

Confidence-Driven Background Selection for Presence and Background Learning in Remote Sensing Water Body Mapping

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Abstract. The Presence and Background Learning (PBL) framework has demonstrated a robust performance for Semi-Supervised Learning (SSL) techniques in remote sensing, particularly in case of the scarce labelled data. However, it's a conventional reliance on random sampling to form the background set introduces a critical vulnerability: random selection may inadvertently include pixels from the target class, thereby corrupting the background distribution and degrading the model adjustment. In our paper, we propose a novel modified PBL algorithm that replaces the random background sampling with a confidence-driven pseudo-label selection strategy. Precisely, our naïve PBL model is first trained on a small set of labelled positive samples and a preliminary set of unlabelled samples; its predicted probability scores are then used to filter the full unlabelled pool; only samples with a low presence probability, those unlikely to belong to the target class, are retained as the background. This produces a cleaner, more semantically coherent background distribution, thereby improving the model training. Applied to a water body extraction from a Sentinel-2 imagery over the ecologically complex of the El Kala National Park (Algeria), our method consistently outperforms the naïve PBL baseline across all evaluation metrics, including the Kappa coefficient and F1-score.

Keywords: Presence and Background Learning (PBL), semi-supervised learning, self-training, pseudo labelling, water body extraction, remote sensing images, Sentinel-2.

Izbor ozadja na podlagi zaupanja za učenje prisotnosti pri kartiranju vodnih teles z daljinskimi raziskavami

Metoda učenja prisotnosti in ozadja (PBL) je učinkovita pri polnadzorovanem učenju z omejenim številom označenih podatkov, zlasti pri daljinskem zaznavanju. Vendar lahko naključno izbiranje vzorcev ozadja povzroči vključitev pikslov ciljanega razreda, kar poslabša učenje modela. V prispevku predstavljamo izboljšano metodo PBL, ki naključno vzorčenje nadomešča z izbiro na podlagi zaupanja v napovedi modela. Ta se najprej nauči prepoznavati označene pozitivne vzorce, nato pa z oceno verjetnosti prisotnosti izbere neoznačene vzorce, ki z majhno verjetnostjo pripadajo ciljnemu razredu. Tako oblikovano ozadje omogoča zanesljivejše učenje. Metodo smo preizkusili pri zaznavanju vodnih teles na satelitskih posnetkih Sentinel-2 ekološko raznolikega parka El Kala v Alžiriji. Rezultati kažejo, da predlagani pristop pri vseh uporabljenih metrikah, vključno s koeficientom Kappa in mero F1, presega osnovno metodo PBL.

1 INTRODUCTION

Water is the main source of life in the world for all living organisms which has a significant effect on public health,

development, and environment [1], therefore, it is very important to map spatiotemporally water bodies [2].

Focusing on the surface water, remote sensing has become an invaluable tool for acquiring and evaluating information on changes in a variety of Earth resources. Several machine learning-based techniques and methods are proposed in the literature for water body mapping from optical multispectral images. Bo Liu et al. [3] present a new module named MSFE to extract multi-layer multi-scale features, when using multi-scale features extraction network (MSFENet) and based on MSFE for extraction of water bodies, their results show a good accordance with other methods and a good performance in GID and loveDA datasets. Rajendiran et al. [4] extract the surface water body by using spectral indices and Gabor filters as pixel-level feature (PLF) maps combined with machine learning models such as KNN (K-Nearest Neighbors), RF (Random Forest), SVM (Support Vector Machine), and XGBoost (eXtreme Gradient Boosting). Their results show that PLF with XGBoost achieves a superior accuracy and efficiency, enabling an effective water resource monitoring and analysis of the surface water dynamics over time. N. Yagmur et al. [5] investigate shallow water mapping

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based on machine learning techniques from the Sentinel-2 imagery. They integrate spectral bands and water indices with SVM to improve their results and combine SVM with the RFE (Recursive Feature Elimination) feature selection technique to enhance a good performance. It should be noted that their approach is particularly useful for shallow water areas.

Currently, deep learning provides an effective approach to water body extraction for automatic learning features at multiple levels. Cao et al. [6] propose a new enhanced network model (EU-Net) enabling an accurate water body extraction from high-resolution remote sensing images. The method integrates improved residual connections, attention mechanisms, and multi-scale dilated convolution technique with feature fusion to extract the captured complex spatial patterns. Their experimental results show that the EU-Net method improves the accuracy, boundary detection, and robustness compared to other models, especially in cases with complex varying water body shapes and backgrounds. [7] proposes an automated method for extracting water bodies from the satellite imagery using the Faster R-CNN (Region-based Convolutional Neural Network) algorithm. The method is evaluated on Sentinel-2 and Landsat-8 datasets. The results demonstrate an improved accuracy compared to the CNN-based methods, and highlight the method effectiveness in detecting and mapping water bodies. Ma et al. [8] propose a combined method named Water Index and Swin Transformer Ensemble (WISTE). It combines Fully Convolutional Networks (FCN), Swin Transformer, and Normalized Difference Water Index (NDWI) within the Bayesian averaging strategy to capture both the local and global features. The measured experimental results on the GID and DeepGlobe datasets demonstrate that their method outperforms the other segmentation methods. [9] shows that an accurate mapping of the water bodies from a remote sensing imagery is essential but challenged by mixed pixels, cloud contamination, and noise in optical and SAR (Synthetic Aperture Radar) data. It proposes a feature collaborative convolutional neural network (DeepOSWSRM) that fuses the Sentinel-1 and Sentinel-2 imagery for a super-resolution water mapping. The approach integrates the complementary information to mitigate the missing data and enhance the detection of small water bodies. The experiments using simulated and real datasets demonstrate that the method achieves a high accuracy and produces detailed, and fine-resolution water maps outperforming the existing techniques. [10] proposes a Multiscale Feature and Global context Fusion Network (MSGFNet) method, based on a deep learning network enabling a body extraction from remote data. The method improves the segmentation accuracy in complex regions and areas. Experimental results on the GF-1 and Sentinel-2 datasets demonstrate a high performance compared to other models in the literature in terms of the boundary delineation and accuracy. The method effectively reduces the noise, supports

applications in hydrological monitoring as well as resource management. [11] investigates the semantic water body extraction using a High-Quality Segment Anything Model (HQ-SAM) combined with the optical and SAR remote sensing imagery. The model is evaluated on several datasets and proves its high accuracy. The results show that HQ-SAM outperforms the traditional index-based methods, especially for large and complex lakes while maintaining a strong generalization capability. The method highlights the potential of the AI-driven segmentation for an efficient water resource analysis and monitoring.

The above machine learning and deep learning methods need a complete and exhaustively labelled sample set for model training. Specifically, the training set should usually contain labelled samples of all land classes that appear in the imagery. They are split into positive and negative sample sub-partitions. The sample manual annotation is time-consuming and labour-intensive, specifically when the objective is to map a specific land coverage on large scales, such as water bodies. Moreover, the manual annotation is not likely to include all land-cover classes, particularly in complex scene areas. This makes the training set insufficient, thus limiting the model accuracy. However, the Semi Supervised Learning (SSL) and especially the Positive Unlabelled Learning (PUL), use a training set that includes unlabelled samples in addition to the labelled positive samples. The unlabelled samples belong to any class, including the class of interest, but their labels should be known. Consequently, they can be collected without any annotation effort [12]. In [13], the PBL method is proposed for mapping burned areas, the performance of their method is evaluated by a comparative analysis. Zeping Min et al. [14] make a theoretical analysis by using a pseudo label-based algorithm. Their findings show the effectiveness of their method. Beibei Wu et al. [15] propose a Boundary-Enhanced Consistency SSL (BECSSL) framework. They use an innovative approach for water extraction in limited-annotation scenarios. They particularly address the boundary-aware feature learning through integrated architectural components. Their approach requires an enhancement in the completeness and the accuracy for the small-scale water. Results are in good accordance with the obtained experimental values. Xu et al. [16] propose DPLM, a Dynamic Pseudo-label updating framework for Large-scale, Multi-scenario lake-water body mapping, to enable an automated vector-based extraction with no manual annotations. With a dual-branch transformer architecture incorporating a dynamic quality gating mechanism for an iterative noise label filtering, the authors demonstrate that DPLM outperforms the existing state-of-the-art water body extraction models under diverse and challenging acquisition conditions. Lu et al. [17] improve the SSL techniques by integrating the segmentation and discriminating networks via adversarial training, hence augmenting the performance with little labelled data.

Alsamman et al. [18] present a deep semi-supervised self-learning technique known as a teacher-student based on a multi-scale UNet classifier for the water body extraction. The teacher is trained in the inaccurate labelled data and then in pseudo labelling remaining unlabelled data. The student is trained in the labelled and the pseudo-labelled data. Their results demonstrate the superiority of their model compared to other water body detection classifiers. Feng et al. [19] propose S2CNet-APG, a semi-supervised method for a multi-source remote sensing image classification based on adaptive pseudo label generation. It uses adaptive thresholds to control the selection of pseudo-labels from the unlabelled data and incorporates a spatial neighbourhood information to improve the reliability of these labels. The experiments conducted on three multi-source remote sensing datasets show that the method achieves a superior performance compared to the existing methods. In [20], the authors use a river extraction method for high-resolution remote sensing images using a non-uniform sampling and SSL. Sampling is made in high-frequency areas by maintaining the edge details while minimizing the computational requirements and integrating the unlabelled data to enhance the feature learning. This method outperforms the state-of-the-art methods by improving the accuracy and IoU (Intersection over Union). Effectively addresses the limited labelled data and detail loss as well as generalization across datasets and diverse environmental conditions.

[21] evaluates the PBL method for the water body extraction from the Sentinel-2 imagery. Framed as a one-class classification problem, PBL uses the positive and unlabelled samples, thus reducing the dependence on the extensive labelled data. Its performance is compared with the NDWI, TWI (Triangle Water Index), and SWM (Sentinel Water Mask) indices in an Algerian coastal region. The results demonstrate that PBL achieves a high accuracy and reliability, effectively delineating the lakes while simplifying the model selection and minimizing the manual processing requirements.

In our paper, the PBL method is used to detect remote sensing water bodies from the high-resolution Sentinel-2 images. It is based on SSL using limited labelled data (presence) and unlabelled data (background).

To achieve a good accuracy, the pseudo labelling based on the confidence thresholding parameter is used to improve the random selection of the samples. The choice of good samples adds more precision to the model by avoiding the results to be being biased. To select more representative samples, three cases are identified and parametrized.

The obtained numerical results are compared with several experimental metrics to validate the potential of our method.

The main contribution of our paper is the improvement of the naïve PBL technique based on a novel sample-selection strategy that replaces random sampling with a pseudo-label filtering strategy.

The main contributions of our paper are:

1. Presentation of our sampling selection strategy based on pseudo labelling to retain only low-confidence samples as the background to distinguish between the water bodies and the land boundaries in unlabelled pools;
2. A minimal level of false positive samples;
3. An improved robustness of the PBL algorithm;
4. An evaluation and experimental metrics comparative study of the proposed PBL technique.

Our paper is organized as follows. Chapter 1 gives a brief overview of the related works and the contributions of the proposed method. Chapter 2 describes the methodology of the enhanced PBL model. Chapter 3 analyses the case study, makes comprehensive experiments on the Sentinel-2 dataset, and compares it with naïve PBL method. Chapter 4 draws conclusions of our work.

2 METHODOLOGY

2.1 Overview of the Proposed method

The water body extraction under limited annotation conditions constitutes a typical SSL problem. Only samples of the target class (water) are available for supervision, with no accurate negative samples. The PBL framework [12] addresses the issue by estimating posterior presence probability $\Pr(y = 1/x)$ from the labelled positive samples and an unlabelled background set selected from the study area. While effective, naïve PBL depends on random sampling to constitute the background, a strategy that generates systematic contamination when the landscape is spectrally heterogeneous as is the case in coastal wetland environments, such as El Kala National Park in Algeria. To overcome this limitation, we propose a principled enhancement of PBL that replaces the random background sampling using a confidence-driven pseudo-label selection strategy. The proposed framework consists of three main components: (1) a Naïve Model Initialization module that provides the initial presence probability scores over the full unlabelled pool; (2) a Pseudo-Label Background Filtering module that partitions the pool into reliable background, ambiguous, and pseudo-positive sets; and (3) a Refined PBL Training module that retrains the classifier on the purified background and recalibrates constant c^* .

2.2 Theoretical Foundations of PBL

Let $X^+ = \{X_i\}_{i=1}^n$ denote the set of the n -labelled positive (presence) samples and let $U = \{X_j\}_{j=1}^N$ denote a large pool of the N -unlabelled pixels (Background). The PBL aim, one of the most known Positive Unlabelled Learning (PUL) algorithms, is to estimate the posterior presence probability:

$$Pr(y = 1/x) = \frac{1-c}{c} \times \frac{Pr(s = 1/x, \eta = 1)}{1 - Pr(s = 1/x, \eta = 1)} \quad (1)$$

where $S = 1$ is a labelled positive sample. The unlabelled samples are $S = 0$. The model is trained under the presence and background strategy ($\eta = 1$); represented as $Pr(s = 1/x, \eta = 1)$, and c is a calibration constant estimated as:

$$c = \frac{1}{n} \sum_{x \in O} Pr(s = 1/x, \eta = 1) \quad (2)$$

with O a held-out positive validation set of size n .

2.3 Background Contamination under Random Sampling

In the basic PBL formulation, the background set $B \subset U$ is constructed by random sampling from U . The derivation of $Pr(s = 1/x, \eta = 1)$ assumes that the background samples are drawn from the marginal distribution $P(x)$, which, by definition, includes target-class pixels with the probability equal to their natural probability $Pr(y = 1)$. In practice, however, random sampling over a spectrally complex region such as the coastal wetland of El Kala, which combines open water, marshes, riparian vegetation, and coastal dunes; is likely to integrate water pixels into the background set beyond their natural prevalence. This contamination has two cascading effects. First, naïve model $Pr(s = 1/x, \eta = 1)$ is trained on a corrupted supervision signal, reducing its ability to discriminate water from non-water. Second, and more critical calibration constant c is positively biased when the target class pixels are over-represented in the background. The mean predicted probability over validation set O is inflated, causing equation (1) to systematically underestimate $Pr(y = 1/x)$ and increasing the false negative rate. This bias propagates directly to the final water mask, manifested as missed detections along lake boundaries and in shallow water zones.

2.4 The proposed Pseudo-Label Background Selection Module

The random sampling selection strategy is suboptimal and can be replaced with the confidence-guided strategy described below:

2.4.1 Naïve Model Initialization

The preliminary naïve model is trained on labelled positives X^+ and small, randomly drawn initialization subset $B_0 \subset U$. Although B_0 may itself contain some water pixels, it is sufficient to produce a coarse but reliable scoring function. Let $f_0: \mathbb{R}^d \rightarrow [0, 1]$ denote the Random Forest (RF) probability estimator trained in this phase equation (1). Even an imperfect naïve model provides a reliable signal at the extremes of the score distribution, pixels with very low $f_0(x)$ are almost certainly non-water, while pixels with very high $f_0(x)$

are likely water. The filtering strategy exploits precisely this property.

$$f_0(x) = Pr_0(s = 1/x, \eta = 1) \quad (3)$$

2.4.2 Confidence Threshold Selection

Naïve model f_0 is first applied to entire unlabelled pool U , assigning each sample presence probability $f_0(x_i)$. Samples are then partitioned using two confidence thresholds τ_{low} and τ_{high} :

- Samples with $f_0(x) < \tau_{low}$ are retained as reliable background instances, forming refined background set B^* .
- Samples satisfying $\tau_{low} \leq f_0(x) \leq \tau_{high}$ are considered uncertain and discarded.
- Samples with $f_0(x) > \tau_{high}$ are treated as pseudo-positives and excluded from B^* .

Formally, the filtered background set is defined as:

$$B^* = \{x_j \in U: f_0(x_j) < \tau_{low}\} \quad (4)$$

The choice of confidence thresholds τ_{low} and τ_{high} is critical, as these parameters control the trade-off between the size and purity of the background set. Rather than using arbitrary fixed values, we use a data-driven approach based on the empirical score distribution of naïve model f_0 . Specifically, the thresholds are set to the 15th and 85th percentiles of the predicted presence probabilities over unlabelled pool U :

$$\tau_{low} = P_{15}(f_0(U)), \quad \tau_{high} = P_{85}(f_0(U)) \quad (5)$$

This percentile-based approach is theoretically justified by the bimodal structure of the score distribution in spectrally heterogeneous environments, where the lower mode captures unequivocal non-target pixels and the upper mode corresponds to target-like signatures. By anchoring the thresholds to the natural modes of the distribution, the method remains adaptive across sensors, seasons, and regions without requiring additional labelled data or parameter tuning.

To evaluate the sensitivity of lower threshold τ_{low} , three representative values $\tau_{low} \in \{0.2, 0.3, 0.4\}$ are tested. They span the practical range where B^* is both large enough for a stable RF training and sufficiently clean to reduce the bias. Below $\tau_{low} = 0.2$, B^* contains less than 80 samples on the El Kala dataset, this is insufficient given the small positive set (< 80 pixels). Above $\tau_{low} = 0.5$, the filter becomes overly permissive, retaining ambiguous pixels and causing the method to revert to contaminated naïve PBL. The selected values thus provide an effective balance between the sample size and the background purity. The data-driven threshold selection aligns with the key advances in semi-supervised learning. While FixMatch [22] relies on a fixed confidence threshold, FlexMatch [23] and FreeMatch [24] demonstrate the superiority of the distribution-aware

adaptive thresholds. Accordingly, our framework derives τ_{low} and τ_{high} directly from the naïve model score distribution (Equation 5), providing a robust and tuning-free solution well-suited for the label-scarce remote sensing applications. Following the recent advances in the PU learning [25] [26], spatial and spectral filtering are applied to pseudo-positive candidates to ensure a geographic proximity and spectral coherence with reference water samples.

2.4.3 Refined PBL Training and Calibration

In this step, the RF model is trained on labelled positives X^+ and filtered background B^* , yielding an improved naïve posterior:

$$f^*(x) = Pr^*(s = 1/x, \eta = 1) \quad (6)$$

The calibration constant is recomputed on B^* :

$$c^* = \frac{1}{n} \sum_{x \in O} Pr^*(s = 1/x, \eta = 1) \quad (7)$$

The final presence probability is then obtained via equation (1) with f^* and c^* , and RF binary classification is performed at decision threshold 0.5. (Equation (8)).

$$Pr^*(y = 1/x) = \frac{1 - c^*}{c^*} \times \frac{Pr^*(s = 1/x, \eta = 1)}{1 - Pr^*(s = 1/x, \eta = 1)} \quad (8)$$

The complete process is summarized in Algorithm 1.

Algorithm: Self-training Guided Presence and Background Learning

Input: Labelled positives X^+ , unlabelled pool U , validation set $O, \tau_{low}, \tau_{high}$

Output: Presence probability map $Pr^*(s = 1/x)$ for all test pixels

1. Sample small initialization subset $B_0 \subset U$ randomly
2. Train naïve RF model f_0 on $X^+ \cup B_0$ (Equation(3))
3. Set $\tau_{low} = P_{15}(f_0(U))$, $\tau_{high} = P_{85}(f_0(U))$ (Equation(5))
4. Compute the presence probability for all $x_j \in U$: compute $f_0(x_j)$
5. Build $B^* = \{x_j \in U: f_0(x_j) < \tau_{high}\}$ (Equation(4))
6. Train refined RF model f^* on $X^+ \cup B^*$ (Equation(6))
7. Estimate $c^* = \frac{1}{n} \sum_{x \in O} f^*(x)$ (Equation(7))
8. Compute $Pr^*(s = 1/x)$ for all test pixels (Equation(8))
9. Return: water if $Pr^*(s = 1/x) \geq 0.5$, non-water otherwise

3 EXPERIMENTS

3.1 Study Area and Data

3.1.1 Study Area

Experiments are conducted over the El Kala National Park, north-eastern Algeria (36.7°N–8.7°N, 8.2°E–8.7°E), during the winter season of 2024 (January–March). The study area is a Ramsar-designated wetland complex of an exceptional ecological significance,

encompassing three principal lakes, Oubeïra, Tonga, and Mellah, within a heterogeneous mosaic of dense Mediterranean forests, coastal dunes, marshes, and agricultural zones. This spectral heterogeneity makes El Kala a particularly challenging environment for the Water Body Extraction and a representative test case for the proposed background purification strategy.

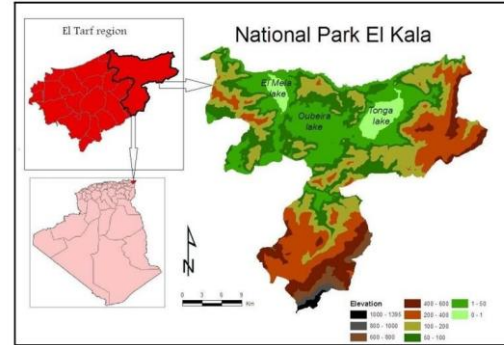


Figure 1. EL Kala National Park localization [27].

3.1.2 The Data

Sentinel-2 is a high-resolution optical remote sensing satellite that provides data to support resource monitoring, land management, and environmental protection. With advancements in the remote sensing technology, Sentinel-2 imagery has been utilized in water-related studies. Sentinel-2A, launched in June 2015, and Sentinel-2B, launched in March 2017, form part of the European Copernicus program. Both satellites carry a Multi-Spectral Instrument (MSI) and operate in a sun-synchronous polar orbit at an altitude of 786 km, providing a combined 10-day revisit cycle. The constellation acquires a multispectral imagery in 13 spectral bands at spatial resolutions of 10 m, 20 m, and 60 m. [28] For our study, atmospherically corrected Level 2A surface reflectance products, freely available through the Google Earth Engine (GEE), are used in our analysis to ensure the radiometric consistency and reliability, six spectral bands with a 10 m spatial resolution are used as input the features: Blue (B2, 490 nm), Green (B3, 560 nm), Red (B4, 665 nm), NIR (B8, 842 nm), SWIR-1 (B11, 1610 nm), and SWIR-2 (B12, 2190 nm).



Figure 2. False composite of the Sentinel 2 image used in our study.

3.2 Model Implementation and Parameter Tuning

Labelled positive set X^+ consists of 78 water pixels manually digitized by qualified technicians from three principal lakes. They are distributed across open water zones, shallow water areas, and transitional riparian zones. X^+ is split into a training subset (70%) used for the model training and a calibration subset (30%) reserved exclusively for computing calibration constants c and c^* to ensuring that no training samples are used in the calibration process. Unlabelled pool U comprises 1000 randomly generated points distributed across the study region. All the processing is performed within GEE using an RF classifier with 100 trees and probability output mode.

The confidence threshold analysis reveals a strongly biased presence probability distribution over unlabelled pool U . The majority of the pixels have a very low probability ($\tau_{low} = 0.0028$) affected by the naïve model. The deviation is consistent with the imbalanced class in the water body mapping, where the water pixels represent a small fraction of the landscape. The P15/P85 percentile configuration produces three balanced partitions: 427 reliable negative-set pixels (B^*), 343 ambiguous pixels, and 88 pseudo-positive pixels. The pseudo-positive fraction (8.8% of U) is consistent with the estimated water prevalence in the El Kala area, validating the ecological coherence of the filtering strategy.

As demonstrated by the UMAP embedding (Uniform Manifold Approximation and Projection) (Figure 3), the percentile-based thresholding strategy imposes a clear three-cluster structure on the originally continuous probability landscape. Reference water samples map reliably to the high U-score regions, while the 15th and the 85th percentiles delineate the high-confidence negatives and pseudo-positive candidates, respectively. The approach enables a robust, conservative selection of non-water pixels and provides reliable positive training seeds for a semi-supervised refinement.

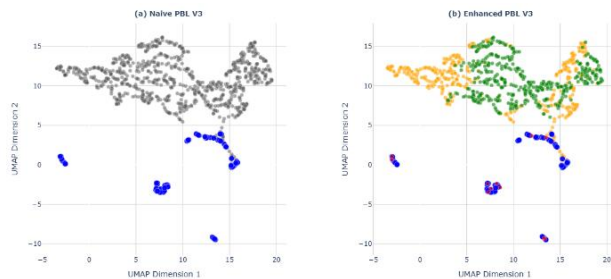


Figure 3. Comparison of (a) naïve and (b) enhanced PBL feature spaces. (a) Naïve PBL: unlabelled background points (grey) with raw U-scores from the f_0 classifier. (b) Enhanced PBL: after applying the 15th/85th percentile thresholds, the background points are partitioned into reliable negative (green), ambiguous (orange), and pseudo-positive (red) categories. The water reference points (blue) are displayed in both panels.

In the Enhanced PBL framework, a spatial and spectral filtering is applied to refine the initial pseudo-positive

candidates, they are derived from the 85th percentile (τ_{high}) of the U-score distribution [29]. As shown in Figure 3(b), the initial set of the 124 pseudo-positive candidates is reduced to 11 high-confidence pseudo-positives after applying a 500 m spatial buffer around the reference water points and a spectral Euclidean distance threshold of 0.25 relative to the mean water signature. The UMAP visualization shows that the retained pseudo-positives (red) form a tight cluster near the water reference samples (blue), whereas the remaining discarded pseudo-positive candidates occupy more distant or transitional regions of the feature space [30]. This confirms that the spatial and spectral filtering should be used to retain only those pseudo-labels that exhibit both the geographic and the spectral coherence. High-quality pseudo-labels enrich the positive training set while effectively mitigating the risk of introducing false positives during the iterative model refinement process [25].

3.3 Model Evaluation

The model performance is assessed by a cross-validation against four spectral water indices computed from the same Sentinel-2 imagery serving as the ground truth. The Normalized Difference Water Index (NDWI) [31], Sentinel Water Mask (SWM) [32], Automated Water Extraction Index (AWEI) [33], and Triangle Water Index (TWI) [34] are applied with their thresholds to generate binary reference water maps. The threshold values are determined through a combination of the literature-based references and visual interpretation to ensure an optimal discrimination between the water bodies and the surrounding land surfaces. Table 1 presents the spectral formulas of the water indices.

Table I. Spectral formulas of the water indices used in the study.

Water Index	Formula
NDWI	$\frac{Green - NIR}{Green + NIR}$
SWM	$\frac{Blue + Green}{NIR + SWIR1}$
AWEI	$4 \times (Green - SWIR2) - (0.25 \times NIR + 2.75 \times SWIR1)$
TWI	$\frac{(2.84 \times (RedEdge1 - RedEdge2))}{(Green + SWIR2)} + \frac{(1.25 \times (Green - Blue) - (Nir - Blue))}{(Nir + 1.25 \times Green - 0.25 \times Blue)}$

4 EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Evaluation Metrics

The Kappa coefficient (K) and the F1 score (F1) metrics are used to evaluate the classification results. The formula of the two indicators is:

$$F1 = \frac{2TP}{2TP + FP + FN} \quad (9)$$

Kappa Coefficient

$$= \frac{2 \times (TP \times TN - FP \times FN)}{(TP + FP) \times (FP \times TN) + (FP + FN) \times (FN + TN)} \quad (10)$$

where TP (True Positives), is the correctly predicted water body pixel, TN (True Negatives) is the correctly predicted non-water body pixel, FP (False Positives) is the incorrectly predicted water body pixel, and FN (False Negatives) represents the incorrectly predicted non-water body pixel.

4.2 Results

Table 2 shows the Kappa coefficients and F1-score values for the naïve PBL and the proposed PBL algorithms, validated against four spectral water indices. The proposed PBL model reliably outperforms the naïve PBL model across all reference indices and both evaluation metrics, with relative Kappa gain values. The experimental results shown in Table II indicate that there is a significant improvement in the Kappa coefficients and F1-score metrics for water body mapping. This is mainly due to the optimal choice of the pseudo-label background purification strategy for negative unlabelled samples.

The performance variation between the two algorithms is evident. To highlight the details of the water body extraction results, Figure 4 shows the water extraction results of three enlarged sample areas. The selected areas comprise the water bodies in complex conditions and boundaries. Our quantitative and visual evaluations of the water body classifications confirm that the proposed algorithm achieves a superior water extraction performance compared to other methods, particularly for the Oubeira and Mellah lakes. A visual assessment shows that the naïve PBL method is highly susceptible to the salt-and-pepper noise, with pronounced effects observed in the Tonga and Mellah Lake area, as illustrated in Figure 4.

This benefits from the power of the percentile-based approach and the choice of confidence thresholds τ_{low} and τ_{high} . The parameters control the trade-off between the size and purity of the background set in which the details and boundaries of the water bodies are better captured. Overall, the proposed PBL algorithm demonstrates an excellent water extraction performance on high-resolution optical images.

5 DISCUSSION

5.1 Overall performance improvement of the proposed PBL

The proposed PBL algorithm consistently outperforms the classic PBL method across the four water indices (NDWI, SWM, AWEI, and TWI), providing a strong empirical validation of the self-training background purification strategy. As shown in Table II, the proposed approach significantly improves both the Kappa coefficient and the F1-score. However, a more

Table II. Classification results of the water body extraction.

Index	Method	Kappa	K-gain (%)	F1	F1-gain (%)
NDWI	PBL	0.8206	—	0.830	—
	Proposed PBL	0.8547	+ 4.15	0.864	+4.10
SWM	PBL	0.8733	—	0.880	—
	Proposed PBL	0.8837	+1.19	0.892	+1.36
AWEI	PBL	0.8663	—	0.874	—
	Proposed PBL	0.8883	+2.54	0.898	+2.75
TWI	PBL	0.8292	—	0.839	—
	Proposed PBL	0.9303	+12.20	0.935	+11.44

significant advancement is observed for NDWI (+4.15%), particularly TWI (+12.20%). A positive variation in the performance gains reflects a variable sensitivity of each spectral water index to the background contamination, which is effectively addressed in the proposed purification strategy. The TWI index, formulated using the Red Edge and SWIR bands to form the water body triangles in the Cartesian coordinate system, is particularly sensitive to the spectral confusion in the shallow water and transitional riparian zones, the areas most affected by mixing with the surrounding vegetation. The substantial rise in TWI (+12.20 % in Kappa) indicates that the proposed PBL model is particularly efficient at retrieving water pixels under various conditions.

5.2 The effect of the background purification strategy on water extraction results

The enhanced performance of the proposed PBL technique is defined by two complementary mechanisms. First, by systematically excluding the water-like pixels from background set B^* , our framework defines a more representative decision boundary between the water and non-water land cover. Second, the self-training strategy ensures that the background purification is fully data-driven and adaptable. The percentile-based threshold strategy automatically adjusts the score distribution of the study area, avoiding the need for additional labelled samples.

The key finding of the study is that in semi-supervised one-class classification scenarios with limited labelled positive samples, the purification of the unlabelled background set plays a role that is at least as important as, and in some cases even more decisive, than that of the positive samples.

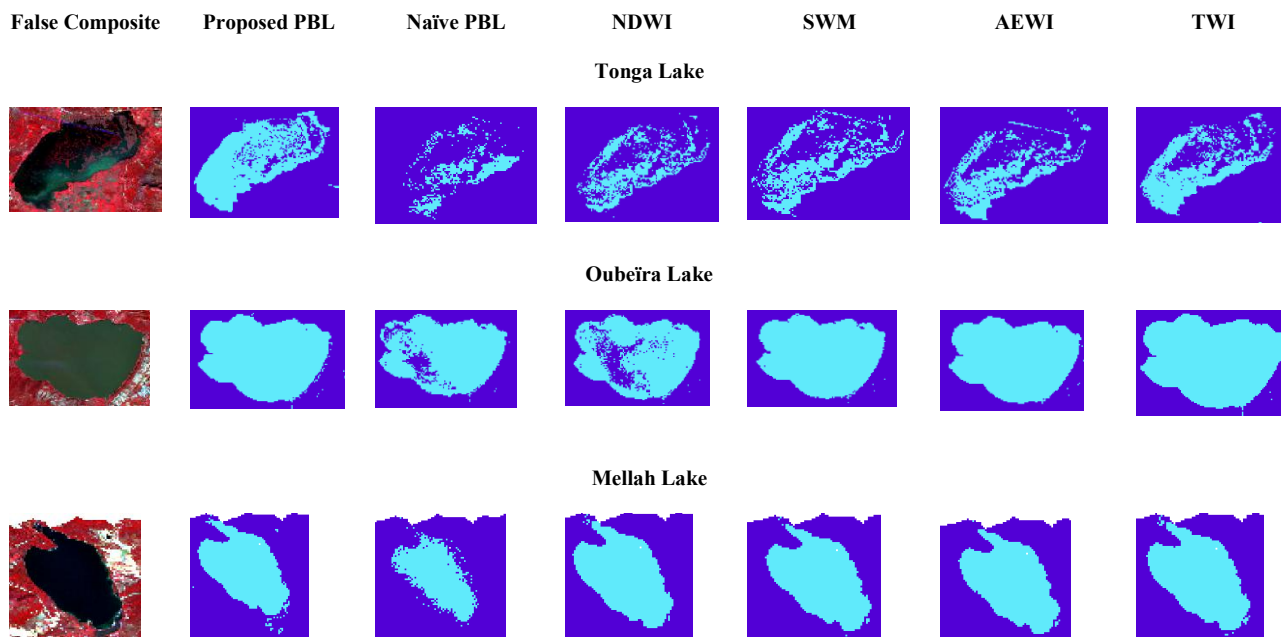


Figure 4. Extraction results for Tonga, Oubeira, Mellah lakes (from left to right: the false colour composite image, proposed PBL, Naïve PBL, NDWI, SWM, AWEI and TWI).

5.3. Evaluation and comparison with spectral water indices

Our comparative validation against conventional spectral water indices confirms the effectiveness of the proposed PBL method. Despite relying on only six spectral bands (B2, B3, B4, B8, B11, and B12) and less than 80 labelled positive samples, the method achieves the Kappa coefficient of 0.9303 when validated against the TWI reference, demonstrating a performance competitive with the existing water extraction techniques. It is important to note that the results further highlight the effectiveness of the proposed background purification mechanism. Notwithstanding the absence of the manual spectral knowledge, the method achieves a high level of agreement comparable to the established water indices, demonstrating its ability to learn discriminative representations directly from the data. This observation supports recent trends in remote sensing towards data-driven, weakly supervised, and semi-supervised approaches able to reduce the dependence on expert-designed features while maintaining a high mapping accuracy.

6 CONCLUSION

The study presents a principled enhancement of the Presence and Background Learning (PBL) framework for extracting water features from remote sensing imagery by addressing the fundamental drawback of the naïve PBL algorithm, the background contamination due to random sampling. By introducing a confidence-driven

pseudo-label selection mechanism, the proposed method constructs a clean and more representative background set, significantly improving model reliability under limited labelled data conditions. The experimental results, conducted on the Sentinel-2 imagery over the spectrally heterogeneous environment of El Kala National Park, demonstrate consistent performance gains across multiple evaluation metrics, including the Kappa coefficient and F1-score. These improvements confirm that the proposed filtering strategy effectively mitigates the inclusion of the target-class pixels within the background, leading to a more accurate water body detection, especially in the challenging areas such as shallow water zones and complex boundaries. The major contribution of our method is its data-driven percentile-based thresholding that adaptively determines the reliable background samples needing no manual labelling. This adaptability permits the model to generalize across diverse environmental conditions while maintaining its robustness. Furthermore, the integration of self-training enhances the separability between the water and non-water classes, producing more coherent spatial outputs and reducing the noise compared to the standard PBL algorithm. It is important to note that the findings highlight the background sample quality as a critical factor in semi-supervised one-class classification problems. In some scenarios, the effective background purification has a more decisive impact on the performance than increasing the number of the positive-labelled samples. This insight has broader implications for remote sensing applications where labelled data are

scarce. Overall, the proposed Pseudo-Label-guided PBL framework offers a robust, efficient, and scalable solution for the water body extraction, achieving a high accuracy while significantly reducing the reliance on extensive manual labelling. It contributes to advancing the data-driven approaches in environmental monitoring and provides a solid basis for future research in semi-supervised remote sensing analysis.

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