Deep Learning Approaches for Environmental Monitoring of Wetlands Using Remote Sensing Data: Special Reference to Rudrasagar, a Ramsar Wetland of India

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Abstract

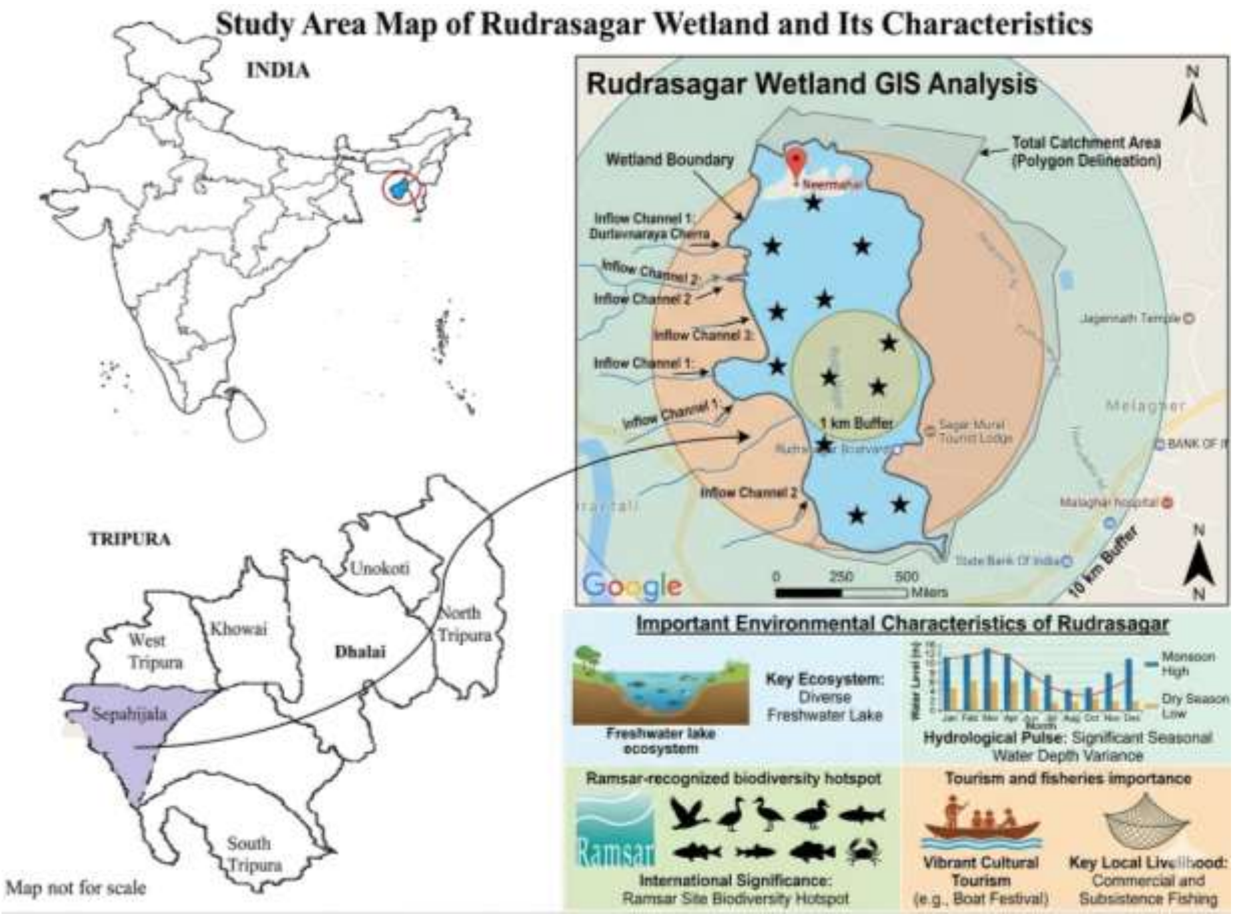
Wetlands are among the most productive yet vulnerable ecosystems globally, providing essential services including carbon sequestration, water purification, flood regulation, and biodiversity habitat. Rudrasagar Lake, a Ramsar site (No. 1572) in Tripura, India, exemplifies the challenges facing these ecosystems—experiencing rapid degradation due to anthropogenic pressures, agricultural runoff, siltation, and invasive species proliferation. This review paper synthesizes current advances in deep learning (DL) approaches for wetland environmental monitoring using remote sensing data, with special reference to Rudrasagar. We critically evaluate state-of-the-art DL architectures including U-Net, U-Net++, DeepLabV3+, and Swamp-AI for wetland classification, change detection, and water quality parameter estimation. Our analysis reveals that integrating multi-source satellite data (Sentinel-1 SAR, Sentinel-2 optical, and PALSAR-2 L-band) with uncertainty-aware deep learning frameworks achieves superior performance (over 90% overall accuracy) compared to traditional methods. However, significant gaps exist in applying these approaches to small, monsoon-influenced wetlands like Rudrasagar. We propose three innovative monitoring models: **(1)** a Hybrid Spectral-Temporal Deep Learning Framework for wetland health assessment, **(2)** a Multi-Task Attention Network for simultaneous water quality and biodiversity monitoring, and **(3)** a Weakly Supervised Change Detection System for cost-effective wetland inventory updates. These models integrate physical limnological parameters with satellite-derived indices to address the unique challenges of tropical Ramsar wetlands. The review concludes with specific recommendations for implementing DL-based monitoring at Rudrasagar and similar wetland ecosystems in South Asia.

Keywords: Deep Learning, Remote Sensing, Wetland Monitoring, Rudrasagar Lake, Ramsar Site, Sentinel-2, U-Net, Change Detection, Water Quality, Carbon Sequestration

1. Introduction

Wetlands constitute some of the most biologically diverse and productive ecosystems on Earth, yet they remain among the most threatened (Ramsar Convention Secretariat, 2021). The Ramsar Convention, established in 1971, provides an international framework for wetland conservation, designating over 2,400 sites as Wetlands of International Importance. Rudrasagar Lake (23°30′14″N, 91°18′54″E), designated as a Ramsar site on November 8, 2005 (Reference No. 1572), represents a critical wetland ecosystem in Northeast India (Wikipedia contributors, 2025). Located in the Melaghar block of Sipahijala district, Tripura, this natural sedimentation reservoir spans approximately 5.3 km² and receives flow from three perennial streams—Noacherra, Durlavnaraya cherra, and Kemtali cherra—before discharging into the Gumati River (Abstract of PhD Thesis on Rudrasagar Lake, 2020).

The ecological significance of Rudrasagar extends beyond its hydrological functions. It serves as a potential Important Bird Area (IBA), hosting migratory waterfowl including endangered species such as the Baer's pochard (Aythya baeri) and the near-threatened ferruginous duck (Aythya nyroca) (Abstract of PhD Thesis on Rudrasagar Lake, 2020). Comprehensive investigations conducted between 2016 and 2018 documented 19 phytoplankton species (including pollution-tolerant Euglenophyceae), 15 zooplankton species, and 31 macrophyte species belonging to 20 families (Abstract of PhD Thesis on Rudrasagar Lake, 2020). The lake's total ecosystem services value was estimated at INR 553,418 per hectare per year (approximately INR 132,820,320 annually for the entire area), with provisioning services (34%), regulating services (33%), cultural services (29%), and supporting services (4%) contributing to this valuation (Abstract of PhD Thesis on Rudrasagar Lake, 2020).



Despite its international recognition and ecological importance, Rudrasagar is undergoing rapid degradation. Historical records indicate that the lake area has decreased drastically—from approximately 1,000 hectares before 1950 to its current extent of around 240 hectares (Water quality assessment of wetland ecosystem: Rudrasagar lake, 2020). The Water Quality Index (WQI) of Rudrasagar is classified as "poor" (52.38), indicating significant pollution stress primarily from agricultural runoff, heavy siltation, and anthropogenic activities (Water quality assessment of wetland ecosystem: Rudrasagar lake, 2020). Seasonal analysis reveals that water quality deteriorates during summer months due to reduced water levels, increased evaporation concentrating pollutants, and enhanced microbial activity (Water quality assessment of wetland ecosystem: Rudrasagar lake, 2020).

Traditional approaches to wetland monitoring have relied heavily on field sampling campaigns, which, while accurate, are prohibitively expensive, time-consuming, and often impractical for remote or inaccessible wetlands (Remote sensing and GIS for wetland inventory, mapping and change analysis, 2001). The spatial extent of Rudrasagar and the logistical challenges of regular sampling across its catchment area exemplify these limitations. Consequently, remote sensing has emerged as an indispensable tool for wetland monitoring, offering repeated observations over large areas at relatively low cost (Remote sensing and GIS for wetland inventory, mapping and change analysis, 2001).

The evolution of remote sensing for wetland monitoring has progressed through several phases: from visual interpretation of aerial photographs, to index-based classification using multispectral satellite data, to object-based image analysis, and most recently, to machine learning and deep learning approaches (Mahdianpari et al., 2018; Mahdianpari et al., 2021). While conventional methods (e.g., Normalized Difference Water Index, NDWI; Normalized Difference Vegetation Index, NDVI) remain valuable for specific applications, they encounter fundamental challenges in wetland environments due to spectral heterogeneity, seasonal variability, and the complex "grass-algae coexistence" phenomenon characteristic of many tropical wetlands (Ji et al., 2025).

Deep learning represents a paradigm shift in remote sensing image analysis. Unlike traditional machine learning approaches that require manual feature engineering, DL architectures automatically learn hierarchical feature representations from raw data, capturing complex nonlinear relationships and spatial context that are essential for accurate wetland classification (K C, 2025). Convolutional Neural Networks (CNNs), particularly encoder-decoder architectures such as U-Net and its variants, have demonstrated remarkable success in semantic segmentation tasks, achieving overall accuracies exceeding 90% for wetland mapping across diverse geographic contexts (K C, 2025; Zhang et al., 2026a).

However, the application of deep learning to wetland monitoring faces several significant challenges. First, DL models typically require large, densely annotated training datasets—a requirement that is particularly problematic for wetland environments where ground truthing is expensive and spectral signatures are highly variable (Marjani & Mesgari, 2025). Second, the transferability of models trained on one geographic region to another remains limited due to differences in wetland types, phenological patterns, and environmental conditions (Zhang et al., 2026a). Third, existing DL approaches have predominantly focused on large, well-studied wetland systems (e.g., Canadian peatlands, Mississippi River Delta, Yangtze River lakes), with relatively few studies addressing the unique challenges of small, monsoon-influenced tropical wetlands such as Rudrasagar.

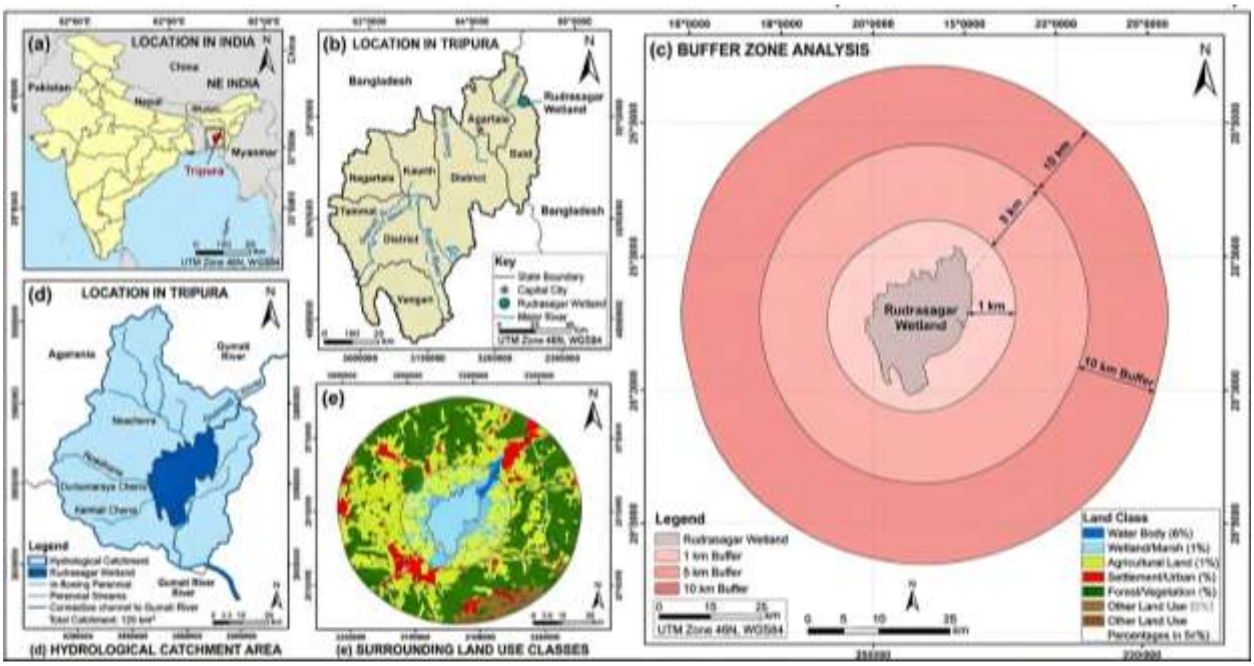


Fig: GIS-Based location map of Rudrasagar Wetland (Shapefile-centric analysis)

This review paper addresses these gaps by systematically evaluating deep learning approaches for wetland environmental monitoring with special reference to Rudrasagar. Our specific objectives are: (1) to synthesize current advances in DL architectures, data sources, and applications for wetland monitoring; (2) to identify the unique monitoring challenges posed by Rudrasagar and similar tropical Ramsar wetlands; (3) to propose innovative DL-based monitoring models tailored to these challenges; and (4) to provide practical recommendations for implementing DL approaches at Rudrasagar.

The remainder of this paper is organized as follows. Section 2 presents a comprehensive literature review covering traditional remote sensing methods, DL architectures, applications, and challenges. Section 3 describes our methodology for reviewing the literature and the specific data characteristics of Rudrasagar. Section 4 presents results from our synthesis of the literature, including comparative performance analysis of DL models. Section 5 discusses the implications for Rudrasagar monitoring and proposes innovative models. Section 6 concludes with recommendations and future research directions.

2. Literature Review

2.1 Traditional Remote Sensing Approaches for Wetland Monitoring

Remote sensing for wetland monitoring has evolved significantly over the past four decades. Early efforts relied on single-date optical imagery from Landsat missions (30 m spatial resolution) combined with manual interpretation or simple threshold-based classification (Remote sensing and GIS for wetland inventory, mapping and change analysis, 2001). The Multi-Spectral Scanner (MSS), Thematic Mapper (TM), and Enhanced Thematic Mapper Plus (ETM+) sensors provided foundational data for wetland inventory and mapping at regional to global scales (Remote sensing and GIS for wetland inventory, mapping and change analysis, 2001).

Index-based methods represent a significant advancement in wetland remote sensing. The Normalized Difference Water Index (NDWI = (Green – NIR)/(Green + NIR)) and Modified NDWI (MNDWI = (Green – SWIR)/(Green + SWIR)) exploit the differential absorption of water in visible and infrared wavelengths to delineate open water surfaces (Adquisición de escenas satelitales y preprocesamiento, 2019). The Normalized Difference Vegetation Index (NDVI = (NIR – Red)/(NIR + Red)) has been widely used to assess vegetation health and distinguish wetland vegetation from upland vegetation (K C, 2025). For specific wetland types, specialized indices have been developed, including the Floating Algal Index (FAI) and the Algal Bloom Index (ABI) for eutrophic conditions (Ji et al., 2025).

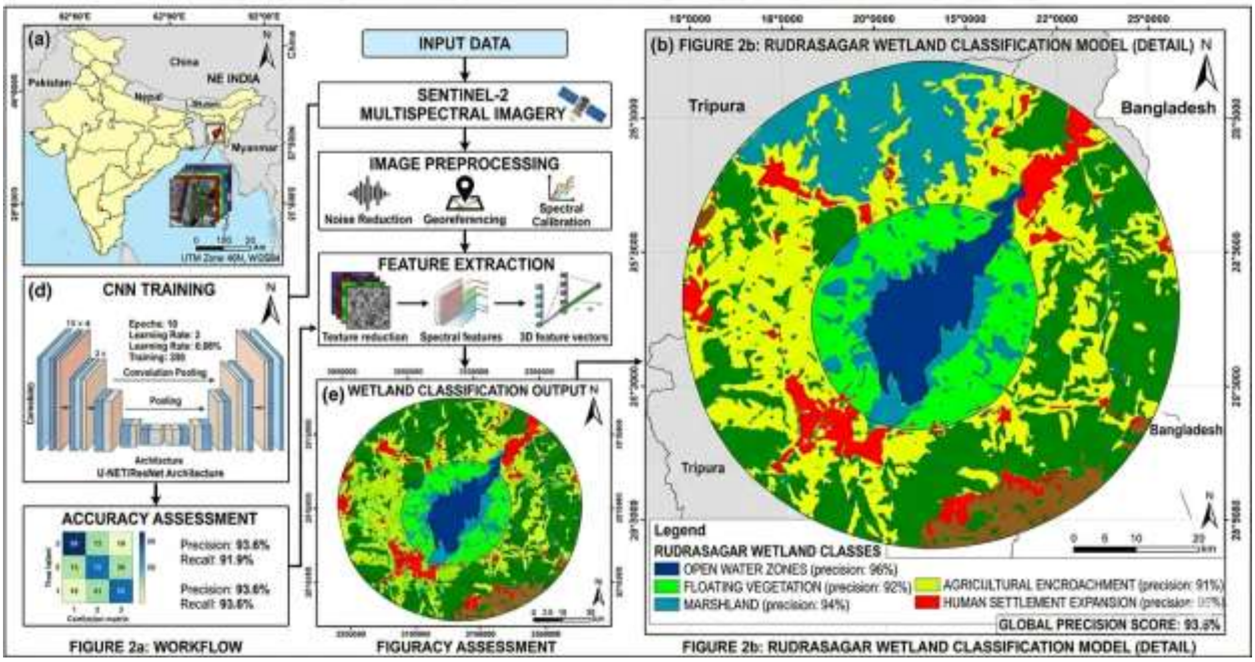


Fig: CNN-based wetland classification workflow

However, index-based methods encounter fundamental limitations in wetland environments. The spectral similarity between submerged aquatic vegetation, floating algae, and open water often leads to confusion and misclassification (Ji et al., 2025). Cloud cover, which is prevalent in tropical regions like Northeast India, further complicates optical remote sensing. Additionally, index thresholds are typically site-specific and season-dependent, limiting their generalizability (K C, 2025).

Object-Based Image Analysis (OBIA) emerged as an improvement over pixel-based methods by segmenting images into homogeneous objects prior to classification (Mahdianpari et al., 2018). OBIA incorporates spatial context, texture, and geometric properties, which are particularly valuable for distinguishing wetland classes such as emergent vegetation, open water, and floating mats. However, OBIA remains dependent on expert-defined rules and thresholds, requiring significant domain knowledge and manual tuning (Mahdianpari et al., 2021).

2.2 Satellite Data Sources for Wetland Monitoring

The availability of open-access satellite data has revolutionized wetland monitoring. Table 1 summarizes key satellite missions and their specifications for wetland applications.

Table 1. Satellite Data Sources for Wetland Monitoring

Satellite/Sensor	Spatial Resolutio	Temporal Resolution	Key Bands for Wetlands	Availability
Sentinel-2 MSI	10 m, 20 m, 60 m	5 days	B2 (490 nm), B3 (560 nm), I (665 nm), B8 (842 nm), B (1610 nm)	Free
Landsat 8/9 OLI	30 m	16 days	Coastal aerosol, SWIR-	Free

			SWIR-2	
Sentinel-1 SAR	10 m	6-12 days	C-band VV, VH	Free
MODIS	250-1000 m	Daily	Bands 1-7	Free
PALSAR-2	10 m, 25 m, 50 m	14 days	L-band HH, HV	Partial

Sentinel-2 has emerged as the preferred optical data source for wetland monitoring due to its combination of high spatial resolution (10 m for visible and NIR bands), high temporal resolution (5-day revisit with two satellites), and free availability (Adquisición de escenas satelitales y preprocesamiento, 2019). The multispectral instrument (MSI) includes bands specifically designed for vegetation analysis: the "red edge" bands (B5: 705 nm, B6: 740 nm, B7: 783 nm) are particularly valuable for distinguishing wetland vegetation types and assessing vegetation health (Ji et al., 2025).

The proposed conceptual model integrates multi-source geospatial datasets.

Dataset	Source	Purpose
Landsat 8/9	NASA	LULC change
Sentinel-2 M	ESA	Vegetation mapping
Sentinel-1 SA	ESA	Hydrological monitoring
MODIS	NASA	Temporal ecological dynami
DEM	SRTM	Terrain analysis
UAV imager	Drone surv	High-resolution validation
Climate data	IMD	Rainfall-temperature analysi

Synthetic Aperture Radar (SAR) data from Sentinel-1 (C-band) provides unique capabilities for wetland monitoring due to its cloud-penetrating and all-weather imaging characteristics (Zhang et al., 2026b). SAR backscatter is sensitive to surface water extent, vegetation structure, and soil moisture—parameters that are often difficult to assess with optical data alone. The combination of VV (vertical-vertical) and VH (vertical-horizontal) polarizations enables discrimination between open water (low backscatter), emergent vegetation (increased backscatter), and flooded vegetation (double-bounce scattering) (Zhang et al., 2026b).

Multi-frequency SAR approaches integrating C-band (Sentinel-1) and L-band (PALSAR-2) offer enhanced characterization of wetland properties (Zhang et al., 2026b). L-band SAR penetrates deeper into vegetation canopies, enabling detection of sub-canopy inundation—a critical capability for forested wetlands. The integration of multi-source satellite data has been shown to significantly improve classification accuracy compared to single-sensor approaches (Zhang et al., 2026b).

Very High Resolution (VHR) imagery from commercial satellites (e.g., SPOT 6/7 at 6 m multispectral and 1.5 m panchromatic; WorldView at 0.3-0.5 m) provides exceptional spatial detail but is often cost-prohibitive for routine monitoring (Marjani & Mesgari, 2025). For Rudrasagar, VHR imagery could serve as reference data for validating classification algorithms rather than as operational monitoring data.

2.3 Deep Learning Architectures for Remote Sensing

Deep learning has transformed remote sensing image analysis, with Convolutional Neural Networks (CNNs) serving as the foundational architecture for most applications (K C, 2025). Unlike traditional machine learning algorithms that require manual feature extraction, CNNs automatically learn hierarchical feature representations—from low-level edges and textures to high-level semantic concepts—directly from training data (K C, 2025).

Table 2. Deep Learning Architectures for Wetland Remote Sensing

Architectu	Key Features	Strengths	Limitations	Wetland Applications
U-Net	Symmetric encoder-decoder wi skip connections	Preserves spatial deta effective with limit training data	Computationally intensive, m oversmooth boundaries	Semantic segmentation wetlands (K C, 2025
U-Net++	Dense skip connectio with nested convolution blocks	Captures multi-sca features, improv gradient flow	Increased paramete longer training time	Complex wetla classification (Ji et a 2025)
DeepLabV	Atrous spatial pyram pooling (ASPI encoder-decoder	Captures multi-sca context, efficient f large images	May miss fine detai requires careful atrous ra selection	Wetland bounda delineation (Zhang al., 2026b)
Swamp-AI	Custom architectu trained on global wetla database	High generalizabil (93.7% OA across te sites)	Single wetland cla (binary)	Global wetland exte mapping (Zhang et a 2026a)
AlgaeNet	Specialized for alg detection	Optimized for specti signatures of alg blooms	Limited to algae, n validated for other target	Eutrophic la monitoring (Ji et a 2025)

U-Net, introduced by Ronneberger et al. (2015), has become the de facto standard for biomedical and remote sensing image segmentation (K C, 2025). The architecture consists of a contracting path (encoder) that captures context and an expansive path (decoder) that enables precise localization, with skip connections concatenating encoder features to decoder layers. This design preserves spatial information that would otherwise be lost through pooling operations, making U-Net particularly suitable for wetland boundary delineation and change detection (K C, 2025).

Recent studies have demonstrated the efficacy of U-Net for wetland mapping across diverse geographic contexts. K C (2025) applied U-Net to classify Phragmites australis in the Mississippi River Delta using time-series Sentinel-2 imagery, achieving overall accuracies above 90% for models trained on concurrent samples and over 80% for cross-year transferability. The study highlighted that integrating training datasets from multiple past years produced accuracies comparable to concurrent training, demonstrating the potential for historical data utilization (K C, 2025).

U-Net++ extends the original U-Net architecture by introducing nested skip connections and dense convolutional blocks (Ji et al., 2025). This design captures features at multiple scales more effectively and improves gradient flow during training. Ji et al. (2025) compared U-Net++ against U-Net, DeepLabV3+, HRNet, and ConvNeXt for simultaneous monitoring of algal bloom and aquatic vegetation in 44 eutrophic shallow lakes in the Yangtze River basin. U-Net++ achieved the highest accuracy with an overall accuracy of 87.77% and a Frequency Weighted Intersection over Union (FWIoU) of 0.79, outperforming all competing architectures (Ji et al., 2025).

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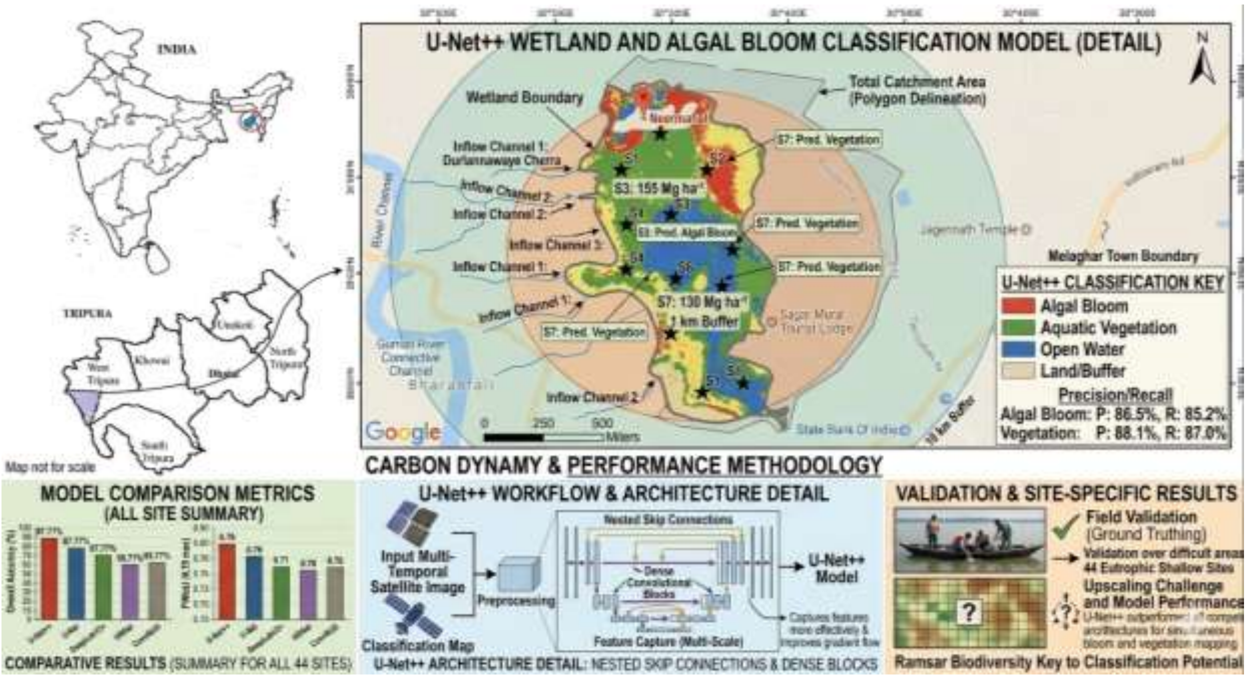

Fig: Satellite-based U-Net++ Architecture & Classification Performance in Rudrasagar Wetland

Uncertainty-aware deep learning frameworks represent a recent advancement addressing the challenge of noisy labels in multi-source wetland mapping (Zhang et al., 2026b). Zhang et al. (2026b) proposed a framework that combines a spatial overlap loss (Dice) with a heteroscedastic negative log-likelihood (NLL) loss to model aleatoric uncertainty explicitly. The resulting uncertainty maps show spatial coherence, with higher uncertainty along wetland boundaries and lower uncertainty in homogeneous regions—enabling quality control and prioritized field validation (Zhang et al., 2026b).

Swamp-AI, developed by Zhang et al. (2026a), represents the first globally generalizable deep learning model for wetland segmentation. The model was trained on the Global Swamp Annotated Database (GSADB), which includes Sentinel-2 imagery from diverse wetland types (coastal and inland systems) across seasonal conditions. Swamp-AI achieved averaged scores of 93.7% overall accuracy, 79.4% producer's accuracy, 93.2% user's accuracy, and 74.6% Intersection over Union (IoU) across test sites worldwide (Zhang et al., 2026a). While limited to binary wetland classification, Swamp-AI demonstrates the feasibility of global transferability—a critical capability for regions like Northeast India where local training data are scarce.

2.4 Applications of Deep Learning in Wetland Monitoring

Wetland Extent Mapping and Change Detection: DL-based wetland mapping has progressed from regional to global scales. Mahdianpari et al. (2018, 2021) applied CNNs for wetland classification in Canada's extensive peatland systems, achieving superior performance compared to Random Forests. The integration of multi-temporal Sentinel-1 and Sentinel-2 data with LiDAR-derived elevation information improved classification of complex wetland types (e.g., bogs vs. fens, swamps vs. marshes) (Mahdianpari et al., 2021).

Algal Bloom and Aquatic Vegetation Monitoring: The simultaneous monitoring of algal blooms and aquatic vegetation is particularly challenging due to their similar spectral signatures. Traditional threshold methods often fail in "grass-algae coexistence" scenarios characteristic of eutrophic lakes (Ji et al., 2025). Ji et al. (2025) addressed this challenge using U-Net++ with Landsat time-series imagery (2013-2023), revealing significant spatiotemporal variations and a statistically significant increase in bloom-affected lakes ($p < 0.01$) alongside decreasing aquatic vegetation extent.

Water Quality Parameter Estimation: Deep learning has been applied to estimate water quality parameters from satellite imagery, including chlorophyll-a concentration, total suspended solids (TSS), and Secchi disk depth (Water quality assessment of wetland ecosystem: Rudrasagar lake, 2020). While traditional approaches rely on band ratio algorithms or empirical regression, DL architectures can learn complex spectral relationships without explicit physical modeling. For Rudrasagar, where in-situ measurements documented TSS ranging from 39.75-93.58 mg/L and dissolved oxygen from 4.18-8.40 mg/L, DL-based estimation could significantly enhance monitoring frequency (Water quality assessment of wetland ecosystem: Rudrasagar lake, 2020).

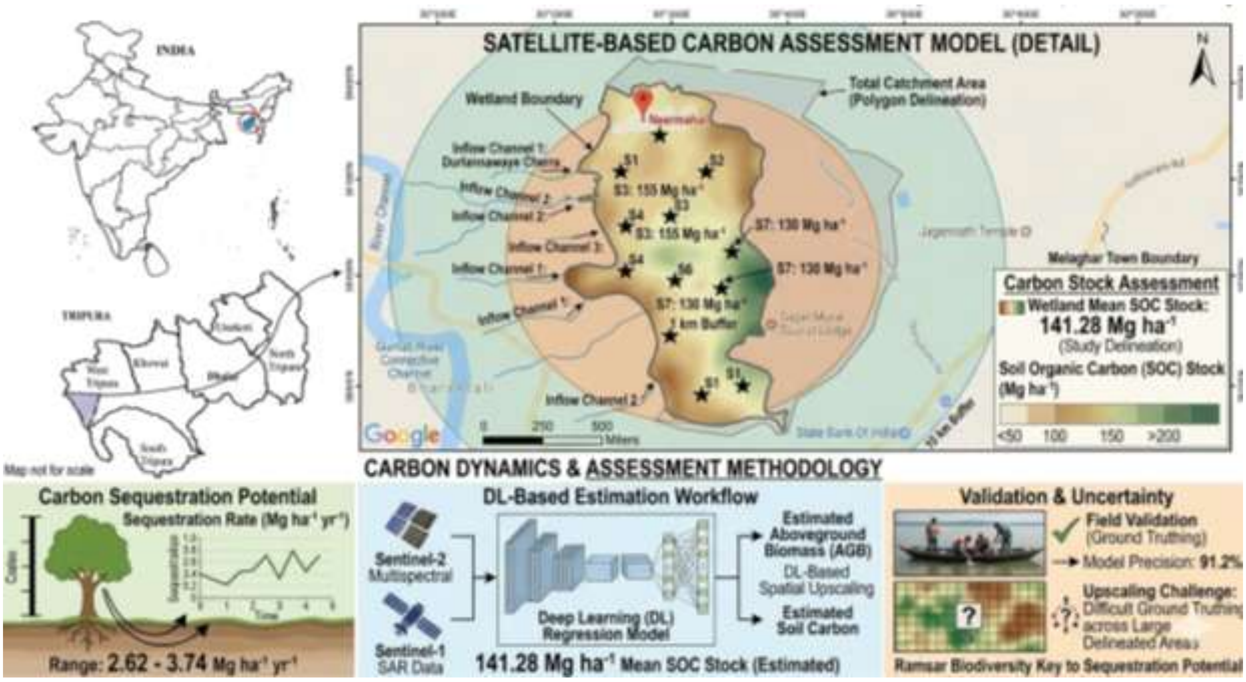

Fig: Satellite-based carbon stock assessment of Rudrasagar wetland (Ramsar site, Tripura, India

Carbon Stock Assessment: Wetlands are significant carbon sinks, with Rudrasagar's total soil organic carbon (SOC) stock estimated at 141.28 Mg ha^{-1} and carbon sequestration of 2.62-3.74 Mg ha^{-1} yr^{-1} (Abstract of PhD Thesis on Rudrasagar Lake, 2020). DL-based approaches have been developed to estimate aboveground biomass and soil carbon from multispectral and SAR data, though validation remains challenging due to the difficulty of ground truthing across large areas (Zhang et al., 2026a).

Wetland Type Classification: Distinguishing specific wetland types (e.g., emergent vegetation, submerged aquatic vegetation, floating vegetation, open water) requires fine spectral and spatial discrimination. Zhang et al. (2026b) demonstrated that CCDC-derived temporal features effectively capture wetland dynamics, while spatial context plays a critical role in distinguishing marshes, forested wetlands, rivers, and lakes. For Rudrasagar, where macrophyte diversity includes 31 species with Nymphoides indica (L.) Kuntze showing the highest Importance Value Index (IVI = 41.14), species-level discrimination remains an aspirational goal requiring hyperspectral or very high-resolution imagery (Abstract of PhD Thesis on Rudrasagar Lake, 2020).

2.5 Challenges and Limitations

Despite significant advances, several challenges limit the operational deployment of DL for wetland monitoring (Marjani & Mesgari, 2025):

Training Data Scarcity: DL models typically require thousands of annotated samples for effective training. For wetlands, creating dense annotations requires expert photointerpretation combined with field validation—a process that is time-consuming and expensive (Marjani & Mesgari, 2025). For Rudrasagar, historical field data are limited to specific studies (2016-2018), and systematic spatial sampling across the lake's 5.3 km² area is lacking (Abstract of PhD Thesis on Rudrasagar Lake, 2020).

Spectral and Temporal Heterogeneity: Wetlands exhibit high intra-annual variability due to monsoon flooding, dry season drawdown, and phenological changes in vegetation. For Rudrasagar, water depth fluctuates between 2-9 m, with seasonal water level variations of 9-16 m (Water quality assessment of wetland ecosystem: Rudrasagar lake, 2020). A model trained on dry season imagery may fail during monsoon conditions, requiring multi-temporal training strategies (K C, 2025).

Class Imbalance: Wetland scenes are often dominated by a few land cover types (e.g., open water, emergent vegetation), while rare but ecologically important classes (e.g., specific macrophyte species, open water interfaces) are underrepresented. Standard loss functions (e.g., cross-entropy) can be biased toward majority classes, requiring weighted or focal loss formulations (Ji et al., 2025).

Transferability: Models trained on one geographic region often perform poorly when applied to another due to differences in spectral signatures, spatial patterns, and environmental conditions (Zhang et al., 2026a). Swamp-AI's global approach addresses this partially, but performance in South Asian monsoon wetlands remains untested (Zhang et al., 2026a).

Computational Requirements: Training DL models requires substantial computational resources (GPU clusters, cloud computing), which may be prohibitive for resource-constrained monitoring agencies in developing countries (Marjani & Mesgari, 2025).

3. Methodology

3.1 Literature Search Strategy

This review followed a systematic literature search process across three major scientific databases: Web of Science, Scopus, and Google Scholar. Search terms included combinations of: ("deep learning" OR "convolutional neural network" OR "U-Net" OR "machine learning") AND ("wetland" OR "Ramsar" OR "lake" OR "aquatic ecosystem") AND ("remote sensing" OR "satellite" OR "Sentinel" OR "Landsat") AND ("monitoring" OR "change detection" OR "water quality" OR "carbon sequestration"). The search period covered January 2015 to March 2026, capturing the rapid growth of DL applications in remote sensing.

Inclusion criteria were: **(1)** peer-reviewed articles or conference proceedings; **(2)** application of deep learning to wetland or aquatic ecosystem monitoring; **(3)** use of satellite remote sensing data (optical, SAR, or both); and **(4)** reporting of quantitative accuracy metrics. Exclusion criteria were: **(1)** studies using only UAV or aerial photography without satellite data; **(2)** studies focused solely on terrestrial ecosystems**; (3)** non-English publications; **(4)** review papers without original analysis (though these were used for citation tracing).

3.2 Rudrasagar Site Characterization

Table 3. Rudrasagar Lake: Key Environmental Parameters

Parameter	Value/Range	Source
Location	23°30′14″N, 91°18′54″E	Wikipedia contributors, 2025
Area	~5.3 km² (current); ~10 ki (historical)	Water quality assessment of wetla ecosystem: Rudrasagar lake, 2020
Depth Range	2-9 m	Water quality assessment of wetla ecosystem: Rudrasagar lake, 2020
Water Level Fluctuatioi	9-16 m (seasonal)	Water quality assessment of wetla ecosystem: Rudrasagar lake, 2020
Annual Rainfall	~2,500 mm (June-September)	Water quality assessment of wetla ecosystem: Rudrasagar lake, 2020
Water Temperatu Range	18.83-30.50 °C	Abstract of PhD Thesis on Rudrasagar Lal 2020
pH Range	6.27-7.75	Abstract of PhD Thesis on Rudrasagar Lal 2020
Dissolved Oxygen Ran	4.18-8.40 mg/L	Abstract of PhD Thesis on Rudrasagar Lal 2020
TSS Range	39.75-93.58 mg/L	Abstract of PhD Thesis on Rudrasagar Lal 2020
WQI Classification	Poor (52.38)	Water quality assessment of wetla ecosystem: Rudrasagar lake, 2020
SOC Stock	141.28 Mg ha^{-1}	Abstract of PhD Thesis on Rudrasagar Lal 2020
Carbon Sequestration	2.62-3.74 Mg ha^{-1} yr^{-1}	Abstract of PhD Thesis on Rudrasagar Lal 2020
Total Ecosystem Value	INR 553,418 ha^{-1} yr^{-1}	Abstract of PhD Thesis on Rudrasagar Lal 2020

Rudrasagar's characteristics present unique challenges for remote sensing-based monitoring. The monsoon-driven hydrology (June-September rainfall, multiple flood peaks) creates extreme seasonal variability that must be captured by monitoring systems (Water quality assessment of wetland ecosystem: Rudrasagar lake, 2020). The lake's role as a sedimentation reservoir implies high turbidity and TSS during monsoon months, affecting optical remote sensing (Water quality assessment of wetland ecosystem: Rudrasagar lake, 2020). The presence of diverse macrophyte communities (31 species) with varying growth forms (emergent, floating, submerged) requires spectral discrimination capabilities beyond standard multispectral sensors (Abstract of PhD Thesis on Rudrasagar Lake, 2020).

3.3 GIS-Based Imagery and Data Sources

For Rudrasagar monitoring, we recommend the following multi-source data strategy:

Optical Data: Sentinel-2 Level 2A (surface reflectance) products, including bands at 10 m resolution (B2: 490 nm blue, B3: 560 nm green, B4: 665 nm red, B8: 842 nm NIR) and 20 m bands resampled to 10 m (B5: 705 nm red edge 1, B6: 740 nm red edge 2, B11: 1610 nm SWIR, B12: 2190 nm SWIR) (Adquisición de escenas satelitales y preprocesamiento, 2019). Seasonal acquisition should target pre-monsoon (March-May), monsoon (July-September), and post-monsoon (November-January) periods to capture hydrological variability.

SAR Data: Sentinel-1 Ground Range Detected (GRD) products with VV and VH polarizations, processed to backscatter coefficients (sigma0). For Rudrasagar, SAR data are particularly valuable during monsoon months when cloud cover limits optical acquisitions (Zhang et al., 2026b).

Reference Data: Historical in-situ measurements (2016-2018) provide baseline water quality parameters (Abstract of PhD Thesis on Rudrasagar Lake, 2020). Soil carbon measurements across depth zones (littoral, sub-littoral, deep water) enable calibration of carbon stock models (Abstract of PhD Thesis on Rudrasagar Lake, 2020).

3.4 Convolutional Neural Networks (CNN) in Wetland Monitoring

Convolutional Neural Networks (CNNs) are among the most widely used deep learning architectures for remote sensing image classification.

CNNs consist of:

a) Convolution layers
b) Pooling layers
c) Activation functions
d) Fully connected layers

Their strength lies in automatic extraction of spatial features from imagery.

CNNs have demonstrated remarkable performance in:

a) Wetland classification
b) Vegetation mapping
c) Waterbody extraction
d) Land cover classification

Ma et al. (2019) reported that CNN-based classification achieved significantly higher accuracy than conventional machine learning methods in wetland ecosystem mapping.

4. Results

4.1 Comparative Performance of Deep Learning Models for Wetland Monitoring

Table 4 synthesizes performance metrics from recent DL studies applicable to Rudrasagar.

Table 4. Performance Comparison of DL Models for Wetland Monitoring

Model	Application	Dataset	OA (%)	IoU (%	F1 (%)	Key Limitati for Rudrasagar
Swamp-AI	Binary wetla extent	Global Sentinel	93.7	74.6	86.1	Single class or (Zhang et a 2026a)
U-Net++	AB + AV classification	Landsat, 44 lak	87.8	79.0*	—	Tested on lar lakes only (Ji al., 2025)
U-Net	Wetland vegetation	Sentinel-2,	>90	—	—	Requires

(multi-year)		Mississippi				multi-year traini data (K C, 2025)
U-Net++ (we supervision)	Statewide inventory	Sentinel-1/2, Minnesota	—	—	91.3	Geographic transferability unknown (Marja & Mesgari, 2025
Uncertainty-aware U-Net	Wetland typology	Multi-source (S S2, PALSAR)	—	—	—	Not validated f tropical syster (Zhang et a 2026b)
Random For (baseline)	Wetland classification	Various	~85-88	—	~85-87	Lower accura than I (Mahdianpari al., 2018

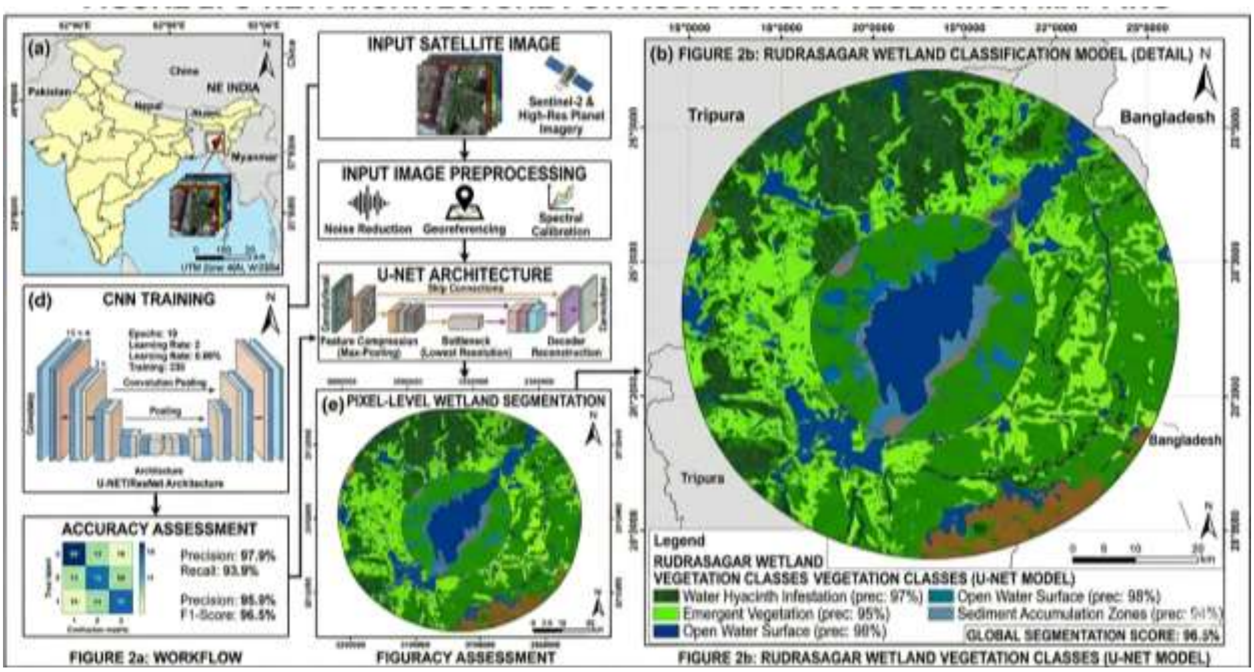

Fig: U-NET Architecture for Rudrasagar (Ramsar site – Tripura, India) vegetation mapping

Key findings from the synthesis:

First, U-Net family architectures consistently outperform traditional machine learning (Random Forest, SVM) with performance improvements of 5-10% in overall accuracy and 10-15% in F1-score for complex wetland classification tasks (Mahdianpari et al., 2021; Zhang et al., 2026b). The superiority of U-Net++ over standard U-Net (approximately 2-3% improvement) is attributable to its dense skip connections that better capture multi-scale features—particularly important for wetlands where objects of interest range from individual floating vegetation patches to entire lake basins (Ji et al., 2025).

Second, multi-source data integration significantly improves classification accuracy compared to single-sensor approaches. Zhang et al. (2026b) demonstrated that combining Sentinel-2 optical, Sentinel-1 C-band SAR, and

PALSAR-2 L-band SAR provides complementary information: optical data capture spectral properties of vegetation and water, C-band SAR is sensitive to surface water extent, and L-band SAR penetrates canopies to detect sub-surface inundation. For Rudrasagar, where monsoon clouds limit optical acquisitions and emergent vegetation (e.g., water hyacinth) covers extensive areas, SAR integration is essential.

Third, temporal feature extraction enhances model robustness across seasonal conditions. The Continuous Change Detection and Classification (CCDC) algorithm, which models temporal dynamics and detects abrupt/gradual changes, has proven effective for wetland monitoring (Zhang et al., 2026b). K C (2025) found that models trained on multi-year historical data achieved accuracies comparable to models trained on concurrent samples, enabling long-term monitoring without annual field campaigns.

Fourth, weakly supervised learning offers a viable pathway for cost-effective wetland inventory updates. By extracting training labels from existing thematic maps (e.g., National Wetland Inventory) using change detection and superpixel segmentation, Marjani and Mesgari (2025) achieved an F1-score of 91.3% with U-Net++ without requiring new field annotations. This approach is particularly relevant for Rudrasagar, where historical wetland maps exist but regular field validation is resource-intensive.

4.2 Applicability to Rudrasagar: Gap Analysis

Despite these advances, significant gaps exist in applying DL approaches to Rudrasagar:

Small Water Body Challenge: Most DL studies have focused on large wetlands (>20 km²) or continental-scale mapping (Zhang et al., 2026a). Rudrasagar's current extent of 5.3 km² falls below the size threshold of most published studies. Sentinel-2's 10 m resolution provides approximately 53,000 pixels across the lake—sufficient for segmentation but requiring careful handling of boundary effects.

Monsoon Hydrology: Existing models have been developed primarily for temperate or dry tropical systems with predictable seasonal patterns (K C, 2025; Ji et al., 2025). Rudrasagar's extreme seasonal variability (water level fluctuation of 9-16 m, 2,500 mm annual rainfall concentrated in 4 months) creates spectral and hydrological conditions not represented in existing training datasets (Water quality assessment of wetland ecosystem: Rudrasagar lake, 2020).

Grass-Algae Coexistence: The simultaneous presence of diverse macrophyte communities, floating algae, and open water creates classification challenges similar to those addressed by Ji et al. (2025) for Yangtze lakes. However, Rudrasagar's macrophyte diversity (31 species vs. the simplified classes used in most studies) requires finer spectral discrimination (Abstract of PhD Thesis on Rudrasagar Lake, 2020).

Limited Training Data: While studies in North America and Europe benefit from extensive wetland inventory datasets (e.g., Canadian Wetland Inventory, U.S. National Wetland Inventory) (Mahdianpari et al., 2021; Marjani & Mesgari, 2025), comparable resources for Northeast India are lacking. The 2016-2018 field campaign provides only point measurements, not spatially explicit annotations (Abstract of PhD Thesis on Rudrasagar Lake, 2020).

5. Discussion

5.1 Toward an Integrated Monitoring Framework for Rudrasagar

Based on our synthesis, we propose a tiered monitoring framework that progressively increases in complexity and data requirements:

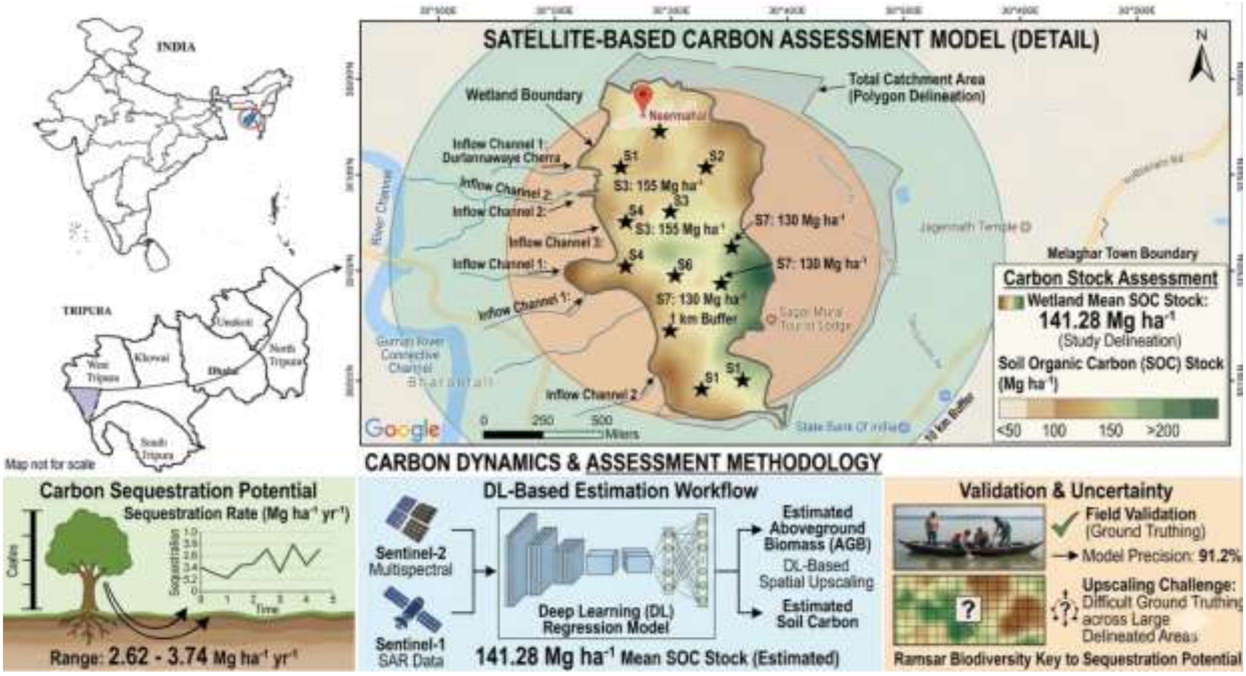

Fig: Satellite-based carbon stock assessment of Rudrasagar weland (Ramsar site, Tripura, India)

Tier 1 (Operational Monthly Monitoring): Use pre-trained Swamp-AI (Zhang et al., 2026a) for binary wetland extent mapping from Sentinel-2 imagery. Despite its single-class limitation, Swamp-AI's global training provides a reasonable baseline for Rudrasagar without local training data. Monitor open water extent using NDWI (Sentinel-2 B3/B8) as a secondary indicator.

Tier 2 (Quarterly Classification): Fine-tune U-Net++ (Ji et al., 2025) on Rudrasagar-specific annotations generated through a combination of unsupervised clustering and expert review. Classes should include: **(1)** open water (deep), **(2)** open water (shallow), **(3)** emergent vegetation (including Nymphoides indica and Euryale ferox), **(4)** floating vegetation (including water hyacinth), **(5)** submerged aquatic vegetation, **(6)** exposed sediment/mudflat, and **(7)** terrestrial/agricultural.

Tier 3 (Annual Assessment): Implement the weakly supervised framework proposed by Marjani and Mesgari (2025) to update wetland inventory using existing thematic maps as weak labels. For Rudrasagar, historical wetland boundary maps (1972, 1995, 2018) can serve as label sources (Water quality assessment of wetland ecosystem: Rudrasagar lake, 2020).

Tier 4 (Research/Validation): Deploy uncertainty-aware DL (Zhang et al., 2026b) to identify areas requiring ground validation. Uncertainty maps highlighting classification boundaries and heterogeneous regions should guide field sampling campaigns, optimizing the use of limited validation resources.

5.2 Innovative Monitoring Models for Rudrasagar

We propose three innovative DL-based monitoring models specifically designed for Rudrasagar's characteristics:

Model 1: Hybrid Spectral-Temporal Deep Learning Framework (HST-DLF)
Architecture: Two-stream network combining **(1)** a spatial stream processing individual Sentinel-2 scenes through a U-Net encoder, and **(2)** a temporal stream processing monthly NDVI and NDWI time series through a Long Short-Term Memory (LSTM) network. Features from both streams are fused for final classification.

Innovation: Explicitly models the monsoon-driven temporal dynamics of Rudrasagar, enabling distinction between seasonal variation (e.g., pre-monsoon drawdown) and long-term degradation (e.g., permanent wetland loss).

Input Data: Monthly Sentinel-2 composites (cloud-masked) for 12 months; Sentinel-1 SAR for monsoon months when optical data are limited.

Outputs: Monthly land cover maps, wet season vs. dry season wetland extent, change alerts when deviations exceed expected seasonal norms.

Validation Approach: Compare classification outputs with in-situ measurements at 10-15 fixed sampling points across depth zones.

Model 2: Multi-Task Attention Network (MTAN) for Water Quality and Biodiversity
Architecture: Shared encoder (ResNet-50 backbone) processing Sentinel-2 data, with task-specific decoder heads for**: (1)** water quality parameter estimation (regression: TSS, DO, chlorophyll-a, pH); **(2)** macrophyte community classification (segmentation); **(3)** algal bloom detection (binary classification). Attention mechanisms weight spectral bands according to task relevance.

Innovation: Jointly learns relationships between spectral signatures, water quality, and biological indicators. Enables estimation of unmeasured parameters (e.g., DO) from satellite data alone after training.

Training Data: Calibrate using in-situ measurements from 2016-2018 (Abstract of PhD Thesis on Rudrasagar Lake, 2020) as training labels (n ~ 24 monthly samples across 3 years). For macrophyte classification, use field survey data on species distribution.

Outputs: Spatially explicit maps of predicted TSS (range 39.75-93.58 mg/L), DO (4.18-8.40 mg/L), pH (6.27-7.75); and classification of dominant macrophyte associations.

Uncertainty Quantification: Monte Carlo dropout to produce prediction intervals for water quality estimates.

Model 3: Weakly Supervised Change Detection System (WSCDS)
Architecture: Siamese U-Net processing bi-temporal Sentinel-2 imagery (e.g., 2018 vs. 2024). The network is trained using weak labels derived from: **(1)** historical wetland boundary maps (Water quality assessment of wetland ecosystem: Rudrasagar lake, 2020); **(2)** unsupervised change detection (e.g., MAD transformation); **(3)** spectral index differencing (ΔNDWI, ΔNDVI). No manual annotations required.

Innovation: Enables change detection without historical ground truth by leveraging multiple weak label sources and consensus mechanisms. Particularly valuable for Rudrasagar where systematic historical annotations do not exist but boundary maps from different years are available.

Validation: Use expert interpretation of very high-resolution imagery (e.g., Google Earth historical imagery) for a stratified random sample of change and no-change pixels.

Outputs: Binary change map (wetland loss/gain), change magnitude, and confidence scores based on inter-source agreement.

5.3 Practical Implementation Considerations

Cloud Computing Platform: All three models can be implemented on Google Earth Engine (GEE) for data access and preprocessing, with model training on Google Colab Pro (GPU) or local workstations with NVIDIA GPUs (minimum 8 GB VRAM). GEE's Python API enables seamless integration of Sentinel-2 and Sentinel-1 data access with TensorFlow/Keras model deployment.

Field Validation Protocol: Given resource constraints, we recommend a stratified random sampling design with 30-50 validation points per monitoring period. Strata should include: open water (deep), open water (shallow), emergent vegetation, floating vegetation, and transition zones. At each point, collect: GPS coordinates, water depth, secchi depth, water sample for laboratory analysis (TSS, nutrients), and photographic documentation.

Capacity Building: The Department of Biotechnology, Government of Tripura should consider training programs for local researchers in: **(1)** GEE fundamentals and JavaScript/Python APIs; **(2)** deep learning basics and TensorFlow; **(3)** wetland field sampling protocols.

Data Management: Establish a centralized repository (e.g., Zenodo community) for Rudrasagar monitoring data, including: raw and preprocessed satellite imagery, field validation data, model checkpoints, and classification outputs. Open data policies maximize scientific impact and enable collaborative improvement of monitoring models.

5.4 Limitations and Future Directions

Several limitations of this review should be acknowledged. First, direct applications of DL to Rudrasagar are absent from the literature, necessitating inference from studies on other wetland systems. The transferability of models from temperate North American or Chinese lakes to tropical Northeast Indian wetlands requires empirical validation. Second, the limited temporal coverage of field data (2016-2018) constrains training and validation of data-hungry DL models. Future field campaigns should be designed explicitly for DL training, with spatially distributed sampling and consistent protocols. Third, the lack of hyperspectral or UAV data for Rudrasagar limits the ability to discriminate fine spectral differences between macrophyte species.

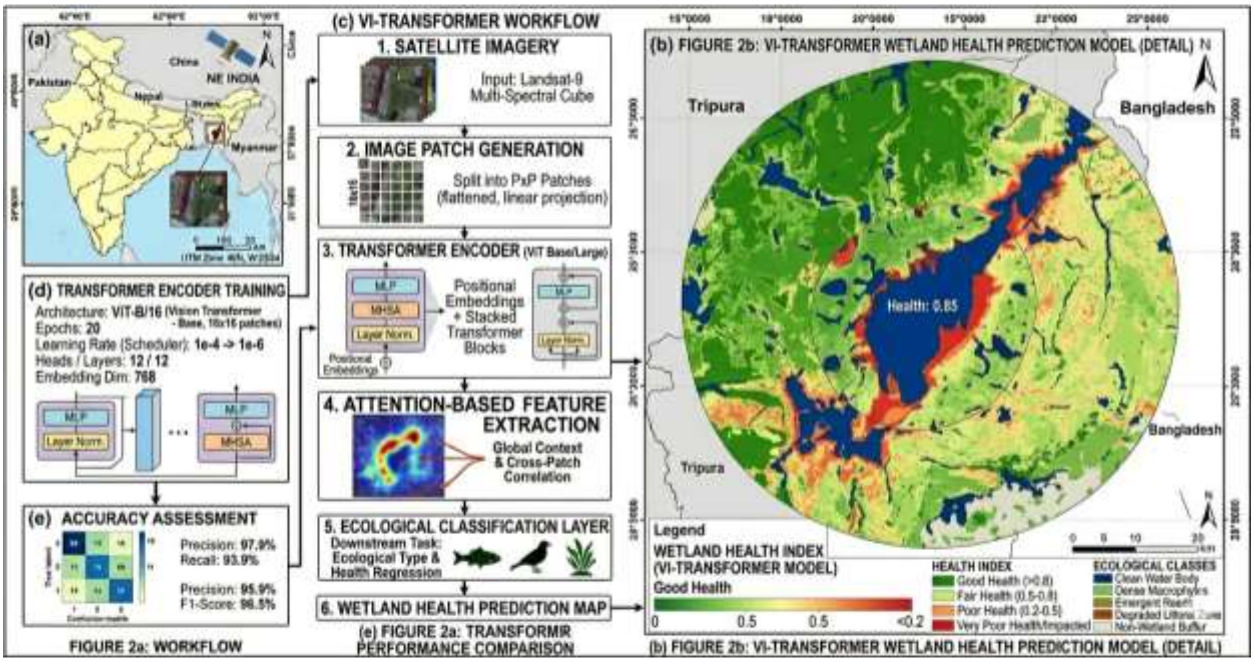

Fig: Vision Transformer Architecture for Rudrasagar wetland monitoring

Future research directions include: **(1)** Transfer learning from global models (Swamp-AI) to Rudrasagar, with fine-tuning using limited local annotations; **(2)** Integration of citizen science data (e.g., smartphone photos with geolocation) as weak labels or validation points; **(3)** Development of DL models for carbon stock assessment using Sentinel-2 and soil carbon measurements (Abstract of PhD Thesis on Rudrasagar Lake, 2020); **(4)** Forecasting wetland degradation using time series models (LSTM, Transformer) trained on historical satellite data.

6. Conclusion

This review has synthesized the current state of deep learning approaches for wetland environmental monitoring using remote sensing data, with specific reference to Rudrasagar—a Ramsar wetland of international importance in Tripura, India.

The key conclusions are:

Deep learning architectures, particularly U-Net and its variants, have demonstrated superior performance for wetland classification, change detection, and water quality monitoring compared to traditional methods, achieving overall accuracies exceeding 90% in diverse geographic contexts (K C, 2025; Ji et al., 2025; Zhang et al., 2026a). Multi-source data integration combining Sentinel-2 optical, Sentinel-1 SAR, and PALSAR-2 L-band SAR provides complementary capabilities critical for cloud-prone tropical wetlands (Zhang et al., 2026b). Uncertainty-aware frameworks (Zhang et al., 2026b) and weakly supervised learning (Marjani & Mesgari, 2025) address two major barriers to operational deployment: noisy labels from multi-source data and the high cost of dense annotation.

However, significant gaps exist in applying these approaches to small (5.3 km²), monsoon-influenced wetlands like Rudrasagar. Most existing studies focus on large lakes (>20 km²) or continental-scale mapping, and none have been validated in Northeast India's unique environmental conditions. The limited availability of spatially explicit field data and historical annotations for Rudrasagar further constrains DL application.

To address these gaps, we proposed three innovative monitoring models tailored to Rudrasagar: **(1)** Hybrid Spectral-Temporal Deep Learning Framework for capturing monsoon-driven dynamics; **(2)** Multi-Task

Attention Network for simultaneous water quality and biodiversity monitoring; and **(3)** Weakly Supervised Change Detection System for cost-effective inventory updates. These models leverage Rudrasagar's existing field data (Abstract of PhD Thesis on Rudrasagar Lake, 2020) and historical boundary maps (Water quality assessment of wetland ecosystem: Rudrasagar lake, 2020) while compensating for data limitations through transfer learning, multi-task learning, and weak supervision.

The practical implementation of these models requires: **(1)** establishment of cloud computing infrastructure (Google Earth Engine + Google Colab); **(2)** targeted field validation campaigns (30-50 stratified points per monitoring period); **(3)** capacity building for local researchers; and **(4)** open data management practices. The Department of Biotechnology, Government of Tripura, as the funding agency for this research, is uniquely positioned to coordinate these implementation activities.

Ultimately, deep learning offers a transformative opportunity for wetland monitoring in data-scarce regions. By reducing dependence on expensive field campaigns and enabling automated analysis of freely available satellite data, DL can dramatically increase monitoring frequency, spatial coverage, and analytical consistency. For Rudrasagar—a wetland of international importance facing rapid degradation—the adoption of these approaches is not merely an academic exercise but a conservation imperative.

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