor data (optical, SAR, LiDAR) to enhance classification accuracy and robustness, and (3) developing automated change detection algorithms capable of identifying and quantifying specific wetland transformations.

5. Conclusion

With an emphasis on hyperparameter optimization, we systematically evaluated several machine learning methods for coastal wetland categorization in this study: Random Forest, Support Vector Machine, Ensemble Learning, and XGBoost. With the highest accuracy (Kappa = 0.835) and the quickest computation time (49 seconds), XGBoost continuously beat the other models in the test. While textural variables made a moderate contribution, feature significance analysis revealed that advanced spectral indices, such as GNDVI and water-related indices, were crucial in differentiating across wetland classes.Our analysis of hyperparameter optimization showed a definite trade-off between computational cost and accuracy. The accuracy of Grid Search was somewhat improved (Kappa = 0.839), but the computational cost was over eight times more than with the usual XGBoost setup. This result implies that default or little adjusted XGBoost settings offer a reliable and effective solution for spectrally uniform and structurally stable coastal wetlands, striking a balance between excellent classification performance and realistic processing requirements.

These findings highlight XGBoost's potential as a dependable instrument for coastal wetland research, providing benefits over conventional classifiers in terms of accuracy and efficiency. However, they also point out that in more complicated or diverse wetland settings, where minute spectrum variations necessitate precise changes, considerable tuning would be most advantageous. This study is restricted to a particular coastal wetland system, despite the promising results. In order to properly monitor temporal dynamics, future study should investigate the integration of multi-sensor data (optical, SAR, and LiDAR), test the suggested framework across various wetland kinds and geographies, and create automated change detection techniques.

All things considered, our study shows that selecting machine learning techniques carefully and adjusting hyperparameters may result in precise, effective, and useful wetland categorization solutions that offer useful advice for ecological research and conservation management.

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