ГЕОІНФОРМАТИКА

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SEA-LAND SEGMENTATION MODELS IN DEEP LEARNING FROM REMOTE SENSING DATA

(Представлено членом редакційної колегії д-ром геол. наук, ст. дослідником О.І. Меньшовим)

Background. ***Coastline changes can have a significant impact on coastal landscape, ecosystems and communities. Therefore, monitoring of such a highly dynamic system as sea-land is an urgent task that can be solved both by traditional methods and by using depth learning techniques to improve the efficiency of processing such as class of tasks. The object of the authors' research is the coastline along the coast of the western part of the Crimean Peninsula, the study of which by traditional methods has become impossible due to the temporary occupation of the Crimean Peninsula since 2014. The paper considers the main coastal indicators and methods of coastline digitization.***

The main types of satellite images as well as their combinations are compared for effective utilization of the shoreline mapping task. Many methods are used to recognize and extract shorelines in satellite images, which are generally divided into three groups: indexing, edge detection and classification methods.

Methods. ***Authors compared the main depth learning models that can be used to efficiently recognize the coastline and its boundaries in satellite images, which include ISODATA (Iterative Self-Organizing Data Analysis Technique), Maximum Likelihood Estimation (MLE), Random Forest (RF), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), U-Net, and Segment Anything Model (SAM).***

Results. ***The outlines of the Crimean Peninsula coastline were obtained on the basis of PlanetScope images using ISODATA, MLE, RF, KNN, SVM, U-Net, SAM methods. The obtained images and their performance were compared. The study included the development of a Python code to automatically generate reports including information on five evaluation metrics, such as accuracy (98.96), recall (99.45), precision (97.27), F1-score (98.34), and IoU (96.74), which facilitated the evaluation of different approaches and methods.***

Conclusions. ***The comparative analysis highlights the advantage of the U-Net model for shoreline extraction from remotely sensed images. U-Net consistently provides the most accurate and detailed segmentation in different scenarios, demonstrating robustness and accuracy.***

Keywords: ***Coastline, Deep Learning Methods, Convolutional Neural Network, U-Net model, Crimean Peninsula.***

Background

Coastal areas are highly dynamic environments, constantly undergoing changes due to various natural processes and human activities (Toimil et al., 2020). These changes can have significant impacts on the coastal landscape, ecosystems, and communities that rely on them (Hawkins, 2012). It is crucial to have effective methods for extracting coastline changes in order to monitor and understand these dynamics (Ballinger, Smith, & Warren, 1994). There are multiple methodologies that can be used to extract coastline changes, ranging from traditional techniques to advanced computational approaches. Traditional techniques for extracting coastline changes include manual digitization from aerial photographs or satellite images, as well as field surveys using GPS or total station instruments. While these traditional methods have been widely used, they can be time-consuming, labor-intensive, and limited in their ability to capture large-scale changes over time. For a more in-depth analysis, it may also be necessary to monitor factors that may influence shoreline change. The control of ground cover and its degradation may also be an important factor influencing shoreline development, which can also be monitored by geophysical surveys (Menshov, 2016). However, in this study the authors used only satellite data for analysis. In our effort to observe variations in the shoreline, we conducted a thorough investigation into several methods for extraction. Our extensive research encompassed a wide variety of techniques, including thresholding methods as well as advanced machine learning algorithms and deep learning approaches. Additionally, we presented a comprehensive analysis of remote sensing datasets to highlight their potential for addressing the specific objective. Moreover, the novel deep learning solutions have progressed to support scalability and broad applicability, enabling coastline detection models to be used in diverse geographical areas and with various satellite sensors with minimal human intervention. This scalability is especially beneficial for extensive coastal monitoring projects and global mapping endeavors.

Shoreline Indicators & types

Coastal indicators are visual characteristics used to represent the position of the coast. These indicators are determined by geomorphological features like coastal dunes, cliffs, or the arrangement of vegetation along the backshore. Comparing of these indicators with actual shorelines is complex due to variations in beach profiles which prevent one single indicator from fitting all coast types uniformly (Toure et al., 2019). Fig. 1 shows the main shoreline indicators. Identifying all the indicators shown in Fig. 1 based on multispectral satellite images is challenging due to their characteristics that may not always be discernible in a two-dimensional image. Nevertheless, it is still possible to use (A, B, C, D, E, J, K, M, and P), which are morphological reference boundaries between water and land and can be recognized even at a less detailed resolution than 10 meters (McAllister et al., 2022). In order to accurately determine the position of the coast, it is necessary to consider different shoreline indicators (Boak, & Turner, 2005). Also, the type of coastline should be taken into account when deciding which method to use for shoreline delineation. A basic method for converting the coastline into digital format involves manually tracing vectors in QGIS or ArcGIS software, using visible features as the previous high-water line or the wet/dry boundary. Advanced approaches use classification and clustering approaches to automate the process of deriving these lines. Also, shorelines could be extracted using tidal datums. In comparison to the actual shoreline position, these methods rely on standard elevation determined by a tide level derived from where the coastal profile intersects with a specific vertical elevation. Proxies for these shorelines include mean high waterline which is based on extracted waterline contours and data related to tidal datums. This approach was successfully used in combination with Landsat optical imageries to map the coastline of Australia (Bishop-Taylor et al., 2021) using Open Data Cube.

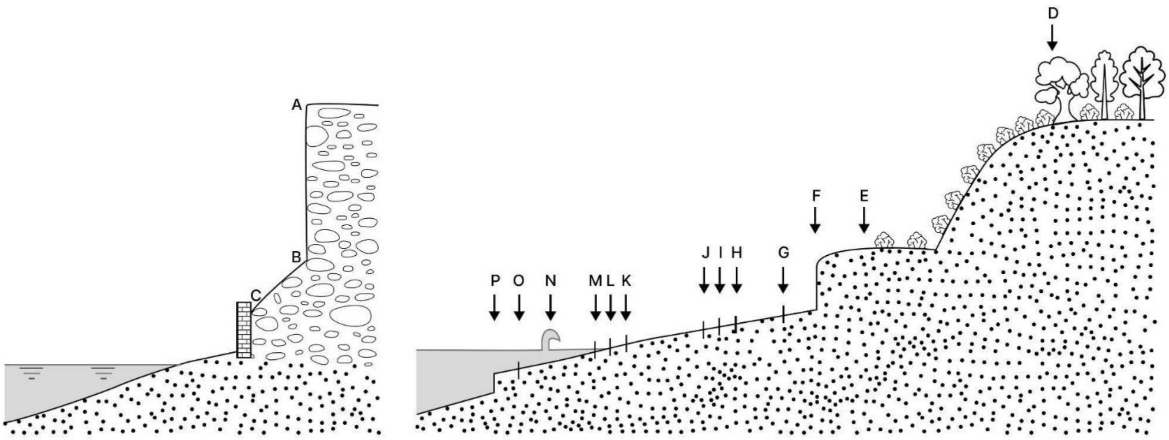

Fig. 1. Shoreline indicators (Boak & Turner, 2005)
A – Bluff top/cliff top, B – Base of the bluff/cliff, C – Landward edge of a revetment structure, D – Seaward stable dune vegetation line, E – Seaward dune vegetation line, F – Erosion scarp, G – Storm/debris line, H – An old high tide water level, I – Previous high tide high water level, J – Mean high water, K – Wet/dry line or runup maxima, L – Groundwater exit point, M – Instantaneous water line, N – Shorebreak maximum intensity, O – Mean lower low water line, P – Beach toe/Crest of beach step

Fig. 2 displays various types of coastline schematic diagrams as outlined by Zheng et al. The artificial coast comprises man-made coastal structures like border dikes, wharves, breakwaters, revetments, and slopes. This type of coastline aligns with these permanent structures and the boundary line near the land is utilized in sea-closure engineering. Rocky coastlines are characterized by rocky outcrops with prominent headlands and bays that extend further into the land, resulting in a twisting coastline defined by the land-water interface of headlands and steep cliffs.

Developed silty muddy coasts feature shrimp ponds, salt fields, and economic areas built on tidal flats along with dams to prevent high seawater inflow. The breakwater indicates the location of the coastline in this instance. Undeveloped silty muddy coasts are shaped by tidal action featuring a gentle beach-face slope several kilometers wide where tidal creeks are generally found connecting to river estuaries; this type uses changes in growth status of salt-tolerant plants as its defining boundary for identifying it as a coastline. Biological coastlines encompass mangrove, coral reef, and reed areas, where the line between the sea and land can be distinguished by features such as inner mangrove boundaries or marked differences between reed abundance and thinning. Sandy coasts form by the accumulation of sand due to wave action. The boundary between the grit and the non-sand features on the land is regarded as the coastline.

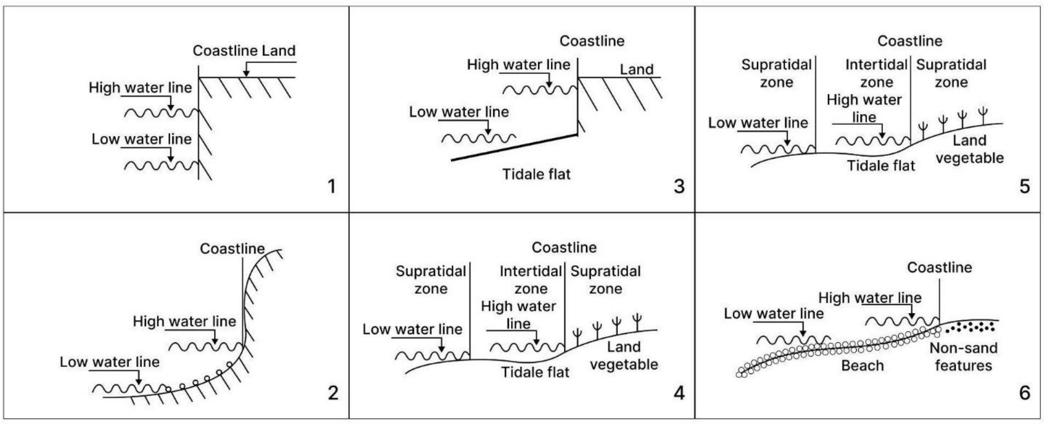

Fig. 2. Coastline Type Schematic Diagrams (Zheng et al., 2023)
1 – Artificial, 2 – Rocky, 3 – Developed Silty Muddy, 4 – Undeveloped Silty Muddy, 5 – Biological, 6 – Sandy

Each schematic diagram highlights the unique characteristics and features of these coastline types, such as the high-water line, low water line, intertidal zones, subtidal zones, supratidal zones, tidal flats, and associated vegetation. Understanding these characteristics is crucial for selecting the appropriate method for shoreline delineation, as different techniques may be better suited for different types of coastlines.

Remote Sensing data

When conducting sea-land segmentation, the choice of the appropriate dataset plays a critical role in ensuring accuracy and reliability in shoreline mapping. Remote sensing data, with its diverse range of imaging techniques, are based on the recording and subsequent interpretation of reflected solar radiation (electromagnetic waves) from the surfaces of soil, vegetation, water, and other objects, as well as the thermal radiation emitted by the Earth (Zatserkovnyi, et al., 2016). They can be divided into active and passive, differentiated by their energy sources for data acquisition. Active remote sensing utilizes synthetic electromagnetic signals, notably radar, to interpret object characteristics through reflected energy. Conversely, passive remote sensing utilizes ambient solar radiation, quantifying energy naturally reflected or emitted from terrestrial surfaces for data collection. Radar and optical images, as well as their fusion, can be effectively utilized for coastline mapping.

Optical satellite imagery is typically used for delineating coastlines due to the capability of optical sensors to collect data across a wide range of wavelengths in the electromagnetic spectrum. By combining spectral channels, it is possible to calculate spectral indices, such as the normalized difference water index (NDWI), which allow for better distinction between water and land classes. For detailed shoreline mapping, channels within the Visible (VIS) and Near Infrared (NIR) parts of the electromagnetic spectrum are most suitable as they usually have higher spatial resolution compared to Short-Wave Infrared (SWIR) and Thermal Infrared (TIR) channels. The spatial and temporal resolutions, data availability ranges, and providers of commercial and publicly available optical satellite images are shown in Fig. 4. In comparing commercial and public available images, commercial ones are expensive to use in large-scale and long-term research. Another major drawback of commercial images is the lack of a worldwide historical archive, as they are typically acquired for specific areas and purposes. On the other hand, an important advantage is that they are traditionally used for detailed mapping as most of them have a very high resolution (VHR) according to the categories defining spatial resolution in Earth observation data (ESA, 2022).

As well as optical images, radar ones are also commonly used for coastal mapping. Radar data is particularly useful for this purpose because of its ability to penetrate cloud cover and operate without dependence on sunlight, providing reliable data in all weather conditions and time of a day. As a result, radar data is less affected by atmospheric conditions than optical data, which ensures consistent and continuous monitoring.

Methods

This section provides a thorough overview of various methods used for extracting coastlines from satellite imagery. It clarifies the underlying theories and procedural steps related to different methodologies, including methods applied in the past for coastline extraction. In the present day, a variety of techniques are employed for recognizing and extracting coastlines from remote sensing (RS) imagery, broadly categorized into three groups: indexing methods, edge detection, and classification. Indexing methods concentrate on remote sensing indices and thresholding. In the case of edge detection approaches, the extraction of coastlines is treated as a problem of detecting edges for water bodies or oceans in the proposed method. Regarding image classification, these methods mainly revolve around object-oriented and pixel-oriented classification (Ge, Sun, & Liu, 2014). RS image classification predominantly relies on the spectral attributes of features, which constitute multi-band measurements of the electromagnetic radiation of these features. These measurements serve as the original feature variables for remote sensing image classification. Furthermore, texture, shape, and other topographical features are incorporated alongside spectral characteristics in the analysis.

Utilizing Indices with Thresholding Methods

At the early stages, water bodies are segmented mainly based on spectral thresholding (Nones, 2020). In the context of remote sensing, thresholding is often applied to remote sensing indices to classify different land cover or land use types within an image. Sea-land segmentation thresholding refers to the process of dividing an image into distinct regions corresponding to sea and land areas based on a predefined threshold. Sea-land segmentation thresholding method involves selecting a threshold value that separates the pixel intensities associated with sea and land. In practice, the values of the remote sensing indices (e.g NDVI, NDWI) or single-band reflectance are treated as objects to be clustered (Zhou et al., 2023).

The thresholding in SLS (Sea-Land Segmentation) process can be implemented using various techniques, including simple intensity thresholding, adaptive thresholding, or more sophisticated methods such as Otsu's method, which automatically calculates an optimal threshold based on the image histogram. Global Thresholding involves applying a single threshold value to the entire image due to separate different land cover classes. The OTSU algorithm, are automated thresholding technique that selects the threshold value by maximizing the between-class variance in pixel intensities. It (style) adapts the threshold determinations for optimal segmentation based on least squares principles (Otsu, 1979).

Unlike global thresholding, adaptive thresholding calculates threshold values for smaller, localized regions within the image. Using a single global threshold for the entire image to distinguish water/land boundaries can overlook local coastline edges due to varying image intensity, leading to fragmented coastline edges in low-contrast areas (Karslı, 2011). In contrast, the local thresholding method dynamically adjusts the threshold based on neighboring pixel characteristics (Vukadinov, Jovanovic, & Tuba, 2017). This capability enables the local thresholding method to outperform global thresholding.

However, sea-land segmentation thresholding has its limitations. It may not accurately distinguish between sea and land areas in complex scenes with varying lighting conditions, shadows, or overlapping textures. Additionally, choosing an appropriate threshold value can be challenging and may require manual adjustment with additional information, such as contextual features or ancillary data, to improve segmentation accuracy.

Edge Detection Methods

Edge detection stands out as a highly efficient automated technique for coastline extraction, particularly in contrast to the manual visual interpretation approach (Chen et al., 2019). Landsat data, renowned for its moderate spatial resolution, emerges as the predominant remote sensing dataset utilized for this purpose (Roelfsema et al., 2013). The most classical image-segmentation methods are edge-differential operators (such as Sobel operator, Canny operator and Roberts operator). The Canny edge detection method was used widely compared with the Sobel detector, Laplacian detector, Robert detector, and Prewitt detector because it can provide more precise results (Chen et al., 2019). The Sobel Edge Detector exhibits sensitivity to both image noise and edge orientations. Laplacian Edge Detector remains a valuable tool in highlighting regions of rapid intensity change, such as the land-water boundary. But it may produce inconsistent edge widths, particularly noticeable in regions where the coastline width varies, thereby affecting the reliability of the detected coastline features (Wei et al., 2021).

As a matter of fact, an approach that combines Canny edge detection methods with Landsat data can efficiently extract shoreline information from remotely sensed images. The average error between the Google Earth image and the extracted coastline falls below the theoretical maximum allowable error, indicating the method's accuracy (Hu, & Wang, 2022). Yet, in scenarios where the background of the coastline image is intricate, traditional methods tend to be susceptible to noise, leading to fragmented extraction outcomes unsuitable for extensive coastline analysis. Manual intervention is often necessary in edge detection, with mathematical morphology employed to refine the results. Enhancing accuracy entails integrating additional methods for a more comprehensive approach (Zhou et al., 2023).

Active Contour Methods

The Active Contour Model, also known as snakes, is an advanced technique for image segmentation. In recent years, the Active Contour Model has been extensively utilized for coastline extraction, owing to its methodology of evolving a contour or curve to precisely align with the boundaries of objects within an image (Klinger et al., 2011). This process uses energy minimization, where internal forces maintain the contour's smoothness, and external forces, derived from the image data, guide the contour towards the edges or other specific features (McAllister et al., 2022)

A researcher has proposed two enhanced level set-based algorithms for extracting coastlines from SAR images (Ouyang, Chong, & Wu, 2010). However, the adjustment of relevant parameters poses a significant challenge and can directly impact the extraction results. The Active Contour Model is highly effective in fields requiring precise boundary detection, but it has several limitations. It can struggle with images containing noise, weak edges, or complex textures, which can lead to inaccurate segmentation. To address these challenges more sophisticated energy functions can be utilized or the Active Contour Model can be combined with other segmentation techniques like machine learning algorithms.

Machine Learning

The multidimensional nature of remote sensing imagery, encompassing various spectral bands, temporal resolutions, and spatial dimensions, has sparked considerable interest in leveraging machine learning tools for automated coastline identification. One advantage of ML-based approaches is their ability to capture subtle and nuanced relationships within the data that may be challenging to express using traditional thresholding or rule-based methods. Generally, machine learning methods can be broadly classified into two primary categories: unsupervised and supervised learning (Shirmard et al., 2022). Different classification algorithms may excel in solving specific problems or datasets but might not perform optimally for others. Therefore, before tackling a problem, it's crucial to explore and compare various classification algorithms tailored to the dataset at hand.

The support vector machine (SVM) is a supervised machine learning method commonly employed for classification and regression tasks (Kalkan et al., 2013). ML algorithms like random forests and support vector machines (SVMs) are highly effective in deciphering intricate patterns and characteristics within remote sensing data. By training these algorithms on datasets labeled with examples of coastal features, they can discern between sea and land areas and accurately delineate coastline boundaries. However, SVMs encountered challenges when applied to large datasets and struggled to yield satisfactory outcomes for perceptual tasks like image classification. Moreover, as SVMs are shallow methods, they require manual extraction of useful representations, termed feature engineering, which can be complex and fragile (Chollet, 2017).

Random forests exhibit versatility across a broad spectrum of problems and are often considered a reliable choice, frequently ranking as the second-best algorithm for shallow machine-learning tasks. Gradient boosting, a technique used to enhance machine-learning models by iteratively training subsequent models to address weaknesses in previous iterations, is employed. It stands as one of the most effective algorithms, particularly for handling non-perceptual data in contemporary contexts (Chollet, 2017). Applying coastal research, the Random Forest technique has been applied to near-infrared bands extracted from LANDSAT-8 and GOKTURK-2 satellite imagery. Manual digitization of each image was conducted, followed by shoreline extraction to evaluate accuracy (Bayram et al., 2017) The results of this accuracy assessment confirm the efficiency of the Random Forest method for shoreline extraction studies across both medium and high-resolution satellite images.

Still, with sufficiently large training sample sizes, Random Forest's (RF) performance showed little disparity between balanced and imbalanced training sets. Notably, it's important to highlight that this observation was made across various satellite imagery datasets (Colditz, 2015; Mellor et al., 2015). This underscores the need to consider the performance of the RF classifier across different satellite imagery datasets when employing various training sample strategies, such as balanced versus imbalanced (Thanh Noi, & Kappas, 2018). Furthermore, it's imperative to acknowledge that RF classifiers may encounter challenges when applied to satellite image segmentation tasks, particularly in scenarios with heterogeneous or complex landscapes where accurate delineation of features may be difficult to achieve.

Unsupervised learning involves identifying patterns without relying on a target property. In this approach, all available factors are treated as input sources. Two of the most commonly used algorithms in remote sensing are the K-means and ISODATA clustering algorithms. The K-means algorithm is implemented through the k-means function, which allows for specifying either the cluster centers' locations or the number of clusters via the center parameter. This function facilitates multiple random partitioning attempts, ultimately returning the partition that minimizes the sum of squared distances (Gentleman, & Carey, 2008). The ISODATA (Iterative Self-Organizing Data Analysis) algorithm is similar to K-means but differs in that it allows for a variable number of clusters, whereas K-means requires the number of clusters to be known beforehand. K-means adjusts clusters on a sample-by-sample basis, while ISODATA statistically examines clusters after each iteration. The ISODATA technique for multispectral WorldView-2 satellite imagery classification demonstrated high reliability and compatibility by closely matching expert-identified reference shorelines and effectively considering the influence of various coastal features on shoreline extraction accuracy (Sekovski et al., 2014). However, a general disadvantage of both the K-means and ISODATA algorithms is that they work best for images with clusters that are spherical and have the same variance. This condition is often not met in remote sensing images, which can limit the effectiveness of these algorithms. Practical implementation of these both methods will be discussed further.

Deep Learning

The application of deep learning techniques to process remote sensing data for coastline extraction is a burgeoning area of research. While previous studies have not only compared deep learning methods with traditional approaches but also evaluated the performance of various deep learning models, there is a compelling need for more extensive exploration in this domain. Studies reveal that machine learning-based algorithms for coastline detection are progressively outperforming traditional statistical methods (Liu et al., 2019). Deep convolutional neural networks (convnets) possess the capability to automatically adapt to the distinct characteristics of various coastal environments, accommodating variations in shoreline types, coastal morphology, and land cover. Another significant factor is its ability to simplify problem-solving by automating the crucial step of feature engineering. Traditional machine-learning techniques, known as shallow learning, typically involve transforming input data into one or two representation spaces through simple methods like high-dimensional non-linear projections (e.g., support vector machines) or decision trees (Chollet, 2017). These techniques often failed to produce the refined representations necessary for complex problems, requiring extensive manual effort to engineer suitable data representations—a process known as feature engineering. In contrast, deep learning automates this entire step, enabling the learning of all features in a single pass. This automation has significantly streamlined machine-learning workflows, often replacing complex, multistage pipelines with a single, end-to-end deep-learning model.

When developing a reliable, universal, and effective tool for detecting changes in the coastline, it is essential to analyze available algorithms that can perform shoreline contour recognition. (Okhrimchuk et al., 2024) Convolutional Neural Network (CNN) is a type of feedforward neural network composed of artificial neurons. It includes a convolutional layer, a pooling layer, and a fully connected layer. CNNs are applied to remote sensing images for feature detection, edge extraction, and pixel-based classification. Convolutional Neural Networks (CNNs) are highly effective for complex coastline extraction tasks, especially when trained on large datasets of remote sensing images (Okhrimchuk, Demidov, & Brudko, 2022). Nevertheless, certain challenges must be addressed, such as the blending of boundary pixels between water and land, and the necessity for a substantial number of trainable parameters and training samples (Tambe, Talbar, & Chavan, 2021). To overcome drawbacks, researchers proposed more robustness and generality modified models based on CNN architecture (Miao et al., 2018).

The Segment Anything Model (SAM) offers clear segmentation results and exhibits flexibility across various types of coastlines. SAM utilizes multi-scale processing to capture details at multiple levels, ensuring precise identification of coastal boundaries. Attention mechanisms within SAM enhance segmentation accuracy by focusing on crucial features such as shoreline contours and coastal structures (Kirillov et al., 2023). SAM offers a flexible and powerful approach to image segmentation, but its general-purpose nature may not match the task-specific performance of models like U-Net for coastline extraction. Particularly, SAM struggles with extremely fine details and complex regions within coastal landscapes.

Segmentation of satellite images is a distinct application of convolutional neural networks. The semantic segmentation approach using U-Net is particularly effective for this task, as it can extract the most informative features and generate interpretable results. Therefore, employing an adaptive mechanism like U-Net for semantic segmentation is recommended for extracting and interpreting key features from input data (Okhrimchuk, Tishaiev, & Zatserkovnyi, 2020). Beyond just developing a robust model, the quality of remote sensing CNN models hinges significantly on the quality and size of the ground truth dataset. Equally crucial is the thorough preprocessing of remote sensing data. The effectiveness of a deep learning model is heavily influenced by the size and diversity of its training samples, underscoring the importance of data augmentation in preparing a comprehensive training dataset (Brudko, Okhrimchuk, & Demidov, 2022).

Results

The evolution of remote sensing sensors, coupled with enhanced computational capabilities and the integration of machine learning techniques, has revolutionized real-time waterline identification, automated coastline extraction, and continuous monitoring (Zhou et al., 2023). While traditional statistical methods historically dominated coastline extraction from remote sensing images, the introduction of machine learning and deep learning models has markedly improved both accuracy and efficiency.

A comparison of various data sources, including radar imagery, has been conducted to assess their effectiveness in sea-land segmentation. Radar data, specifically from C-band SAR sensors, is best suited for global mapping and change detection (Flores et al., 2019). However, the complexity in processing and interpreting radar images emerged as a key factor influencing the overall results. The comparison highlights both the strengths and limitations of radar data. Fig. 3 shows a timeline of available C-band synthetic aperture radar missions between 1990 and 2024, where the resolution corresponds to the maximum spatial resolution that the sensor can achieve.

Optical satellite imageries were utilized in the research due to its effectiveness in achieving high-precision coastline delineation. Additionally, according to Fig. 4, it can be noted that public images are a better option for historical monitoring of coastal changes. In this regard, Landsat has existed since 1982 and offers the opportunity to conduct historical analysis. However, if the investigation focuses on the last decade, Sentinel-2 is more appropriate due to its higher spatial resolution and revisit time. Optical satellite images are invaluable data for delineating coastlines, especially when using spectral indices to make the land-water boundary better defined.

The choice between commercial and public available images depends on the specific needs of the project. While commercial data have a very high resolution suitable for detailed mapping, their essential disadvantages are high cost and limited historical archives. Publicly available images are a more cost-effective solution with a large amount of historical data, making them ideal for global spatial-temporal coastal monitoring. PlanetScope imagery was selected for this research due to its high spatial resolution and frequent revisit times enabling precise shoreline segmentation (Shin et al., 2020). Additionally, PlanetScope offers the advantage of near-daily global coverage, which allows for consistent monitoring of rapidly changing coastal environments.

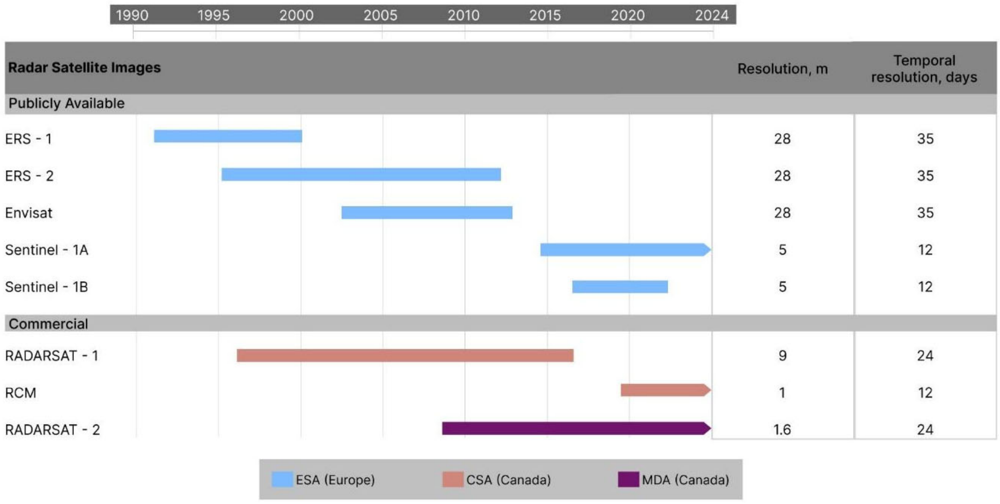

Fig. 3. Timeline of C-band synthetic aperture radar missions between 1990 and 2024 and their main characteristics (ESA, 2021; Flores et al., 2019)

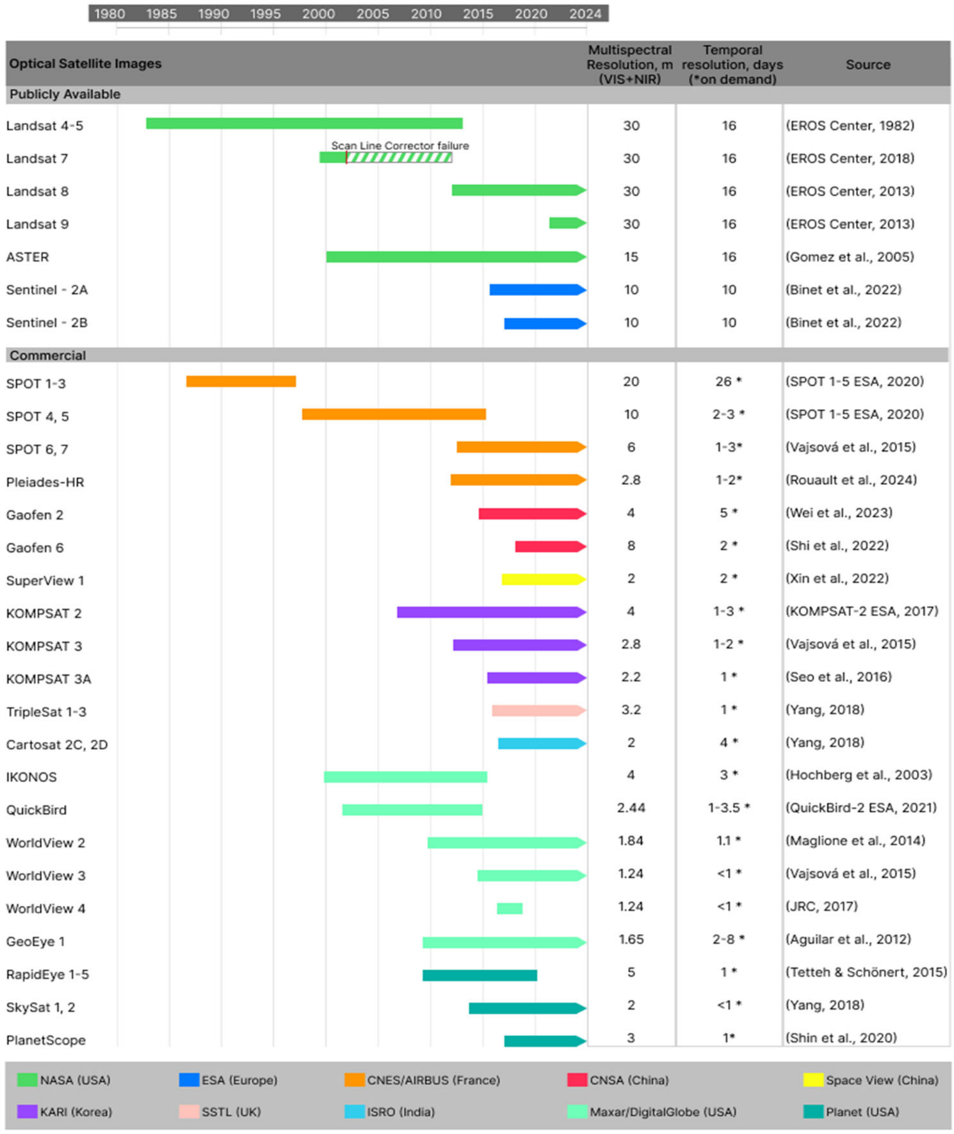

Fig. 4. Timeline of multispectral imaging satellite missions between 1980 and 2024 and their main characteristics (Aguilar et al., 2013; Binet et al., 2022; EROS Center, 1982; EROS Center, 2013; EROS Center, 2018; Gomez et al., 2005; Hochberg et al., 2003; JRC, 2017; KOMPSAT-2 ESA, 2017; Maglione et al., 2014; Rouault et al., 2024; QuickBird-2 ESA, 2021; Seo et al., 2016; Shi et al., 2022; Shin et al., 2020; SPOT 1-5 ESA, 2020; Tetteh, & Schönert, 2015; Vajsová et al., 2015; Wei et al., 2023; Xin et al., 2022, Yang, 2018)

To evaluate the efficiency of various machine learning and deep learning models for sea-land segmentation, a dataset derived from PlanetScope imagery with a spatial resolution of 3 meters was utilized. Specifically, the performance of the following models was evaluated: ISODATA (Iterative Self-Organizing Data Analysis Technique), Maximum Likelihood Estimation (MLE), Random Forest (RF), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), U-Net, and the Segment Anything Model (SAM). The comparative analysis is based on the segmentation results from these models applied to high-resolution optical satellite images, as illustrated in the Fig. 5.

To systematically compare the performance of these models, we applied each technique to a set of multispectral remote sensing images and evaluated the resulting segmentations against ground truth data. The evaluation criteria included accuracy, boundary delineation precision, noise levels, and the ability to handle complex coastal features.

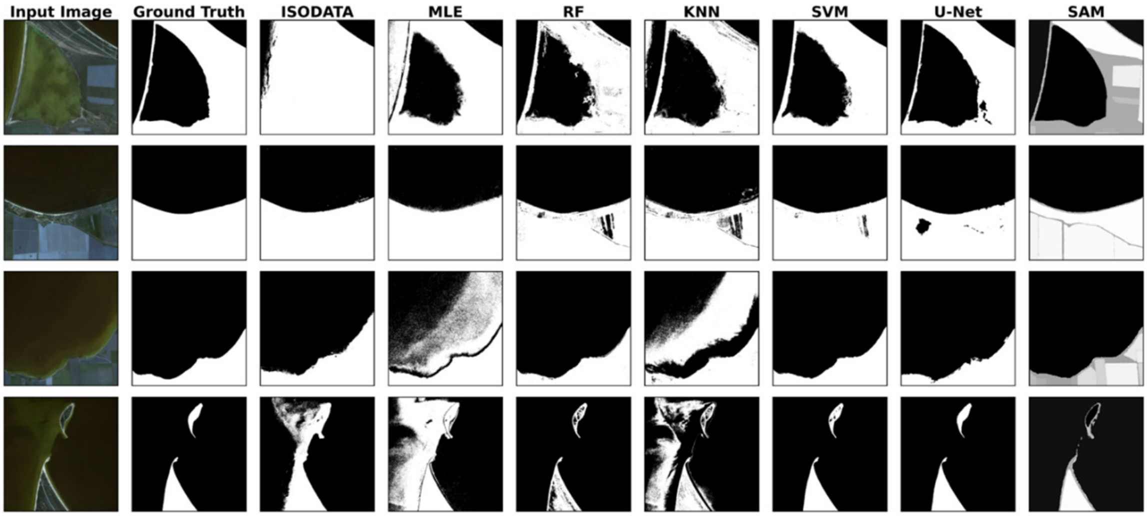

Fig. 5. Results of different sea-land segmentation methods based on PlanetScope imagery

Method	Mean Accuracy (%)	Mean Recall (%)	Mean Precision (%)	Mean F1-score (%)	Mean IoU (%)
ISODATA	84.5	65.99	99.87	77.32	65.97
MLE	78.56	55.74	**99.94**	66.71	55.73
RF	97.07	94.94	93.4	93.92	88.84
KNN	83.91	62.32	95.76	71.17	60.46
SVM	97.92	95.24	99.24	97.16	94.52
U-Net	**98.96**	**99.45**	97.27	**98.34**	**96.74**
SAM	97.91	91.45	95.7	93.5	88.53

Fig. 6. Quantitative comparison of sea-land segmentation methods based on 4 scenes.
The SAM model clustered the land class into subclasses, this division is illustrated by a white gradient.
Bold values indicate the best value

In evaluating methods for sea-land segmentation, it's important to use a variety of metrics that capture different aspects of performance, including accuracy, recall, precision, F1-score (Dice coefficient), and IoU (Jaccard index), as shown in Fig. 6. These metrics provide a broad picture of how each method does well in segmenting sea and land areas. Accuracy shows a general measure of the overall correctness of the predictions compared to the ground truth. On the other hand, recall evaluates how effectively a model identifies all relevant segments, ensuring that sea or land areas are not incorrectly classified as the opposite. Precision measures the model's ability to correctly identify positive instances without including false positives. The F1-score provides an overall sense of the balance between false positives and false negatives. Intersection over Union (IoU) quantifies the overlap between predicted and actual regions on a pixel-by-pixel basis, making it a vital metric for assessing segmentation models' agreement with the ground truth. The observed extremely high precision values suggest that methods such as ISODATA, MLE and SVM are employing overly stringent criteria for identifying positive instances. While this strategy effectively reduces false positives, it also leads to the omission of many true positives. Consequently, although this approach results in high precision, it adversely affects recall and compromises overall segmentation performance.

Discussion and conclusions

Through comparative analysis, these models reveal distinct strengths and weaknesses, offering valuable insights into their applicability for coastline extraction tasks. While traditional statistical methods like ISODATA and MLE provide solid theoretical foundations, their practical applicability is limited by computational complexity, recall to initialization limits and assumptions about data distributions. Machine learning models such as RF, KNN, and SVM offer improved performance and robustness, but can be hindered by computational demands and recall to hyperparameters.

Among these models, the U-Net model stands out as the most effective for sea-land segmentation. Its ability to perform end-to-end learning and handle variations in coastal environments make it superior to other methods. While other models like RF, SVM, and SAM offer reasonable performance, they fall short in handling fine details and complex coastal features compared to U-Net. Despite requiring substantial computational resources and labeled training data, the benefits of U-Net in terms of accuracy and robustness make it the best choice for sea-land segmentation. The SAM model also shows promise, particularly for its versatility and transfer learning capabilities, though it may not yet surpass the task-specific performance of U-Net.

The comparative analysis underscores the superiority of the U-Net model for coastline extraction from remote sensing images. This research reinforces the conclusion that CNN-based models, specifically U-Net, are the best choice for sea-land segmentation tasks. In future work, it is recommended to further explore the integration of deep learning models with other machine learning techniques to enhance segmentation accuracy and efficiency. Additionally, the application of these models to a broader range of coastal environments and the incorporation of more diverse datasets could provide valuable insights into their generalizability and robustness.

Authors' contribution: Roman Okhrimchuk – methodology, data validation; Vsevolod Demidov – conceptualization, methodology, review and editing; Kateryna Sliusar – data treating, formal analysis.

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МОДЕЛІ ГЛИБИННОГО НАВЧАННЯ ДЛЯ СЕГМЕНТАЦІЇ МОРЕ-СУША НА ОСНОВІ ДАНИХ ДИСТАНЦІЙНОГО ЗОНДУВАННЯ ЗЕМЛІ

В с т у п . ***Зміни берегової лінії можуть значно впливати на прибережний ландшафт, екосистеми та спільноти. Тому моніторинг такої високодинамічної системи, як море-суша, є актуальним завданням, яке можна вирішувати як традиційними методами, так і з використанням методів глибинного навчання для підвищення ефективності обробки такого класу завдань. Об'єктом дослідження є берегова лінія вздовж узбережжя західної частини Кримського півострова, вивчення якої традиційними методами стало неможливим через тимчасову окупацію Кримського півострова з 2014 року. У роботі розглянуто основні прибережні індикатори та методи переведення берегової лінії у цифровий формат. Проведено порівняння основних типів супутникових зображень, а також їх комбінацій для ефективного використання завдання картографування берегової лінії. Для розпізнавання та виділення берегових ліній на супутникових знімках використовується безліч методів, які в цілому поділяються на три групи: методи індексування, виявлення країв та класифікації.***

М е т о д и . ***Автори порівнювали основні моделі глибинного навчання, які можна використовувати для ефективного розпізнавання берегової лінії та її кордонів на супутникових знімках, серед яких – ISODATA (Iterative Self-Organizing Data Analysis Technique), Maximum Likelihood Estimation (MLE), Random Forest (RF), K – Nearest Neighbors (KNN), Support Vector Machine (SVM), U-Net, і Segment Anything Model (SAM).***

Р е з у л ь т а т и . ***На основі знімків PlanetScope було отримано контури берегової лінії Кримського півострова методами ISODATA, MLE, RF, KNN, SVM, U-Net, SAM. Проведено порівняння отриманих зображень та ефективності їх роботи. Дослідження включало розробку коду Python для автоматичного створення звітів, що містять інформацію про п'ять оцінювальних метрик, таких як точність (98,96), повнота (99,45), влучність (97,27), коефіцієнт Дайса (98,34) та індекс Жаккара (96.74), що полегшило оцінку різних підходів і методів.***

В и с н о в к и . ***Порівняльний аналіз наголошує на перевазі моделі U-Net для виділення берегової лінії на знімках дистанційного зондування. U-Net постійно забезпечує найбільш точну та детальну сегментацію у різних сценаріях, демонструючи стійкість та точність.***

К л ю ч о в і с л о в а : ***берегова лінія, методи глибинного навчання, згорткова нейронна мережа, модель U-Net, Кримський півострів.***

Автори заявляють про відсутність конфлікту інтересів. Спонсори не брали участі в розробленні дослідження; у зборі, аналізі чи інтерпретації даних; у написанні рукопису; в рішенні про публікацію результатів.

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