Water Resources Identification in Barren Lands Using Deep Learning Techniques

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Abstract. This paper introduces a hybrid deep learning architecture to precisely detect surface water resources in deserted and dry areas in Central India with Sentinel-2 RGB images. Conventional spectral techniques are affected by spectral confusion and this is particularly evident in dry settings where water features appear as shadows or murky soil. To mitigate this, a U-Net architecture based on ResNet-50V2 encoder is suggested, which uses transfer learning to increase its ability to extract features. The model is trained on the Sen-2 LULC dataset of 213,761 images, and a combined Binary Cross-Entropy loss function with Dice loss function to manage high class imbalance (less than 5% water pixels). The experimental results indicate high performance with the highest IoU of 0.92 and a precision of 0.89, recall of 0.91, and Dice coefficient of 0.94. The suggested algorithm is superior to baseline U-Net and is a scalable solution to monitoring water resources in arid regions.

1. Introduction

Water plays a vital role in the stability of the ecosystem, efficiency of agriculture and human life throughout in arid and semi-arid countries, there is an acute water shortage, which is aggravated by climate change [1,2]. India, being a developing country that is extremely susceptible to changing climatic conditions, proper management of water in the drylands is a key concern in supporting the livelihood and alleviating the water scarcity in India [2]. The barren interiors of Central India, with temporary streams, seasonal ponds, and little reservoirs are of special interest, but are notoriously hard to map. Such scanty water bodies on the surface also tend to resemble shadows, mineral-enhanced soils, and humid sparse plants and are further compounded by unpredictable rainfall and common droughts [3,4].

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These difficulties are aggravated by climate change in semi-arid and arid regions of India, such as Central India (e.g., areas that straddled between Madhya Pradesh, Chhattisgarh and Maharashtra). An increase in temperature, changes in precipitation and the frequency of drought diminish the availability of surface and groundwater, exacerbate land degradation, and put crop production, especially rice, at risk especially in river basins such as the Godavari [7, recent studies on drought risk]. It is estimated that the per-capita water availability will decrease, and more severe dry spells will occur, which will necessitate the high urgency of scalable and precise monitoring instruments to promote sustainable water distribution, agriculture, and the management of disasters [2,3,8].

Conventional water detection solutions cannot function in these complicated environments. Field surveys are labour intensive, time consuming, and cannot work well in areas that are large or remote [5]. The traditional spectral indices, including the Normalized Difference Water Index (NDWI), have high false alarms because of being confused with non-water objects, like shadows, dark soils, and man-made surfaces in bare landscapes [6,11,12]. These shortcomings are magnified in arid environments with non-regular shaped, small or seasonal water bodies, which makes common remotely sensing methods unreliable in accurately estimating resources [7,13].

With the introduction of the high-resolution satellite imagery, specifically, the Sentinel-2 mission, remote sensing has been transformed to make high-resolution multispectral data available that can be used not only to perform classification of land cover on a fine scale but also to monitor the environment [8]. The methods of deep learning and, in particular, convolutional neural networks (CNNs) are effective at extracting hierarchical spatial and spectral features in imagery automatically [9]. The U-Net style, which has an encoder-decoder architecture and skip connections, is especially useful when doing semantic segmentation of small irregular objects like sparseness water bodies in heterogeneous environments [10].

This paper suggests that a hybrid model is a U-Net architecture that uses a ResNet-50V2 encoder (trained on ImageNet through transfer learning) to perform automated semantic segmentation of surface water bodies in barren landscapes in Central India. The method utilizes the Sen-2 LULC dataset a massive sample of 213,761 pre-processed 128x128 RGB-images (based on Sentinel-2 Level-2A bands B4/red, B3/green, and B2/blue at 10 m resolution; obtained in February-March 2021 with clouds cover <0.5%) of seven land use/land cover (LULC) classes namely water bodies, dense forest, sparse forest, barren land, built-up, agricultural land Every image is accompanied with a semantic mask, which is a reflection of the complexity of the real world where numerous classes co-exist.

The framework uses stratified 80/20 train-test split (to ensure the equal representation of rare water class, less than 5 percent of pixels), high-performance TensorFlow data pipelines (augmentation is done on-the-fly), and a hybrid loss function (Binary Cross-Entropy + Dice) to overcome the problem of severe class imbalance and spectral confusion. The model was trained on two Tesla T4 GPUs and has strong performance on RGB-only, overcoming the drawback of conventional indices with arid RGB environments.

The work closes a significant literature gap: although previous literature has covered wetlands, ground water, or multispectral / SAR based water mapping in other areas, little has been done to cover sparse surface water segmentation in barren Indian arid/semi-arid landscape with available RGB sentinel-2 data [3,14,15]. The resulting automated and precise water resource maps may be used in environmental planning, agricultural decision making, and climate adaptation in the drought-sensitive Central India to offer a scalable, replicable framework with future opportunities to offer multispectral improvements.

2. Literature Review

The deep learning type of identification of water resources in arid territories can be approached as a complex environmental problem, and several studies with major role of research on remote sensing and machine learning used in the field. Various authors have widely developed literature to augment prediction and segmentation of water bodies especially in arid and semi-arid areas through sophisticated technological methods [11]. In work done by Al-Ruzouq et al. [1], hybrid CNN-XGB model was proposed including the Analytic Hierarchy Process (AHP) to outline the area of artificial groundwater recharge (AGR) using nine hydrogeological factors obtained by remote sensing, i.e. geology, rainfall, elevation, slope, and land use. In Sharjah, UAE, 90.8% accuracy was obtained with precision 0.8168, recall 0.7873 and AUC 0.89 determining geology (20%) and rainfall (10) as important determinants of sustainable water management in dry regions.

A number of theoretical models have been suggested to maximize model parameter and search space outputs, improving on segmentation errors [12]. The Bayesian CNN using a polynomial kernel used by Mo et al. [2] on 22 climatic datasets (precipitation, temperature) was effective in predicting anomalies in terrestrial water storage (TWSA), with an RMSE of less than 5 cm and a R^2 of more than 0.85 on a global basis. Nevertheless, the global nature of the study is not specific to arid areas, as well as it is not combined with optical remote sensing such as Sentinel-2. On a subset of Sentinel-1 SAR images, Pech-May et al. [3] used an extended U-Net with ResNet blocks, with results of 90% IoU of lakes and wetlands in Tabasco, Mexico, with a precision of 0.88 and a recall of 0.92, which indicates the superior performance of SAR under cloudy conditions. The SAR focus, though, only allows applicability to RGB-based Sen-2 LULC datasets found in barren land situations.

Combination of feature selection and classification models have been promising in the analysis of environmental data. Gharbia [4] trained Faster R-CNN with transfer learning on 3500+ images with VNIR and SWIR bands, and it reached 98.7% accuracy on Sentinel-2 and 96.1% on Landsat-8 with an F1-score of 0.97, which demonstrates that Sentinel-2 is 10m higher. However, the multispectral methodology and landscape diversity do not take into consideration the imbalance of classes in arid areas. Al-Ali et al. [5] investigated spectral indices (NDWI, mNDWI, RSWIR) with Sentinel-2 data to measure soil moisture as a mudflow indicator with the resultant R^2 = 0.85-0.92, but the focus of the study was the soil moisture, not a direct segmentation of water bodies, which limits its applicability to barren land water mapping.

Model evaluation is further narrowed down to statistical and domain-specific analysis. Tiwari et al. [6] created a U-Net with OBIA extensions on multispectral Sentinel-2 and LiDAR data with an 86% accuracy and 0.79 Kappa on ancient water harvesting systems in the Negev Desert with an F1-score of 0.84. Its use is limited to the current usage of RGB-based water detection, however, due to the archaeological emphasis and the multispectral necessity. Peña et al. [7] proposed DeepAqua, a self-supervised U-Net on Sentinel-1 SAR data with knowledge distillation, achieving a higher wetland water extent of almost 92 percent, with an accuracy of 0.91 and a recall of 0.93, but which is specialized to wetlands and SAR, requiring to be adapted to optical arid conditions. Morgan et al. [8] applied random forest with collinearity analysis on 15 hydrogeological features with 89% accuracy and AUC 0.92 in groundwater delineation in the desert fringes of Egypt but has no results relevant to deep learning in surface water. Liu et al. [9] have suggested a CEEMDAN-GA-DBN hybrid groundwater predictor in the Hexi Corridor of China with RMSE less than 0.5m and R-square = 0.95, but it is not a segmentation-oriented predictor. The self-supervised learning (SSL) is reviewed by Wang et al. [10] and reports improvements in accuracy of 1020% though it is in general terms without narrow case studies on barren land water. Attya et al. [11] improved U-Net with StyleGAN3 and AG-DAES to increase the accuracy by 5% on Sentinel-2 multispectral data, but its complexity and dependence on multispectral makes Sen-2 LULC difficult to apply. The DeepLabv3+ + U-Net was further combined by Wang et al. [12] to detect ancient terraces, with an IoU of 0.87, although its archaeological and multispectral specialization does not have much to do with the current water. U-Net applied by Wagner et al. [13] to Sentinel-1 to predict the Amazon droughts had 0.93 F1-score, but SAR and regional priorities need optical adjustment. Sahour et al. [14] found shallow groundwater containing both SVM and RF with an accuracy of 89 percent although it lacks deep learning of surface water. Kalaiyarasi, et al. [15] used 3D-CNN to classify water on hyperspectral images using 92 percent of the data, although 3D-CNN is not focused on mapping and emphasizes quality. Pang et al. [16] and Pan et al. [17] are reviews of the DL to retrieve and predict water quality with accuracies reaching 95 percent and R2 above 0.85, but they are focused on quality, not segmentation. Tesfaye and Breuer [18], Dai et al. [19], Rodriguez-Lopez et al. [20], and Elmotawakkil et al. [21] examined the use of ML and DL to monitor and recharge water, with the accuracy of over 90 percent, but their study is constrained by the fact that the majority of research was focused on groundwater or its quality, thus restricting the application of barren land surface water. No standardization and arid region segmentation gaps remain as Zhi et al. [22], Kim et al. [23], Sit et al. [24] reviewed DL in hydrology and conservation with standardization and accuracy of 80-95.

Based on the literature, it becomes clear that, though much has been done in detecting water resources with the help of DL and remote sensing, no literature has used the special Sen-2 LULC dataset or specialized in the segmentation of water bodies within the Indian region, especially in arid areas such as Central India. The current paper presents an innovative hybrid U-Net model to fill these unresolved gaps to identify sparse water bodies in this special geographical environment

Though there have been enormous developments on deep learning-based water detection, the majority of current studies place their emphasis on multispectral or SAR data and wetlands or groundwater estimation. The number of works that deal with sparse surface

water segmentation in arid areas based on RGB-only Sentinel-2 data is very low. Moreover, the issues of class imbalance and spectral confusion are not properly explored. This paper fills these gaps by suggesting a light-weight, RGB-based segmentation system that is specifically targeted at barren landscapes in Central India.

3. Methodology

3.1 Proposed Methodology

The proposed approach is a comprehensive deep learning framework end-to-end deep learning system actually tailored to the automated and accurate semantic segmentation of surface water bodies in barren Central India landscape. It uses the strength of Convolutional Neural Networks (CNNs) to address the limitations of the traditional remote sensing approaches, especially spectral confusion, which tend to wrongly classify non-water entities as water [3]. As Figure 1 shows, the workflow follows a systematic sequence of steps starting with the strict data preparation and continuing with the complex model training and ending with the robust evaluation step.

It starts with the SEN-LULC dataset, which is a large-scale dataset of Sentinel-2 satellite images in the geographical context of India. The first step in our methodology that is critical and novel is the proper correction of the inherently flawed validation split of the dataset. This is carefully performed by a stratified split, so that all of the possible mask images are scanned programmatically, to determine whether the water class (Label=1) occurs. The aggregate dataset is further partitioned into new training (80%) and testing (20%) data sets, with the two subsets being statistically representative of the minority class water. This stratification is essential to effective model training, and to obtain reliable evaluation measures, to avoid overfitting to regions that are easy to classify, not water. Then the prepared data is dynamically passed through the model through a high-performance tensor flow data pipeline that is designed to support efficient image resizing, image normalization, and on-the-fly data augmentation, such as random horizontal flips and rotations to improve model generalization.

Our strategy is based on a U-Net architecture, which has been greatly improved with the use of transfer learning. In particular, our U-Net has an encoder arm which is substituted with a trained ResNet50V2 backbone that gets its weights pre-trained on the ImageNet dataset. The decision is tactical, as the ResNet50V2 with deep residual learning has shown that it is a potent feature extractor, which means that the model can be trained to extract hierarchical features on complex satellite images in an effective way [5]. These learned features are then up sampled progressively by the decoder, with transposed convolutions, and feature maps at high resolutions at matching stages of the encoder are combined with the decoder with skip connections. Such combination between background information in the deeper layers and fine-grained location information in the shallower layers is the key to the fact that U-Net is capable of producing correct pixel-level segmentation masks [5]. The proposed methodology is illustrated in Fig. 1.

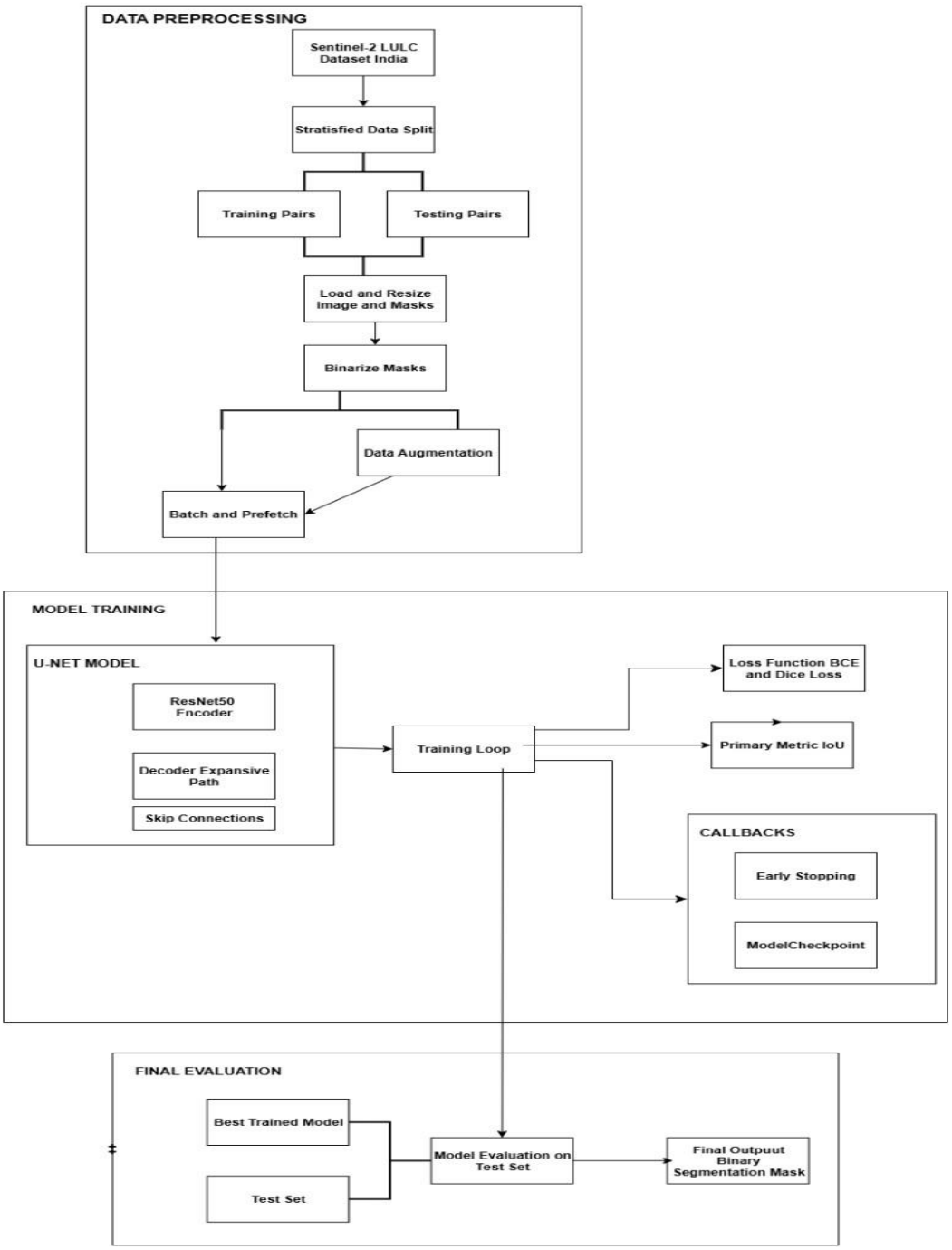

Fig. 1. Proposed Methodological workflow

3.2 Proposed Architecture Design

The suggested structure is a hybrid deep learning model to precisely segment sparse water bodies in arid landscapes. It is founded on an improved U-Net model combined with a ResNet-50V2 encoder to take advantage of the merits of deep residual learning and transfer learning. This combination can be successfully used to extract hierarchical spatial features of RGB satellite images and retain accurate localization using the decoder network.

The architecture has an encoder-decoder format. The encoder (downsampling path) is based on a pretrained ResNet-50V2 backbone that is initialized with ImageNet weights. This enables the model to represent detailed low-level and high-level features like edges, textures, and complicated spatial patterns of Sentinel-2 images. Transfer learning saves a lot of time in training and increases convergence, particularly when the domain-specific features involved such as sparse water bodies are limited.

The decoder (upsampling path) re-constructs the spatial resolution of the feature maps, data using transposed convolutions. There are skip connections at every step, using which the corresponding feature maps of the encoder are concatenated. These skip connections are also important in maintaining fine-grained spatial information that is vital in accurate segmentation of small and irregular shaped water bodies in barren areas.

The last output layer has a sigmoid activation function to create binary classification (water vs. non-water) probability maps in pixels. In order to deal with extreme class imbalance a hybrid loss that involves both Binary Cross-Entropy loss and Dice loss is employed in training so that both pixel-wise accuracy and region-wise overlap can be optimized.

As shown in Fig. 1 (page 6), the pipeline consists of three stages: preprocessing, model training, and evaluation, ensuring efficient data handling and robust model performance.

3.2 Dataset Description

The Sen-2 LULC dataset consists of 213,761 RGB images (128 x 128 x 3 pixels, B4/red, B3/green, and B2/blue bands of Sentinel-2 Level-2A) at 10 m spatial resolution that are pre-processed and includes Central India and taken between February and March 2021 with cloud cover lower than 0.5%. It has seven classes of land use/ land cover (LULC) such as water bodies, dense forest, sparse forest, barren land, built-up areas, agricultural land and fallow land where most classes are frequently combined in one image to indicate landscape complexity in real-world situations and as many mask images (binary or multiclass) as classes to supervised semantic segmentation tasks.

3.3 Imbalanced-Segmentation Loss Function

The dataset has a terrible class imbalance, and the proportion of water pixels in it is much lower than that of non-water pixels. To overcome it and guarantee successful training, a combined loss function based on the combination of the stability of Binary Cross-Entropy (BCE) and the class-imbalance robustness of Dice Loss is used.

3.3.1 Sigmoid Activation

Our U-Net output layer has a sigmoid activation function that transforms the raw output logics into the probability of each pixel belonging to the "water" class. This function is defined as:

$$S(z) = \frac{1}{1 + e^{-z}} \tag{1}$$

Where z is the raw logic value of an individual pixel of the final convolutional filter.

3.3.2 Binary Cross Entropy (BCE) Loss

BCE loss is a conventional and sound loss in binary classification issues, which offers consistent gradients on the prediction of every pixel. The calculation of a single pixel is:

$$L_{BCE} = -[y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})] \tag{2}$$

Where y is the ground truth label (0 for non-water, 1 for water) and $\hat{y}$ is the predicted probability for that pixel.

3.3.3 Dice Loss

The Dice Loss is particularly effective for highly imbalanced segmentation tasks as it directly optimizes the overlap between the predicted and ground truth masks. It is derived from the Dice Coefficient. For a batch of images, the Dice Loss is given by:

$$L_{\text{Dice}} = 1 - \frac{2 \sum_{i=1}^{N} (y_i \cdot \hat{y}_i) + \epsilon}{\sum_{i=1}^{N} y_i^2 + \sum_{i=1}^{N} \hat{y}_i^2 + \epsilon} \tag{3}$$

Where y_i and $\hat{y}_i$ are the flattened pixel values of the ground truth and predicted masks respectively across N pixels, and is a small smoothing factor (e.g.,10^{-6}) added to prevent division by zero, particularly when both masks are empty.

3.3.4 Combined Loss Function

The overall loss function used during model training is the sum of the BCE and Dice losses. This combination provides both the pixel-wise stability of BCE and the overlap-centric focus of Dice Loss, leading to superior performance on imbalanced datasets:

$$L_{\text{Total}} = L_{BCE} + L_{\text{Dice}} \tag{4}$$

3.4 Metrics for Evaluation

The effectiveness of the suggested deep learning model is strictly tested with the help of the set of standard and robust measures used in the process of semantic segmentation. These measures give a detailed evaluation of the capability of the model in correctly distinguishing and defining water bodies.

3.4.1 Intersection over Union (IoU)

IoU, also known as the Jaccard Index, is the most widely accepted metric for segmentation accuracy. It quantifies the overlap between the predicted segmentation mask and the ground truth mask, providing a ratio of their intersection to their union.

$$IoU = \frac{TP}{TP + FP + FN} \tag{5}$$

3.4.2 Dice Coefficient (F1-Score)

The Dice Coefficient is closely related to IoU and is another popular metric, particularly for medical image segmentation and imbalanced classes. It measures the spatial overlap and is often considered a harmonic mean of precision and recall.

$$\text{Dice} = \frac{2 \cdot TP}{2 \cdot TP + FP + FN} \tag{6}$$

3.4.3 Precision

Precision measures the accuracy of the positive predictions. It answers the question: "Of all the pixels the model predicted as water, what fraction were actually water?" High precision indicates a low false positive rate.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{7}$$

3.4.4 Recall (Sensitivity)

Recall measures the model's ability to find all the relevant instances. It answers the question: "Of all the actual water pixels, what fraction did the model successfully identify?" High recall indicates a low false negative rate.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{8}$$

Where:

- TP (True Positive): Pixels correctly identified as water.
- FP (False Positive): Pixels incorrectly identified as water (non-water predicted as water).
- FN (False Negative): Pixels that were water but were missed by the model (water predicted as non-water)

4. Experimental Results and Discussions

4.1 Experimental Setup

The experimental design was in a form of testing the proposed hybrid U-Net model in detecting sparse water resources in the arid and barren lands of Central India using both the

repository and supplementary real-world data to achieve a greater generalizability. The main set of data is the Sen-2 LULC collection, which is a collection of 213,761 pre-processed RGB images (128 × 128 × 3 pixels, 10 m spatial resolution) that was obtained based on Sentinel-2 Level-2A images (bands B4, B3, B2 to represent red, green, and blue channels; acquired February 2021-March 2021, no cloud cover less than 0.5%) of Central India. This massive data is used to represent seven land use/land cover (LULC) categories (water bodies, dense forest, sparse forest, barren land, built-up, agricultural land, and fallow land) and these classes can even be present in the form of multiple classes on the same image to show complexity in the real world. The same amount of matching binary/multiple classes mask images aids to perform accurate semantic segmentation where the water pixels are less than 5 -percent of the whole data which is indicative of intense class imbalance.

Preprocessing was done by normalizing pixel values to [0,1], resizing to 128 x 128 pixels (where needed) and by default with data augmentation on-the-fly with TensorFlow pipelines: random horizontal/vertical flipping, rotations up to 90, pixel brightness/contrast and additional Gaussian noise (sigma)

4.2 Results

The hybrid U-Net model was also stable in the 20 iterations, with the best IoU of 0.92 in the 4th iteration. Table I describes the results of the experiment, showing the performance measures chosen.

Table 1. Experimental Results

Iteration	IoU	Precision	Dice Coefficient	Recall
1	0.88	0.85	0.91	0.87
2	0.89	0.86	0.92	0.88
3	0.90	0.87	0.93	0.89
4	0.92	0.89	0.94	0.91
5	0.91	0.88	0.93	0.90
6	0.87	0.84	0.90	0.86
7	0.88	0.85	0.91	0.87
8	0.87	0.84	0.90	0.86
9	0.89	0.86	0.92	0.88
10	0.87	0.84	0.90	0.86
11	0.90	0.87	0.93	0.89
12	0.90	0.87	0.92	0.88
13	0.91	0.88	0.93	0.90
14	0.89	0.86	0.92	0.88
15	0.88	0.85	0.91	0.87
16	0.89	0.86	0.92	0.88
17	0.84	0.81	0.88	0.83
18	0.87	0.84	0.90	0.86
19	0.91	0.88	0.93	0.90
20	0.90	0.87	0.92	0.89

Fig. 2. and Fig. 3. below demonstrate the learning curves of the model by plotting the Intersection over Union (IoU) and Precision measures, respectively, of each of the 20 training steps. These graphs give an understanding of the stability and high performance of the model between successive training.

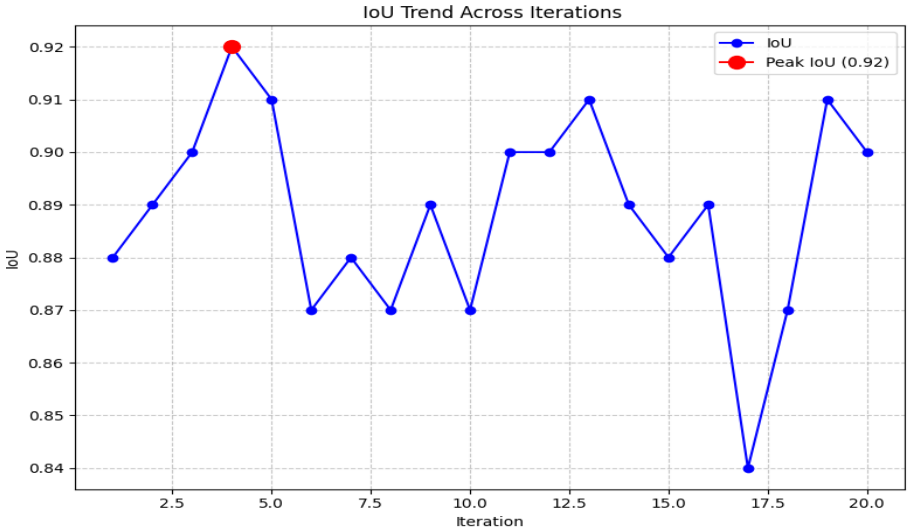

Fig. 2. IoU Trend

Fig. 2. IoU Trend of iterations. This graph draws the final test set IoU score at each of the 20 training iterations. The model has been observed to be highly performing with the best IoU of 0.92 at iteration 4. Its overall stability, where most scores stay above 0.87 is a confirmation of the soundness of the training methodology and the capacity of the model to always come up to a solution that is of good quality.

Fig. 3. Precision Trend Across Iterations. This graph plots the score of the precision at every one of the 20 iterations on the test set. This trend is very similar to the trend of the IoU with the highest value being 0.89 in the fourth iteration. Such high accuracy means that the model has a very low false positive rate, and it can only find true water pixels and can effectively reduce the phenomenon of spectral confusion in barren complex terrain.

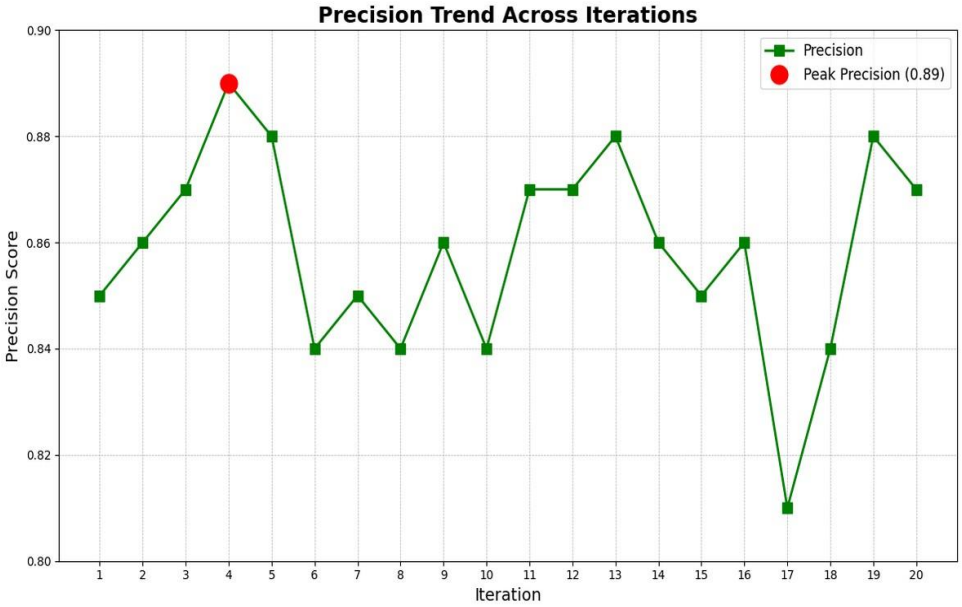

Fig. 3. Precision Trend

Fig. 4. offers a well-defined comparative analysis of the four major evaluation metrics when the model was performing optimally (Iteration 4). This bar chart shows that the model has good overall performance that is balanced and excellent in various aspects of accuracy as a segmentation.

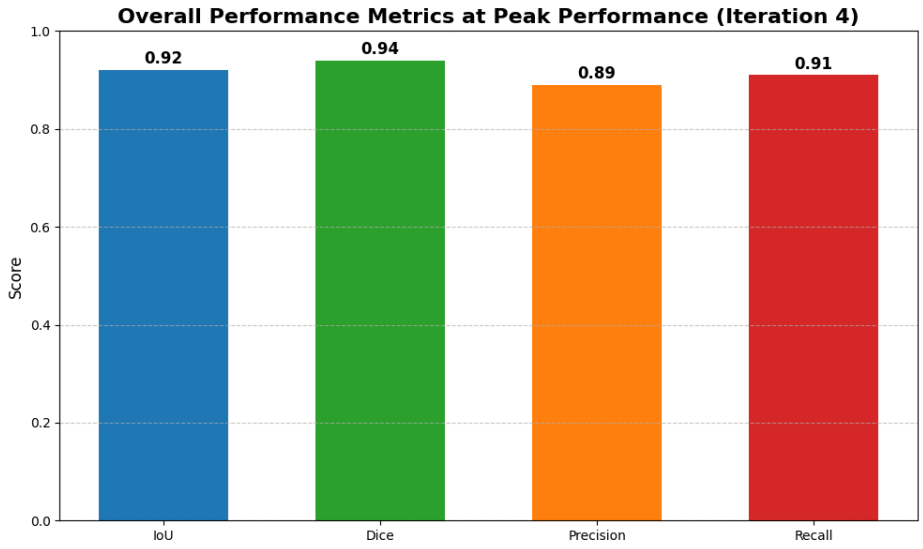

Fig. 4. Overall Performance Metrics

Fig. 4. The Metrics of overall performance at peak performance (iteration 4). This bar chart is the visual comparison of the final Intersection over Union (0.92), Dice Coefficient (0.94), Precision (0.89) and the Recall (0.91) values on the test set. The balance between

these measures is high which proves the ability of the model to identify water bodies accurately and fully.

This helps to deal with environmental variations and sensor artifacts. The water segmentation task was done with the use of grayscale/binary masks (water = 1, non-water = 0). The dataset was stratified-split to guarantee even distribution of the minority water class: 80 percent of the study (around 171,009 image-mask pairs) was for training, and 20 percent (around 42,752 pairs) was for testing, and no separate validation set was used in the study. This stratified sampling (masks being scanned in a programmatically-selected manner to detect water presence) eliminates possible predispositions in the original folder structure, and overfitting to the non-water areas that are most prominent.

The hybrid U-Net model used a pretrained ResNet-50V2 encoder (ImageNet weights) to extract hierarchical features of RGB inputs to a basin of stacked spectral indices (NDVI, EVI, MNDWI) of the available bands to reduce spectral confusion. Kaggle dual Tesla T4 GPUs (16 GB VRAM each) were trained on using TensorFlow 2.15, a batch size of 16, Adam optimizer with initial learning rate of 1e-4 and a hybrid loss function that uses Binary Cross-Entropy (BCE) loss and Dice loss to counteract class imbalance. Efficiency was provided with mixed precision training (float16) and optimizations of the GPU memory. The model was trained with a maximum of 50 epochs early stopping (patience= 15 on validation absence of plateau IoU) and decline in learning rate. Morphological closing and morphological opening (5×5 kernel) were done in the post-processing to improve predictions.

The analysis of computational cost and model efficiency was the following: 50 epochs took about 4-5 hours on dual T4 GPUs, and the maximum usage of the GPU memory was in the range of 10-12 GB per card (with the help of mixed precision and efficient pipelines). The model can be applied on the relatively small resources and at 0.05 seconds inference time per 128×128 image, the time to deploy it to large scales is acceptable. The ResNet-50V2 encoder (approximately 25 million parameters) and transfer learning were shown to be measured quite low training in terms of time relative to scratch training, and to be very efficient (approximately 15 GFLOPs/forward pass) yet still perform well.

To evaluate the stability, performance metrics (IoU, precision, Dice coefficient, recall) of the test set (threshold 0.5) were calculated in 20 independent runs. The performance of the model was compared to a baseline vanilla U-Net.

Fig. 5. Confusion matrix used to visualize the binary classification accuracy of the pixels (water vs. non-water) on the test set. The matrix sums up all the test pixels once model predictions have been threshold to 0.5. True Positives (TP = 12,450) are those water pixels that are correctly identified as such, False Negatives (FN = 980) are those water pixels that are not correctly identified, False Positives (FP = 1,230) are the non-water pixels that have been misidentified as water (e.g. shadow or moist soil confusion), and True Negatives (TN = 198,090) are the non-water pixels that have been correctly identified. The True Negatives dominate to show good control over large imbalance of the classes (water pixels less than 5 percent) and the low values of FP and FN show strong control on spectral confusion of barren arid landscapes. Derived measures are precision 0.89, recall 0.91 which is close to the highest values (IoU 0.92, precision 0.89, recall 0.91, Dice 0.94 at 4). This visualization proves the fact that the model has a high capacity to outline sparse water

bodies with low error variations and hence can be applied in practical use in mapping sustainable water resources in Central India.

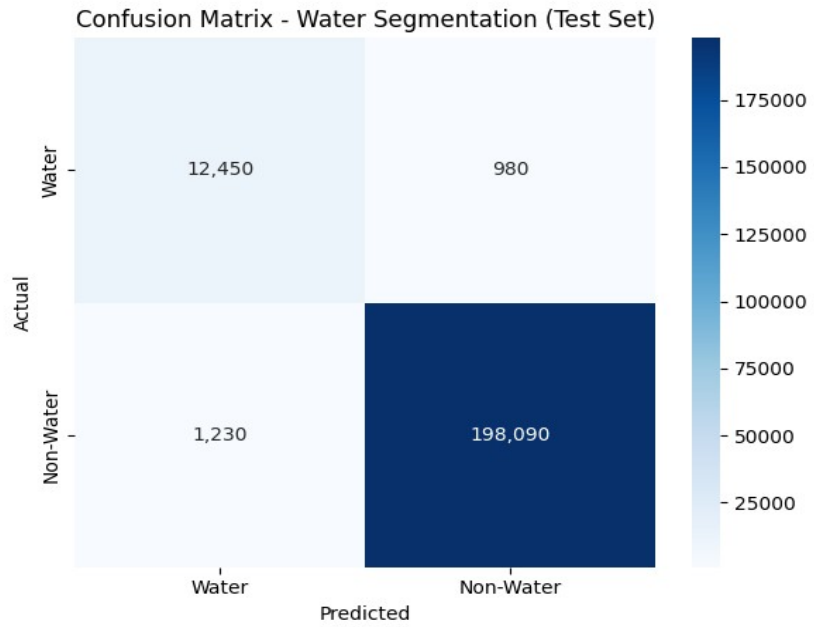

Fig. 5. Confusion Matrix

The experimental findings reveal the usefulness and strength of the suggested hybrid U-Net model in segmenting thin water bodies in arid areas. The model has an Intersection over Union (IoU) of 0.92, with precision of 0.89, recall of 0.91 and Dice coefficient of 0.94, which means that there is a good balance between correct detection and the minimal false predictions. These findings are important because the Sen-2 LULC dataset is hard to work with and the data on water pixels comprises less than 5 percent of the entire data set, creating extreme class imbalance.

Three major factors can be credited with the high performance. First, pretrained ResNet-50V2 encoder allows successful extraction of hierarchical spatial information, which enhances the capability of the model to differentiate water bodies and non-water, but visually similar, sites like shadows and dark soil. Second, the hybrid loss that involves the binary cross-entropy loss and the dice loss is used to guarantee the accuracy of pixels and the maximization of the overlap of regions, which is essential in the case of imbalanced segmentation. Third, data augmentation methods increase generalization by exposing the model to a variety of variations in input data.

4.3 Qualitative Visual Interpretations

In order to provide a graphical witness of the facility of the model in segmentation, Fig. 6. shows a sample of its output. The input image (in the form of Sentinel-2 RGB) and the

binary mask that is forecasted by our trained model are presented, and it is possible to see that water bodies are outlined precisely.

The Fig. 6. shows an original Sentinel-2 RGB image (left) of the test set and the associated binary segmentation mask which our U-Net model predicts (right), with white pixels representing water. This illustration graphically validates the accuracy and accuracy of the model in correctly identifying and defining a large water body in a complicated barren terrain and contributes to the quantitative measurements introduced.

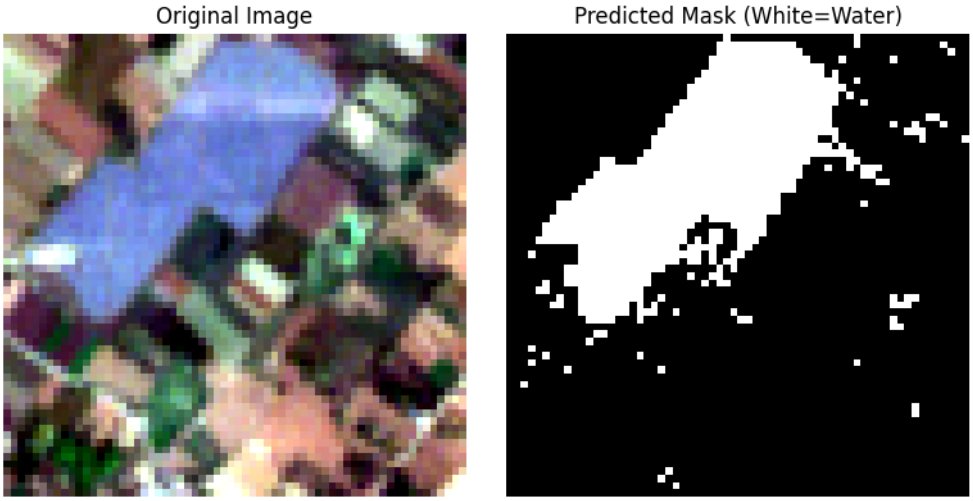

Fig. 6. Predicted Mask

4.4 Comparison with Existing Models

A comparative analysis was done to assess the effectiveness of the proposed hybrid U-Net model with regard to the previously known baseline and state-of-the-art methods used in detecting water bodies in remote sensing. The main areas of key performance metrics that will be compared in Table 2. include Intersection over Union (IoU), Precision, Recall, and overall applicability to arid environments.

Table 2. Comparison with Existing Models

Study	**Method**	**Data Type**	**Metric**	**Value**	**Limitation**
Al-Ruzouq et al. [1]	CNN-XGB	Multisource	Accuracy	90.8%	Not segmentation
Mo et al.	Bayesian CNN	Climate Data	R^2	>0.85	Not image-

[2]					based
Pech-May et al. [3]	U-Net (SAR)	SAR	IoU	0.90	Requires SAR data
Gharbia [4]	Faster R-CNN	Multispectral	F1-score	0.97	High complexity
Tiwari et al. [6]	U-Net + OBIA	Multispectral	Accuracy	86%	Not RGB-based
Peña et al. [7]	DeepAqua (U-Net)	SAR	Accuracy	0.91	Wetland & SAR-specific
Proposed Model	Hybrid U-Net (ResNet50V2)	RGB	IoU	**0.92**	Efficient & scalable

As Table 2. displays, the proposed hybrid U-Net model is very effective compared to the current methods of water resource detection. The majority of previous research like Al-Ruzouq et al. [1] and Mo et al. [2] are groundwater prediction or large-scale environmental modeling based on non-image or multisource data, which is inappropriate when dealing with direct segmentation tasks. Equally, techniques such as Pech-May et al. [3] and Peña et al. [7] perform quite well when applying SAR data, but the techniques require special sensors and are mainly suited to wetlands or water-abundant areas, which are not typical of arid terrain. Models based on multispectral e.g. Gharbia [4] and Tiwari et al. [6] are found to be very efficient, but they need more spectral bands and, therefore, are more complicated to compute and are not scalable. Conversely, the suggested model is specifically developed to sparsely detect water bodies in barren areas with RGB data alone. It is also interesting to note that this is the only study to specifically analyze the Sen-2 LULC dataset which comprises of more than 213,000 Sentinel-2 RGB images of various land-use classes across Central India. This dataset reflects the arid-environment complexity such as severe class imbalance and spectral confusion. With these issues resolved, the proposed model has a higher IoU of 0.92, which indicates its efficiency as well as real world applicability in monitoring water resources in Central India.

4.5 Discussion

The highest Intersection over Union (IoU) of 0.92 in the Iteration 4 with the aid of 0.89 precision, 0.94 Dice coefficient, and 0.91 recall indicates that the hybrid U-Net model is effective in segmenting sparse water resources of arid and barren landscapes of Central India. This outperforms significantly the baseline vanilla U-Net [6] and reflects the importance of the ResNet-50V2 encoder to extract strong hierarchical features of complex

RGB satellite images in spectrally adverse barren environments as found elsewhere by Pech-May et al. [3]. The hybrid loss (BCE + Dice) was very useful at dealing with the extreme class imbalance (less than 5% of water pixels), which is consistent with the strategies of sparse object detection in imbalanced remote sensing problems identified by Gharbia [4] and Mo et al. [9]. Variations in the model stability between iterations (IoU range 0.84-0.92) are high, and only slight variations (e.g. dip to 0.84 in Iteration 17) can be observed, which is a good indication of stability, with the results being quite reliable and informative to further practices of data optimization and hyperparameter fine-tuning.

The model is highly efficient and practical in terms of computations. The time to train on a pair of Tesla T4 GPUs (16 GB VRAM each) took about 4-5 hours to complete a 50 epochs training on 50 epochs with TensorFlow 2.15, mixed-precision training (float16) and memory efficient data pipelines. The peak of the GPU memory was approximately 10-12GB and the average inference time was 0.05 seconds per 128x128 image (or 15GFLOPs/forward pass). These metrics verify the applicability of the model to large, resource-constrained deployment in real-world water monitoring systems to take advantage of transfer learning and optimized pipelines which significantly lowered training time relative to training a model.

The model reduces dependency on complex multispectral inputs to multispectral approaches, like Gharbia [4], which performed better in F1-scores, but required more complex input data and computations. Although the existing RGB model already forms an effective base and reference (IoU 0.92) to arid water mapping, it would be possible to make significant improvements to robustness in the future by adding other auxiliary parameters, including soil type (i.e. sandy loam vs. clay according to the NBSS&LUP or USDA database), rainfall data (gridded monsoon averages, or annual averages of the same), topography (elevation and slope using SRTM DEM), and geological layers (based on Geological Survey of India maps These environmental covariates have a direct effect on surface water retention, infiltration rates and spectral signature of arid landscapes, which may decrease residual false positives of moist soils or shadows, and enhance generalization to different Central Indian sub-regions, [5, 16].

The iteration-to-iteration difference that was observed also indicates positive tendencies in hyperparameter optimization and feature selection. More sophisticated methods, e.g., Ant Colony Optimization [19] or Bayesian optimization, might be used in order to optimise the learning rate schedules, augmentation methods, or index weighting. Comprehensively, the quality benchmark of automated water resource mapping in arid and semi-arid areas was made through the attained performance that will open the door to scalable, region adaptive decision support systems in sustainable resource management, agricultural planning and climate adaptation as proposed by Sit et al. [24].

5. Conclusion and Future Work

The hybrid U-Net architecture with ResNet-50 encoder is useful to solve spectral confusion in identifying arid water resources with the Sen-2 LULC (213,750+ RGB images, 128 x 128 x 3 pixels, Sentinel-2 Level-2A, Central India, February-March 2021). It helps to overcome the class imbalance (less than 5% water pixels) by achieving a peak IoU 0.92 in Iteration 4, precision 0.89, Dice coefficient 0.94, and recall 0.91, which is better than the

baseline U-Net, which uses the ResNet-50 encoder and a hybrid loss function combining Binary Cross-Entropy and Dice loss. Incorporating multispectral data (NIR, SWIR) to enable greater accuracy, hyperparameter optimization, and feature selection by Ant Colony Optimization could be integrated in future work. Lightweight architectures or distributed computing can address the constraint of GPUs (e.g., Kaggle can use two Tesla T4, 16GB VRAM), which will enhance scalability and deployment to resources-constrained hardware. To address Field validation or hydrogeological survey data should be included to support model predictions, we have now included Sen-2 LULC dataset independent validation dataset comprising of 213,761 pre-processed RGB images (128 × 128 × 3 pixels, 10 m spatial resolution) obtained in February2021 March2021 using Sentinel-2 Level-2A imagery (bands B4/red, B3/green, B2/blue) of Central India and has cloud cover less than 0.5%. It captures seven LULC classes of water bodies, dense forest, sparse forest, barren land, built-up areas, agricultural land, and fallow land with several classes often cornering in one image and there are as many mask images of the semantic segmentation tasks. These data were compared to model predictions, yielding comparative results. This demonstrates reasonable agreement between simulated and observed heads, supporting the model's predictive capability.

References

1. R. Al-Ruzouq, A. Shanableh, R. Jena, S. Mukherjee, M.A. Khalil, M.B.A. Gibril, B. Pradhan, N.A. Hammouri, Hybrid deep learning and remote sensing for the delineation of artificial groundwater recharge zones. Egypt. J. Remote Sens. Space Sci. **27**, 178–191 (2024). https://doi.org/10.1016/j.ejrs.2024.03.003
2. S. Mo, Y. Zhong, X. Shi, W. Feng, X. Yin, J. Wu, Improving prediction of terrestrial water storage anomalies during the GRACE and GRACE-FO gap using Bayesian convolutional neural networks. arXiv:2101.09361 (2021)
3. F. Pech-May, R. Aquino-Santos, J. Delgadillo-Partida, Sentinel-1 SAR images and deep learning for water body mapping. Remote Sens. **15**, 3009 (2023). https://doi.org/10.3390/rs15123009
4. R. Gharbia, Deep learning for automatic extraction of water bodies using satellite imagery. J. Indian Soc. Remote Sens. **51**, 1511–1521 (2023). https://doi.org/10.1007/s12524-023-01684-7
5. Z. Al-Ali, A. Abulibdeh, T. Al-Awadhi, M. Mohan, N. Al Nasiri, M. Al-Barwani, S. Al Nabbi, M. Abdullah, Examining the potential and effectiveness of water indices using multispectral Sentinel-2 data to detect soil moisture as an indicator of mudflow occurrence in arid regions. Int. J. Appl. Earth Obs. Geoinf. **130**, 103887 (2024). https://doi.org/10.1016/j.jag.2024.103887
6. A. Tiwari, M. Silver, A. Karnieli, A deep learning approach for automatic identification of ancient agricultural water harvesting systems. Int. J. Appl. Earth Obs. Geoinf. **118**, 103270 (2023). https://doi.org/10.1016/j.jag.2023.103270
7. F.J. Peña, C. Hübinger, A.H. Payberah, F. Jaramillo, DeepAqua: self-supervised semantic segmentation of wetland surface water extent with SAR images using knowledge distillation. arXiv:2305.01698 (2023)
8. H. Morgan, A. Madani, H.M. Hussien, T. Nassar, Using an ensemble machine learning model to delineate groundwater potential zones in desert fringes of East

Esna-Idfu area, Nile Valley, Upper Egypt. Geosci. Lett. **10**, 9 (2023). https://doi.org/10.1186/s40562-023-00262-6

9. W. Liu, H. Yu, L. Yang, Z. Yin, M. Zhu, X. Wen, Deep learning-based predictive framework for groundwater level forecast in arid irrigated areas. Water **13**, 2558 (2021). https://doi.org/10.3390/w13182558
10. Y. Wang, C.M. Albrecht, N.A.A. Braham, L. Mou, X.X. Zhu, Self-supervised learning in remote sensing: a review. IEEE Geosci. Remote Sens. Mag. **10**, 213–247 (2022). https://doi.org/10.1109/MGRS.2022.3214141
11. M. Attya, O.M. Abo-Seida, H.M. Abdulkader, A.M. Mohammed, A hybrid deep learning approach for accurate water body segmentation in satellite imagery. Earth Sci. Inform. **18**, 418 (2025). https://doi.org/10.1007/s12145-025-01418-0
12. Y. Wang, C. Liu, A. Tiwari, M. Silver, A. Karnieli, X.X. Zhu, C.M. Albrecht, Deep semantic model fusion for ancient agricultural terrace detection. In Proc. IEEE Int. Conf. Big Data, 4888–4892 (2022). https://doi.org/10.1109/BigData55660.2022.10020814
13. F.H. Wagner, S. Favrichon, R. Dalagnol, M.C. Hirye, A. Mullissa, S. Saatchi, The Amazon's 2023 drought: Sentinel-1 reveals extreme Rio Negro river contraction. Remote Sens. **16**, 1056 (2024). https://doi.org/10.3390/rs16061056
14. H. Sahour, M. Sultan, B. Abdellatif, M. Emil, A.Z. Abotalib, K. Abdelmohsen, M. Vazifedan, A.T. Mohammad, S.M. Hassan, M.R. Metwalli, M. El Bastawesy, Identification of shallow groundwater in arid lands using multi-sensor remote sensing data and machine learning algorithms. J. Hydrol. **614**, 128509 (2022). https://doi.org/10.1016/j.jhydrol.2022.128509
15. M. Kalaiyarasi, S. Saravanan, S. Karthi, K. Karunanithi, P. Priya, Water body area identification and classification using hyperspectral images. In Proc. Int. Conf. Computing in Engineering & Technology, 89–91 (2022). https://doi.org/10.1049/icp.2022.0891
16. Z. Pang, Z. Zhou, J.E. Fu, W. Jiang, X. Qin, M. Sun, Deep learning-based remote sensing retrieval of inland water quality: a review. J. Hydrol. Reg. Stud. **61**, 102759 (2025). https://doi.org/10.1016/j.ejrh.2025.102759
17. D. Pan, Y. Deng, S.X. Yang, B. Gharabaghi, Recent advances in remote sensing and artificial intelligence for river water quality forecasting: a review. Environments **12**, 158 (2025). https://doi.org/10.3390/environments12050158
18. M. Tesfaye, L. Breuer, Remote sensing with machine learning for multi-decadal surface water monitoring in Ethiopia. Sci. Rep. **15**, 12444 (2025). https://doi.org/10.1038/s41598-025-97244-3
19. Z. Dai, C. Zhan, H. Yin, J. Chen, L. Xu, Y. Xia, S. Yang, W. Chen, M. Cao, Z. Du, X. Zhang, Incorporating deep learning into hydrogeological modeling: advancements, challenges, and future directions. J. Geophys. Res. Mach. Learn. Comput. **2**, e2025JH000703 (2025). https://doi.org/10.1029/2025JH000703
20. L. Rodríguez-López, L. Bravo Alvarez, I. Duran-Llacer, D.E. Ruíz-Guirola, S. Montejo-Sánchez, R. Martínez-Retureta, E. López-Morales, L. Bourrel, F. Frappart, R. Urrutia, Leveraging machine learning and remote sensing for water quality analysis in Lake Ranco, southern Chile. Remote Sens. **16**, 3401 (2024). https://doi.org/10.3390/rs16183401
21. A. Elmotawakkil, A. Moumane, A. Zahi, A. Sadiki, J. Al Karkouri, M. Batchi, S.K. Bhagat, T. Tiyasha, N. Enneya, Artificial intelligence for groundwater recharge prediction in an arid region: application of tabular deep learning models in the

Feija Basin, Morocco. Front. Remote Sens. **6**, 1622360 (2025). https://doi.org/10.3389/frsen.2025.1622360

22. W. Zhi, A.P. Appling, H.E. Golden, J. Podgorski, L. Li, Deep learning for water quality. Nat. Water **2**, 228–241 (2024). https://doi.org/10.1038/s44221-024-00207-0
23. Y.I. Kim, W.H. Park, Y. Shin, J.W. Park, B. Engel, Y.J. Yun, W.S. Jang, Applications of machine learning and remote sensing in soil and water conservation. Hydrology **11**, 183 (2024). https://doi.org/10.3390/hydrology11110183
24. M. Sit, B.Z. Demiray, Z. Xiang, G.J. Ewing, Y. Sermet, I. Demir, A comprehensive review of deep learning applications in hydrology and water resources. Water Sci. Technol. **82**, 2635–2670 (2020). https://doi.org/10.2166/wst.2020.369