

# ESTIMATING SHALLOW-WATER BATHYMETRY FROM SENTINEL-2 IMAGERY USING MACHINE LEARNING: A CASE STUDY IN COASTAL AREA OF GIA LAI, VIETNAM

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## Abstract

This study investigates the potential of applying machine learning algorithms to estimate shallow-water bathymetry from Sentinel-2 satellite imagery in the coastal waters of Gia Lai province, Vietnam. A Sentinel-2 Level-2A image acquired on January 23, 2020, under clear and stable optical conditions, was used after atmospheric correction. In-situ bathymetric data were collected using a GPS-integrated single-beam echo sounder and employed as training and validation datasets. Five machine learning models, including Multiple Linear Regression (MLR), Random Forest (RF), Decision Tree (DT), K-Nearest Neighbors (KNN), and Long Short-Term Memory (LSTM), were developed and compared for bathymetric estimation accuracy. The results indicate that the coefficient of determination ( $R^2$ ) ranges from 0.80 to 0.91, with Root Mean Square Error (RMSE) values between 0.72 m and 1.05 m, and Mean Absolute Error (MAE) values ranging from 0.49 m to 0.72 m. These findings demonstrate the feasibility of integrating Sentinel-2 imagery with machine learning for accurate shallow-water bathymetric mapping. Furthermore, the proposed approach shows strong potential for application to other coastal regions of Vietnam with comparable environmental and optical characteristics.

**Keywords:** Bathymetry; remote sensing; Sentinel-2; machine learning; water depth estimation; coastal mapping.

## 1. Introduction

Vietnam possesses an extensive marine area with a coastline stretching approximately 3,350 km. Bathymetric information plays a vital role in various fields such as coastal resource management, port planning, coastal erosion studies, marine environmental research, as well as socio-economic development and national defense. However, traditional bathymetric survey methods, including single-beam and multi-beam echo sounding, are often costly, time-consuming, and labor-intensive. These techniques are particularly challenging in shallow waters, areas with complex topography, or regions that undergo rapid seasonal changes.

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In this context, optical remote sensing has proven to be an effective and efficient tool for estimating shallow-water bathymetry based on the reflection of light from the seabed to the water surface. For instance, Stumpf *et al.* [1] established a relationship between water depth and the attenuation of blue and green light, which has been widely adopted for depth estimation. Wu *et al.* [2] integrated multiple datasets and machine learning algorithms to enhance bathymetric estimation in turbid harbor waters. Optical-based methods have generally demonstrated greater accuracy and simplicity compared to SAR-based approaches, with hyperspectral imagery outperforming multispectral techniques [3]. Doxani *et al.* [4] investigated the potential of WorldView-2 eight-band imagery for precise bathymetric mapping by applying the linear Lyzenga depth model to areas with varying seagrass coverage. The integration of multispectral imagery with acoustic and GPS-based depth data has also been shown to improve bathymetric accuracy [4]. These advances in satellite-derived bathymetry offer cost- and time-efficient solutions for estimating water depth, particularly in inaccessible areas, and demonstrate great promise for the continued development of shallow-water depth inversion technologies [3].

In Vietnam, several studies have employed satellite imagery for bathymetric mapping. For example, Hung and Phu [5] utilized Landsat-8 imagery for bathymetric estimation, while Hang and Hung [6] applied stereophotogrammetric techniques using WorldView-2 imagery, achieving maximum depth measurements of over 42 m in the Spratly Islands. N. H. Nguyen *et al.* [7] proposed a method for assessing seabed morphological changes by determining depth using Sentinel-2 satellite data. In recent years, the advancement of machine learning techniques has opened new opportunities for bathymetric estimation by enabling the modeling of complex nonlinear relationships between spectral reflectance and actual water depth. Numerous studies conducted in Vietnam and worldwide have shown that models such as Random Forest (RF), Support Vector Regression (SVR), and Neural Networks can achieve high accuracy, particularly in shallow waters (< 15–20 m). However, in the coastal region of Gia Lai, research on the application of machine learning for bathymetric estimation using Sentinel-2 imagery remains very limited. Therefore, this study aims to evaluate the potential of machine learning algorithms in estimating water depth from Sentinel-2 imagery for the coastal area of Gia Lai, Vietnam, thereby demonstrating the feasibility and potential for extending this approach to other Vietnamese coastal regions with similar optical and environmental characteristics. Besides, we selected the Google Earth Engine (GEE) cloud computing platform to process satellite imagery data. GEE has been widely utilized in various studies in Vietnam for example, using multi satellite imagery and GEE to monitor land cover

changes with the Random Forest algorithm [8], or developing land subsidence prediction models with multiple machine learning approaches [9]. However, the application of GEE for bathymetric estimation remains extremely limited in Vietnam.

## 2. Materials and methodology

### 2.1. Study area

The study was conducted in the coastal area of Bai Dai, located in Quy Nhon city, Gia Lai province, Vietnam. Bai Dai lies between latitudes  $13^{\circ}41'50'' - 13^{\circ}42'20''\text{N}$  and longitudes  $109^{\circ}13'10'' - 109^{\circ}13'41''\text{E}$ , approximately 2.5 km southeast of the Quy Nhon city center (Fig. 1). The beach extends for about 1 km along the coastline. Bai Dai is strongly influenced by ocean waves and currents from the East Sea (South China Sea), which significantly affect the coastal morphology and sediment dynamics. Continuous wave action and tidal currents reshape the coastline, forming distinct landforms such as sandbars, dunes, and rocky reefs. Natural coral reefs are also distributed along the nearshore zone. The water depth in the study area ranges from 0 m to approximately 11 m.

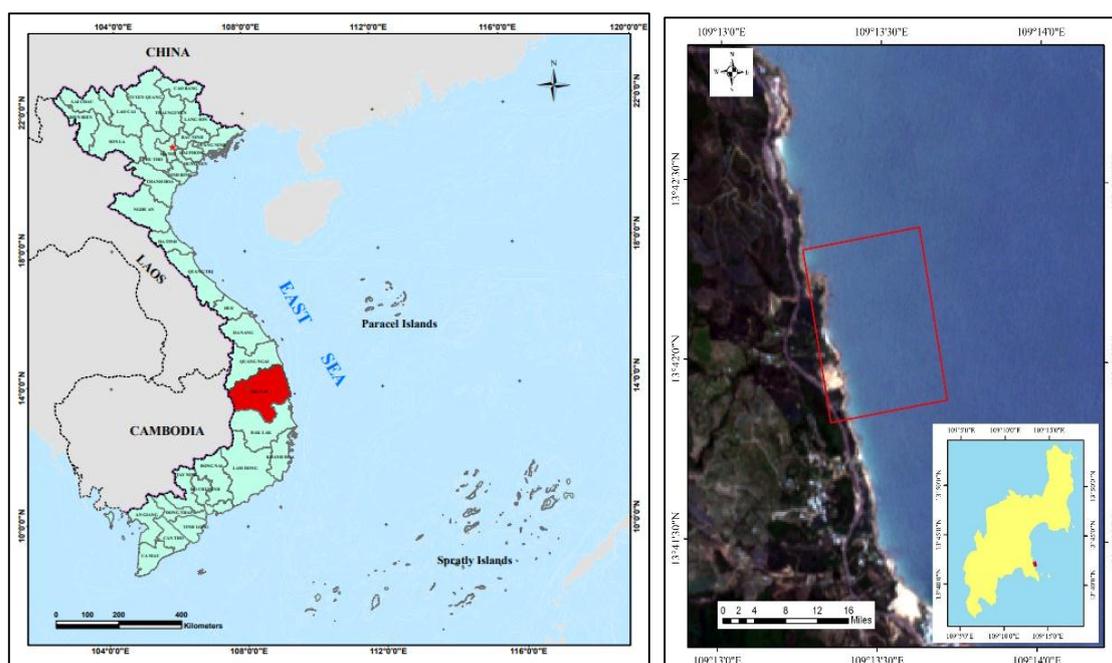


Fig. 1. Location of the study area in Bai Dai, Gia Lai, Vietnam.

### 2.2. Data sources

This study employed Sentinel-2 satellite imagery acquired on January 23, 2020, under clear-sky conditions. The data were obtained at Level-2A, which provides atmospherically corrected surface reflectance products in an orthorectified format. Four

spectral bands were selected for bathymetric modeling: Band 2 (Blue, 10 m), Band 3 (Green, 10 m), Band 4 (Red, 10 m), and Band 8 (Near-Infrared, 10 m).

In-situ bathymetric data were collected in the Bai Dai area using a single-beam echo sounder integrated with a GPS receiver. The transducer was mounted on a survey vessel that followed pre-defined transects to obtain depth measurements across the study area. The single-beam echo sounding method typically provides an accuracy of 10–20 cm, depending on water conditions and vessel speed.

The collected depth measurements were processed and exported in Shapefile format to enable integration with Sentinel-2 imagery and subsequent model development. A total of 10,000 depth points were used in this study. Following a 75/25 data-splitting strategy, 7,500 points were assigned to the training set and 2,500 points to the testing set. Both datasets covered depth values ranging from 0 m to –10 m. To ensure an objective evaluation of model performance and avoid spatial autocorrelation bias, the training and testing samples were spatially separated into two distinct subregions (Fig. 2).

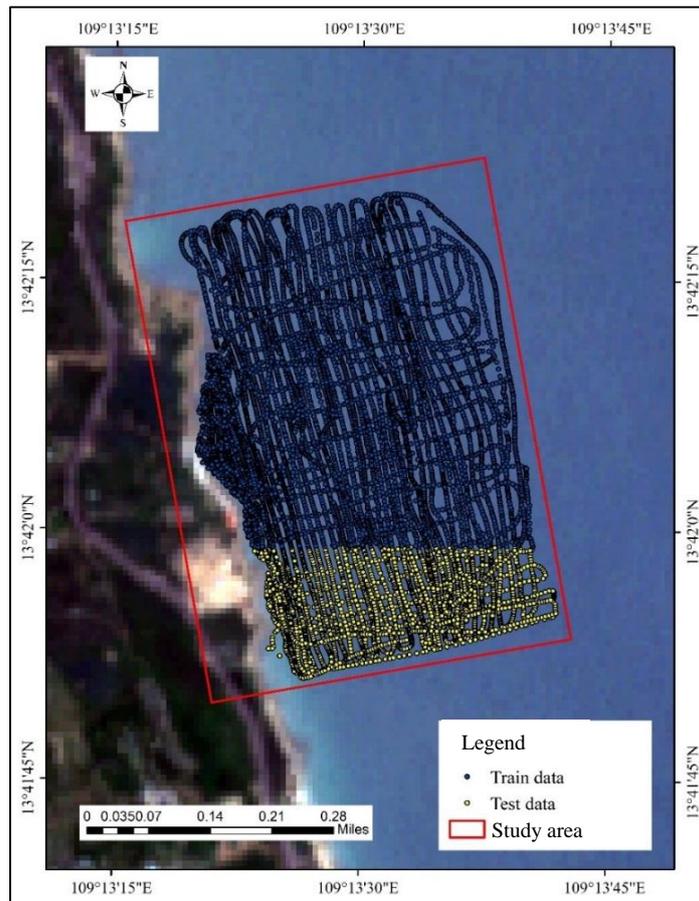


Fig. 2. In-situ bathymetric measurements were acquired using a single-beam echo sounder integrated with a GPS receiver.

### 2.3. Methodology

The process of using machine learning to estimate bathymetry from Sentinel-2 satellite imagery is illustrated in Fig. 3.

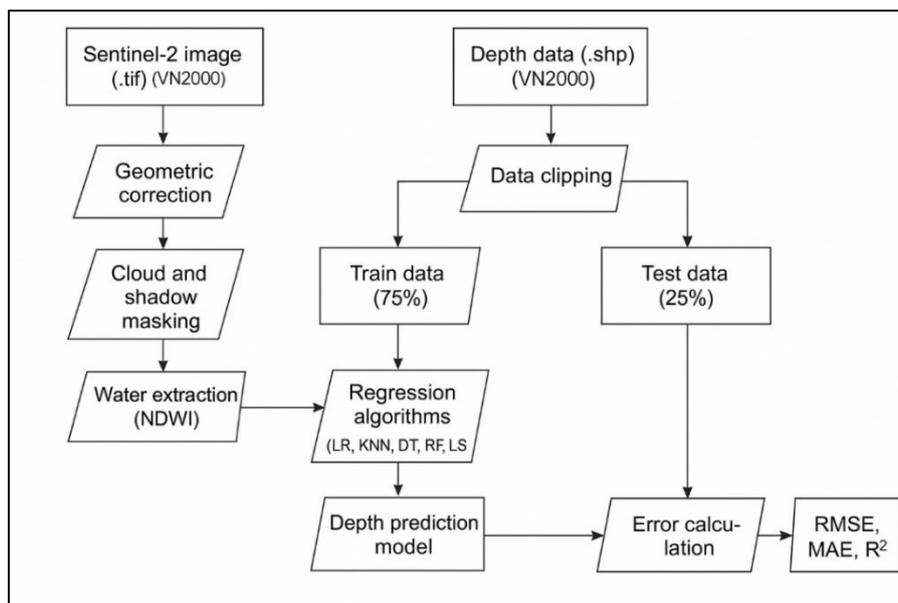


Fig. 3. Workflow for depth estimation from Sentinel-2 satellite imagery.

The methodology used in this study consists of the following main steps:

- **Preprocessing of Sentinel-2 imagery**

First, cloud filtering was performed on the Sentinel-2 surface reflectance dataset based on parameters such as the study area, cloud coverage, and acquisition time. Images with minimal cloud cover over the study area were selected to reduce noise caused by clouds and cloud shadows in the surface reflectance data. This step is crucial because cloud and shadow interference can lead to significant errors in depth estimation derived from remote sensing data.

- **Separation of water and non-water areas**

The next step is to apply the Normalized Difference Water Index (NDWI) to enhance the contrast between water and land features and extract the water surface area. This process ensures that only water pixels are used in the depth estimation, minimizing the influence of land-based noise. The NDWI was calculated using the formula proposed by [10]:

$$NDWI = \frac{\rho_{GREEN} - \rho_{NIR}}{\rho_{GREEN} + \rho_{NIR}} \quad (1)$$

where  $\rho_{GREEN}$ ,  $\rho_{NIR}$  represent the reflectance values in the GREEN (Band 3) and NIR (Band 8) bands of Sentinel-2 imagery. The reflectance values were then used to compute the remote sensing reflectance (Rrs) based on established algorithms.

• **Bathymetric estimation**

Before being fed into the machine learning models, all input features, including bathymetric depth values ranging from negative (below sea level) to zero, were normalized to the [-1, 1] range using Min-Max scaling:

$$x' = 2 \frac{x - x_{\min}}{x_{\max} - x_{\min}} - 1 \quad (2)$$

where  $x_{\min}$  and  $x_{\max}$  are the minimum and maximum values of each feature in the training dataset. Normalization ensures that all variables contribute proportionally during model training and improves the convergence and stability of the models.

The training data were then used to develop prediction models using various machine learning algorithms, including:

- Linear Regression (LR): A fundamental machine learning algorithm used for predicting continuous values. It establishes a linear relationship between one or more independent variables and a dependent variable, fitting a straight line that best predicts the target variable [11].

- Decision Tree (DT): A popular algorithm for both regression and classification. It divides data into subsets based on decision rules represented as a tree structure. Each node represents a test condition, each branch an outcome, and each leaf a predicted value or class label [12].

- K-Nearest Neighbors (KNN): A simple supervised learning algorithm that does not explicitly learn a model (lazy learning). Predictions for new data are made based on the labels of the k nearest training samples in the feature space [12].

- Random Forest (RF): An ensemble learning algorithm that builds multiple decision trees using bootstrapped subsets of the training data. The final prediction is derived by aggregating the results (voting or averaging) from all trees. This approach reduces bias and variance, helping the model overcome overfitting [12].

- Long Short-Term Memory (LSTM): A special type of Recurrent Neural Network (RNN) designed to handle sequential data such as time series or spatially correlated data. Unlike traditional RNNs, LSTM networks can retain important information over long dependencies, effectively addressing the “vanishing gradient” problem. Although LSTM networks are typically applied to time-series data, they are also capable of learning

complex nonlinear relationships and sequential dependencies among input features. Incorporating the LSTM model into our comparison framework allows us to examine whether a sequence-based deep learning architecture can effectively capture the spectral structure of Sentinel-2 data and thereby improve the accuracy of bathymetric estimation [13].

**• Evaluation of results**

The accuracy of the bathymetric estimations derived from remote sensing data is validated against field-measured depth values. The evaluation employs three common statistical metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination ( $R^2$ ).

- Mean absolute error (MAE): is one of the performance evaluation indicators of a predictive model, especially popular in regression problems. It measures the average deviation between the predicted value and the actual value of a variable. The smaller the MAE value, the more accurate the model, that is, the closer the predicted value is to the actual value. To calculate the mean absolute error (MAE), we calculate based on the actual depth points in the test data set and the corresponding values of those points on the predicted depth map according to formula (2):

$$MAE = \frac{1}{n} \sum_{i=1}^n |Z_{SDB\_i} - Z_{pred\_i}| \tag{3}$$

where  $n$  is the number of test points;  $Z_{SDB\_i}$  is the predicted depth value of point  $i$ ;  $Z_{pred\_i}$  is the actual depth value of point  $i$ .

- Root mean square error (RMSE) is an important statistical index used to measure the deviation between predicted values and actual values in forecasting models. In other words, RMSE indicates how much the average model's predictions deviate from the actual values. The smaller the RMSE value, the more accurate the model, that is, the closer the predicted value is to the actual value. Root mean square error (RMSE) is calculated according to formula (3):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Z_{SDB\_i} - Z_i)^2} \tag{4}$$

where  $n$  is the number of test points;  $Z_{SDB\_i}$  is the predicted depth value of point  $i$ ;  $Z_i$  is the actual depth value of point  $i$ .

- The coefficient of determination  $R^2$  is calculated according to formula (5):

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \quad (5)$$

where *SSE* (Sum of Squared Errors) is the sum of squares of errors between the predicted and actual values, *SST* (Total Sum of Squares) is the sum of squares of the differences between the actual value and the mean of the predicted values, *SSR* (Sum of Squares due to Regression) is the sum of squared differences between the predicted values and the mean of the observed values.

• ***The hyperparameters setting***

The hyperparameters for all machine learning models were selected based on recommended default values commonly used in practice and supported by the respective libraries. For instance, the Random Forest (RF) model used 300 trees (*n\_estimators* = 300), *max\_features* = sqrt, *min\_samples\_split* = 2, *min\_samples\_leaf* = 1, and *bootstrap* = True (using bootstrap sampling and random feature selection at each split to reduce overfitting), which are standard defaults recommended for regression tasks. These choices provide a good balance between model complexity and generalization, ensuring reliable performance without extensive hyperparameter tuning. Similarly, the LSTM model parameters, including 50 units per layer and typical dropout rates of 0.2-0.5, were chosen following common practices in time series regression and remote sensing applications.

### **3. Results and discussion**

Based on Sentinel-2 satellite imagery and in-situ bathymetric measurements, this study processes and analyzes the data using the Google Earth Engine (GEE) platform to estimate the bathymetry of the Bai Dai coastal area. The Sentinel-2 imagery, with a spatial resolution of 10 m, provides sufficient detail for capturing nearshore bathymetric variation while maintaining computational efficiency. Atmospheric correction and preprocessing steps ensure radiometric consistency and minimize the influence of surface and environmental noise. The processed multispectral bands are then integrated with field-measured depth samples to train and validate several machine learning models.

The resulting bathymetric maps exhibit depth estimations at a 10 m spatial resolution, corresponding to the native resolution of the Sentinel-2 bands. Figure 4 illustrates the bathymetric distributions derived from five different machine learning algorithms: Multiple Linear Regression (MLR), Decision Tree (DT), K-Nearest Neighbors (KNN), Random

Forest (RF), and Long Short-Term Memory (LSTM). Each model produces a distinct spatial pattern of depth estimation, reflecting its capacity to capture the nonlinear relationship between spectral reflectance and water depth. The comparison among these models provides insight into their respective strengths and limitations in modeling shallow-water bathymetry under tropical coastal conditions (Fig. 5).

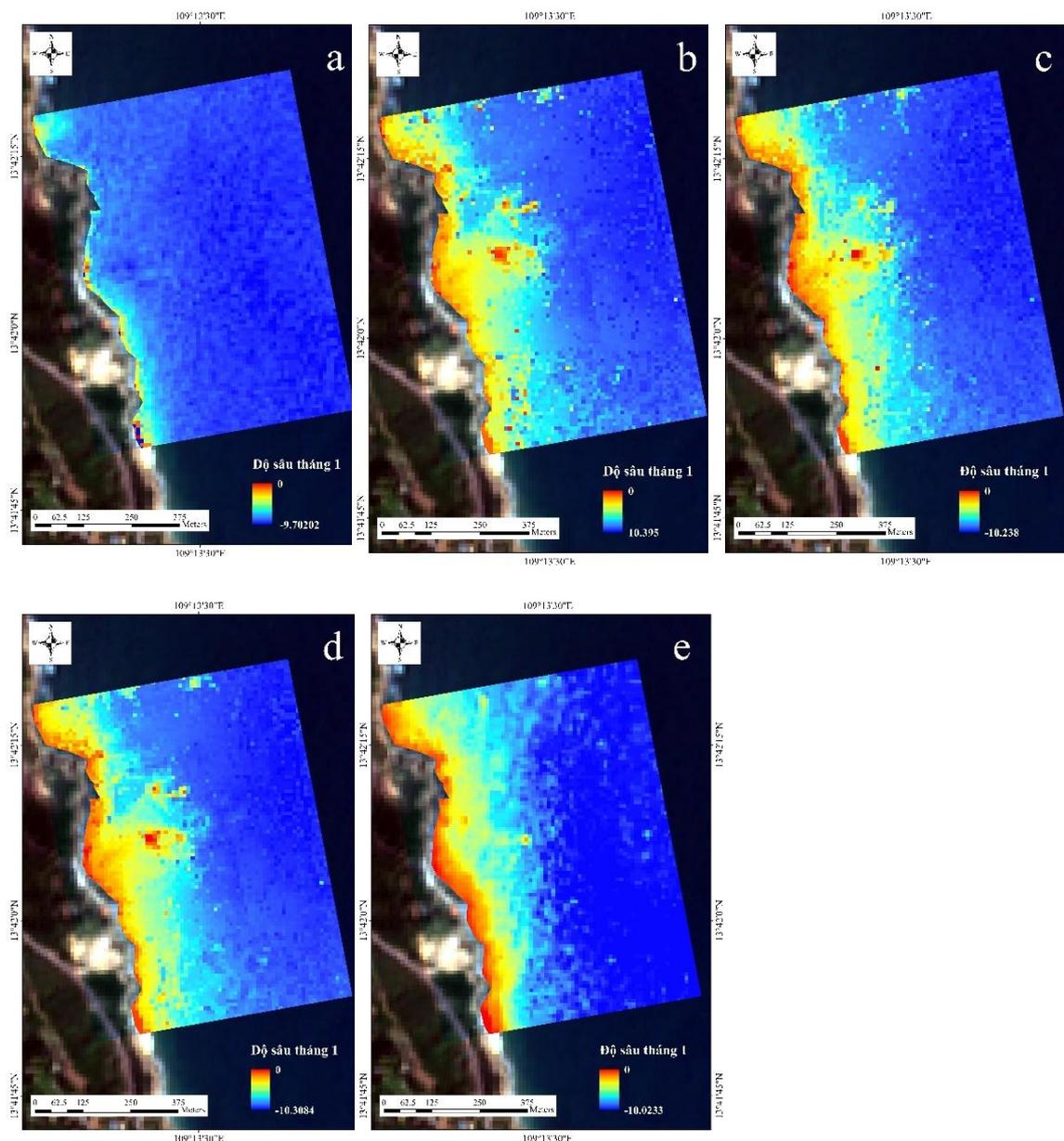


Fig. 4. Bathymetry derived from Sentinel-2 satellite images: (a) Linear Regression, (b) Decision Tree, (c) K-Nearest Neighbors, (d) Random Forest, (e) LSTM.

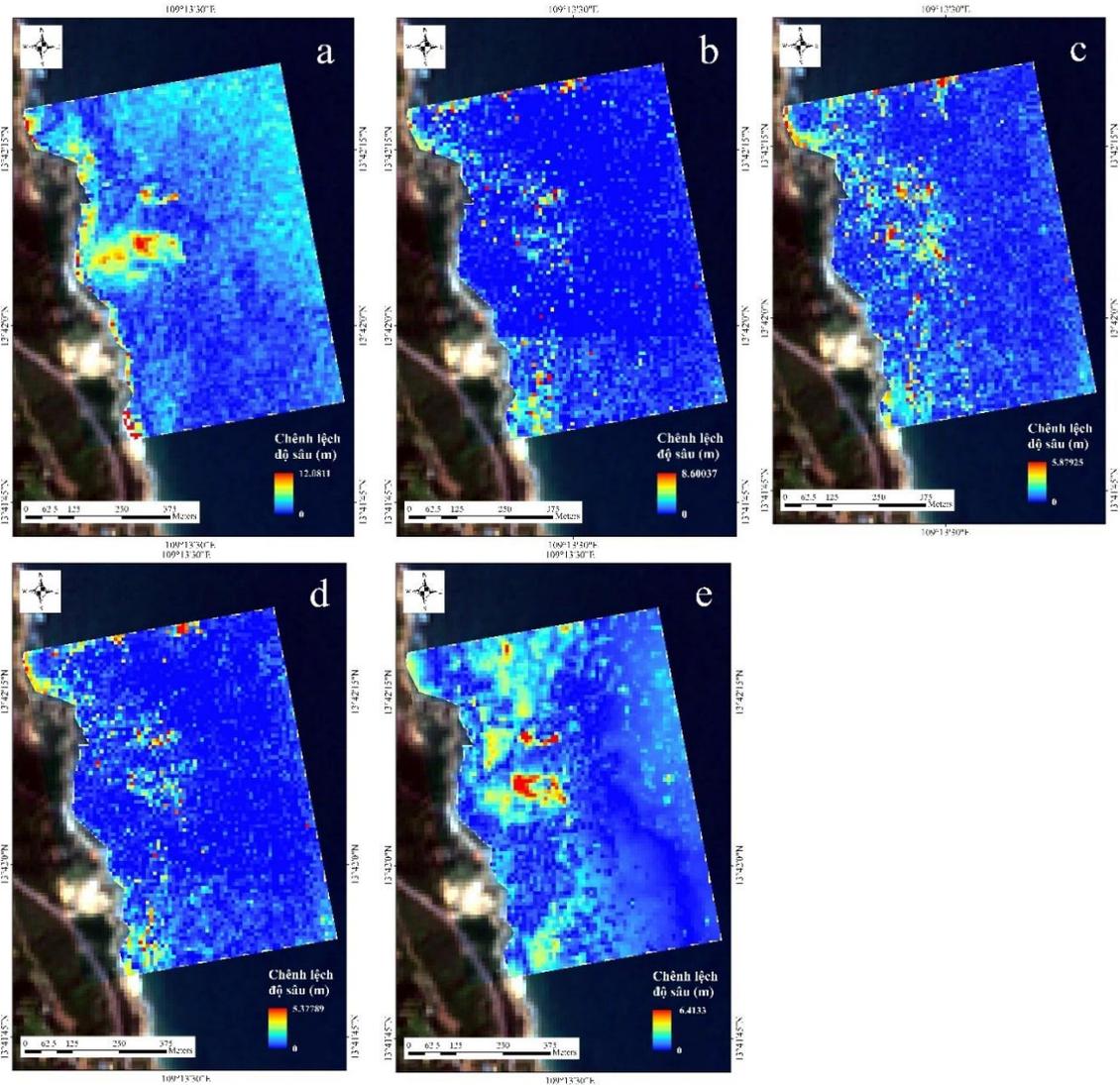


Fig. 5. Comparison between bathymetry derived from Sentinel-2 images and field-measured bathymetry: (a) Linear Regression, (b) Decision Tree, (c) K-Nearest Neighbors, (d) Random Forest, (e) LSTM.

To provide a more comprehensive and intuitive comparison of the post-prediction performance among the evaluated algorithms, a longitudinal cross-section is generated across the test region, extending from shallow nearshore waters to deeper offshore zones (Fig. 6). This cross-sectional analysis allows for the visualization of depth variations predicted by each model relative to the actual in-situ measurements, thereby highlighting local discrepancies and systematic biases. By examining how each algorithm reproduces the gradual change in bathymetry along this transect, the study offers deeper insight into their respective capacities to model spatial depth gradients in optically shallow waters.

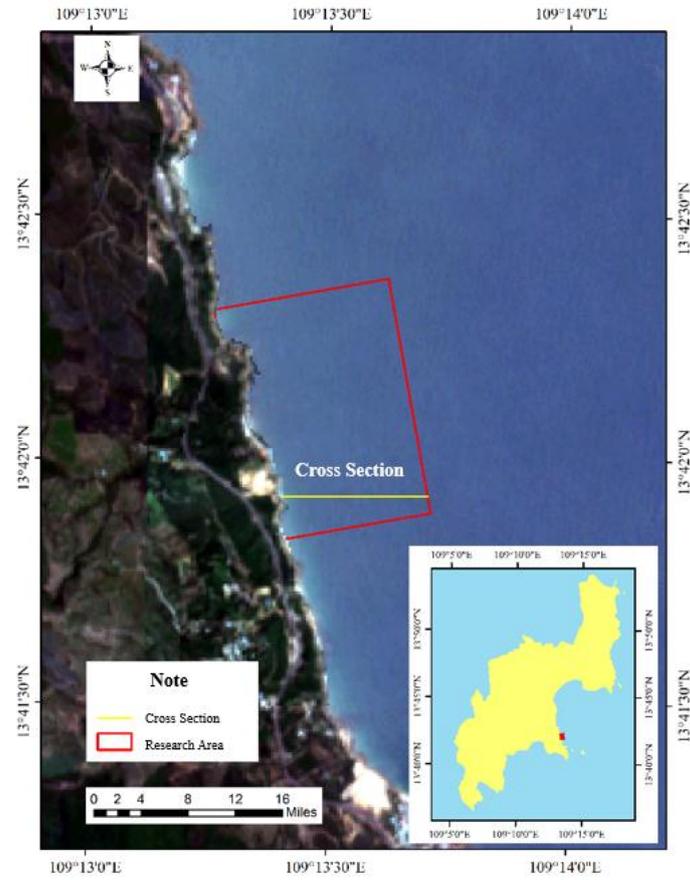


Fig. 6. Cross-section line from shallow to deep areas in the test region.

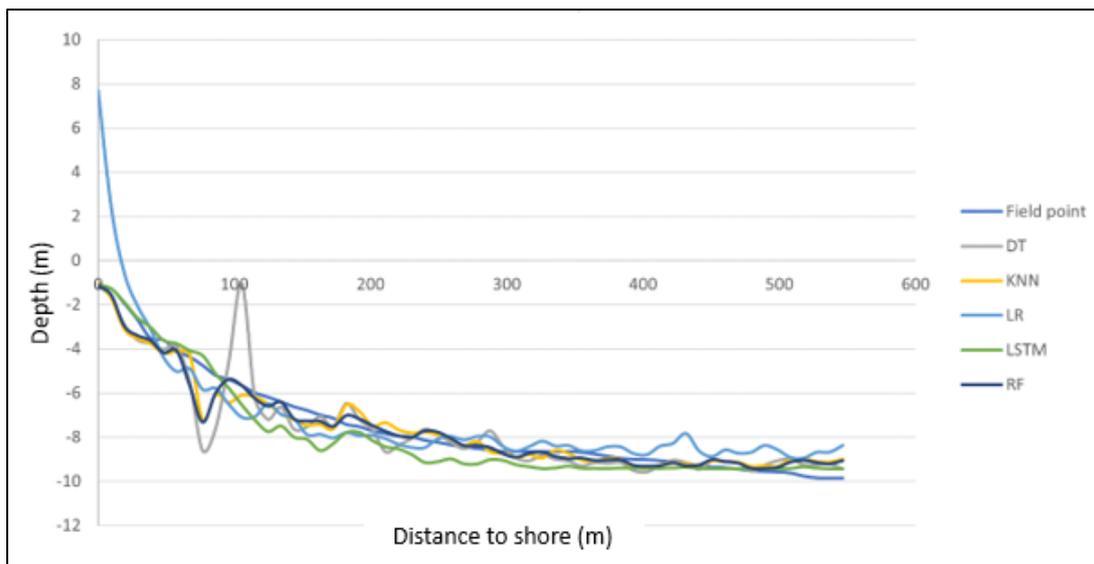


Fig. 7. Longitudinal profiles of bathymetry predicted by different algorithms.

Observing Fig. 7, it is evident that the cross-sectional depth profiles predicted by the Random Forest and K-Nearest Neighbors (KNN) algorithms exhibit a close correspondence with the actual in-situ measurements, reflecting a high level of agreement with the measured bathymetry across both shallow and deeper zones. These models effectively capture the nonlinear variations in depth, demonstrating their robustness in handling the optical complexity of coastal waters. In contrast, the Linear Regression model shows the poorest performance, particularly within the nearshore zone (0–100 m), where depth fluctuations are more abrupt and strongly influenced by nonlinear optical and geomorphological factors. This discrepancy highlights the limitations of linear models in representing the intricate relationships between spectral reflectance and water depth in heterogeneous coastal environments.

After constructing the prediction models, the algorithms are applied to Sentinel-2 imagery to generate bathymetric maps. The test dataset is used to evaluate model performance based on three statistical indices: RMSE, MAE, and  $R^2$  (Fig. 8).

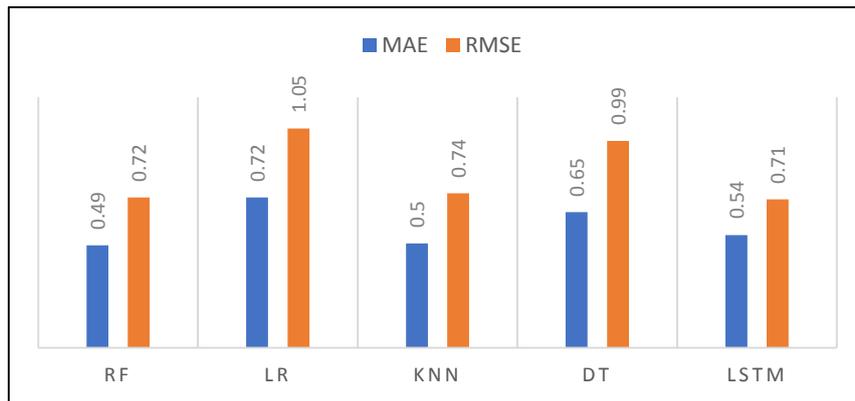


Fig. 8. MAE and RMSE indices of the applied algorithms.

The results reveal that the MAE values derived from Sentinel-2-based bathymetric predictions range from 0.49 m to 0.74 m, with the smallest MAE (0.49 m) achieved by the Random Forest (RF) algorithm and the largest (0.74 m) by the K-Nearest Neighbors (KNN) model. Similarly, RMSE values vary between 0.71 m and 1.05 m, with the LSTM model producing the lowest RMSE (0.71 m) and Linear Regression (LR) the highest (1.05 m).

The  $R^2$  values range from 0.80 to 0.91, indicating a strong correlation between predicted and measured depths (Tab. 1). The Random Forest and LSTM algorithms achieved the highest  $R^2$  value of 0.91, while Linear Regression performed the weakest with  $R^2 = 0.80$ .

Tab. 1.  $R^2$  values of different algorithms

Random Forest	Linear Regression	KNN	Decision Tree	LSTM
0.91	0.80	0.90	0.82	0.91

The evaluation results indicate that the proposed models can effectively estimate shallow-water bathymetry in the Bai Dai coastal area using Sentinel-2 satellite imagery.

#### 4. Discussion

The comparative analysis of the five machine learning algorithms reveals both the strengths and limitations of each approach in estimating shallow-water bathymetry from Sentinel-2 imagery. Among them, the Random Forest (RF) and LSTM models consistently outperformed the others, achieving the highest accuracy metrics with  $R^2$  values of 0.91, MAE of 0.49 m, and RMSE of 0.71 m. Their superior performance can be attributed to their ability to capture complex nonlinear relationships between multispectral reflectance values and water depth. RF effectively handles high-dimensional data and reduces overfitting through ensemble averaging, while LSTM's sequential learning capability enables it to better represent subtle variations in spectral responses related to water-column effects.

In contrast, Linear Regression (LR) showed the weakest performance, mainly due to its inability to model nonlinear interactions between optical reflectance and depth, particularly in nearshore zones where bottom type, turbidity, and water clarity vary considerably. The Decision Tree (DT) model achieved moderate performance but tended to overfit the training data, resulting in less stable predictions in deeper areas. The K-Nearest Neighbors (KNN) algorithm performed reasonably well in shallow regions but exhibited reduced accuracy as water depth increased, likely due to spectral signal attenuation and reduced optical penetration.

Despite these differences, all machine learning algorithms demonstrated a clear potential to derive bathymetric information from multispectral satellite data, confirming the effectiveness of data-driven approaches over traditional empirical or physics-based methods, especially when field data are limited. However, several challenges remain. Model accuracy can be affected by environmental factors such as water turbidity, bottom reflectance heterogeneity, and seasonal variations in optical properties. Additionally, the relatively limited number of in-situ depth samples may constrain model generalization to other coastal regions.

The findings suggest that integrating advanced algorithms, such as deep neural networks or hybrid ensemble methods, could further enhance prediction performance.

Future studies should also explore multi-temporal Sentinel-2 data and data fusion with higher-resolution sensors (e.g., WorldView or PlanetScope) to improve spatial and temporal consistency. From a practical perspective, the integration of Sentinel-2 imagery with machine learning algorithms provides a cost-effective and scalable solution for coastal bathymetric mapping, supporting applications in marine spatial planning, navigation safety, coastal engineering, and environmental monitoring in Vietnam's coastal and island regions.

## 5. Conclusion

This study developed and validated an automatic bathymetry estimation approach for the Bai Dai coastal area using Sentinel-2 satellite imagery combined with in-situ depth measurements. The findings indicate that Sentinel-2 data constitute a valuable resource for deriving bathymetric information in shallow coastal environments, islands, and archipelagos of Vietnam. The performance evaluation of the proposed machine learning-based approach, based on the coefficient of determination ( $R^2$ ), mean absolute error (MAE), and root mean square error (RMSE), confirms its effectiveness in generating reliable bathymetric maps for the study area. Nevertheless, the current research was limited to a single study site and a specific acquisition period. Future work should incorporate larger and more diverse ground-truth datasets, explore advanced machine learning and deep learning algorithms, and assess the applicability of higher-resolution satellite imagery to further enhance the accuracy and generalizability of bathymetric estimation models.

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# ƯỚC TÍNH ĐỘ SÂU BẰNG HỌC MÁY TỪ ẢNH VỆ TINH SENTINEL-2: MỘT TRƯỜNG HỢP NGHIÊN CỨU TẠI VÙNG VEN BIỂN GIA LAI, VIỆT NAM

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**Tóm tắt:** Nghiên cứu này đánh giá tiềm năng ứng dụng các thuật toán học máy trong ước tính độ sâu vùng nước nông từ ảnh vệ tinh Sentinel-2 tại khu vực ven biển tỉnh Gia Lai, Việt Nam. Ảnh Sentinel-2 Level-2A được thu nhận vào ngày 23 tháng 01 năm 2020 trong điều kiện quang học ổn định và ít mây, sau đó được hiệu chỉnh khí quyển trước khi sử dụng. Dữ liệu độ sâu thực địa được thu thập bằng máy đo sâu hồi âm một tia kết hợp với thiết bị định vị GPS và được sử dụng làm tập dữ liệu huấn luyện và kiểm định. Năm mô hình học máy Hồi quy tuyến tính đa biến (MLR), Rừng ngẫu nhiên (RF), Cây quyết định (DT), K-láng giềng gần nhất (KNN) và Bộ nhớ ngắn dài hạn (LSTM) được xây dựng và so sánh về độ chính xác trong ước tính độ sâu. Kết quả cho thấy hệ số xác định ( $R^2$ ) dao động trong khoảng từ 0,80 đến 0,91; sai số bình phương trung bình (RMSE) nằm trong khoảng từ 0,72 m đến 1,50 m và sai số trung bình tuyệt đối (MAE) dao động từ 0,49 m đến 0,72 m. Các kết quả này chứng minh tính khả thi của việc tích hợp ảnh Sentinel-2 với các thuật toán học máy trong thành lập bản đồ độ sâu vùng nước nông với độ chính xác cao. Hơn nữa, phương pháp đề xuất thể hiện tiềm năng ứng dụng mạnh mẽ đối với các khu vực ven biển khác của Việt Nam có điều kiện môi trường và quang học tương tự.

**Từ khóa:** *Đo độ sâu; viễn thám; Sentinel-2; học máy; ước tính độ sâu của nước; lập bản đồ ven biển.*

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