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AI-Based Illegal Sand Mining Detection and Risk Prediction Using Satellite and Drone Data: A Review and Conceptual GIS-Based Framework

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Abstract

Illegal river sand mining is hard to control because extraction sites are scattered along long, remote river reaches that cannot be inspected continuously. This paper reviews twelve studies that use satellite imagery, unmanned aerial vehicles (UAVs), geographic information systems (GIS) and machine or deep learning to monitor sand mining and closely related riverbank or mining processes, together with two reviews of deep-learning change detection, and compares their data, methods and published results. The comparison shows that existing work concentrates on detecting or measuring mining that has already happened, through spectral-index mapping, segmentation of mining areas, dredging-boat detection, shoreline analysis and UAV volumetry, whereas forward-looking risk prediction, and the joint use of satellite and drone data in a learning-based pipeline, are rarely addressed. Building on this gap, we propose a conceptual five-layer framework that links multi-source data acquisition, preprocessing, deep-learning detection, machine-learning risk mapping and a GIS decision-support layer with a UAV verification loop, and we define an evaluation protocol that separates training and test sites and reports class-wise metrics. The paper is a review and design study: it does not implement the framework, train a model or report new experimental results, and every number quoted comes from the cited works, which use different datasets and are not directly comparable.

Keywords: illegal sand mining, remote sensing, UAV, deep learning, risk prediction, GIS, environmental monitoring

Introduction

Sand and gravel are among the most heavily extracted materials in the world. Global river-sand extraction is commonly quoted at 32–50 billion tonnes per year, a figure originating from UNEP and repeated in recent studies [1], [2], and extraction in many rivers now exceeds natural replenishment [2], [3]. When mining is unregulated or unlicensed, the documented consequences include riverbed lowering, bank erosion, falling groundwater levels, higher turbidity and damage to bridges and other structures [1], [3], [4]. Enforcement is difficult because extraction sites are numerous, dispersed and often hard to reach, and because field surveys are costly and spatially discontinuous [4], [5].

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Remote sensing has therefore become the main tool for monitoring. Optical and radar satellites provide repeated, wide-area coverage [2], [6], UAVs provide centimetre-scale detail at selected sites [3], and GIS supports storage, overlay and communication of results [1], [4]. Deep learning has recently been added to this toolbox to segment mining areas and detect dredging vessels automatically [2], [7], [8]. What these studies mostly deliver, however, is a picture of mining that has already occurred. An inspection agency with a limited number of field teams would also benefit from knowing where mining is likely to occur next.

This paper addresses that question at the level of literature analysis and system design. It follows the four objectives of the underlying seminar project: (i) to review satellite-, drone-, GIS- and AI-based methods for detecting and monitoring illegal sand mining (Literature Review); (ii) to examine how satellite, drone and historical or geographical information reveal mining patterns (Background and Data Sources; Literature Review); (iii) to assess which machine-learning and deep-learning techniques suit detection and risk prediction (Literature Review; Proposed Conceptual Framework); and (iv) to propose a conceptual GIS-based framework for monitoring and decision support (Proposed Conceptual Framework; Proposed Evaluation Protocol). The contributions are:

- a structured comparison of twelve application studies and two change-detection reviews, with their data, methods, published results and limitations (Tables II and III);
- an identification of the research gap, namely limited risk prediction and limited integration of satellite and UAV data with learning-based methods;
- a five-layer conceptual framework with a risk-prediction formulation and a UAV verification loop (Figs. 2–4, Table IV); and
- an evaluation protocol designed to avoid optimistic estimates (Table VI).

The contribution is limited to what is stated: no model was trained and no new accuracy figures are reported. The Discussion and Limitations section covers limitations and responsible use, and the Conclusion closes the paper.

Background and Data Sources

A. Why Monitoring Is Difficult

Sand pits are often underwater and cannot be seen directly, so quantifying extraction traditionally needs bathymetric surveys that are expensive and slow, particularly in large multi-channel rivers [2]. Official statistics can also understate extraction where illegal mining is common [2]. Legality has to be judged against permits: in the Romanian case, only 43 licences had been granted along the studied river and the nearest licensed site was about 15 km from the mined location, and a search of the regional permit database for the Greek torrent returned no entries [3]. Any practical system must therefore combine image analysis with permit and lease records, an approach also taken in a Polish study that compared detected extraction with public licensing datasets [5].

B. Sensing Modalities

Table I summarises the data sources used in the reviewed studies and Fig. 1 compares their reported spatial resolution.

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Optical multispectral satellites. Landsat 8 provides bands at 30 m, and Mukherjee [6] showed that sandbank regions can be separated using only the green and two shortwave-infrared bands, but that sandbanks smaller than a 30 m pixel are difficult to detect. Sentinel-2 provides 10 m bands and is widely used for mining mapping [5], [8]. Optical data are limited by cloud: studies restricted themselves to scenes with little cloud, and one excluded the monsoon months altogether [6].

Radar satellites. Sentinel-1 radar operates through cloud and has been used both for boat detection [2], [9] and for interferometric subsidence mapping [4]. Its grey-scale amplitude imagery and coarse resolution make individual vessels hard to identify, so Kumar et al. used PlanetScope images and field photographs to label boats in Sentinel-1 scenes [2].

Very-high-resolution (VHR) satellites. PlanetScope (about 3 m) and SkySat (0.75 m) were used to date the excavation of a river bar to a window of about two weeks, and a pre-mining SkySat image confirmed that the excavation did not yet exist [3].

UAVs. Repeated UAV flights yield orthomosaics and digital surface models (DSMs) with a ground sample distance (GSD) near 1.1 cm, which allowed excavated volumes to be calculated [3]. The same study notes the drawbacks: limited battery life, difficulty flying in wind, rain or fog, aircraft registration rules, and small coverage (0.320 km² and 0.027–0.028 km² per site) [3].

Volunteered geographic information (VGI). A web-GIS platform on the Gadar River collected 359 citizen reports, which were checked by telephone and site visits; participation was strongly skewed (84% male) [4].

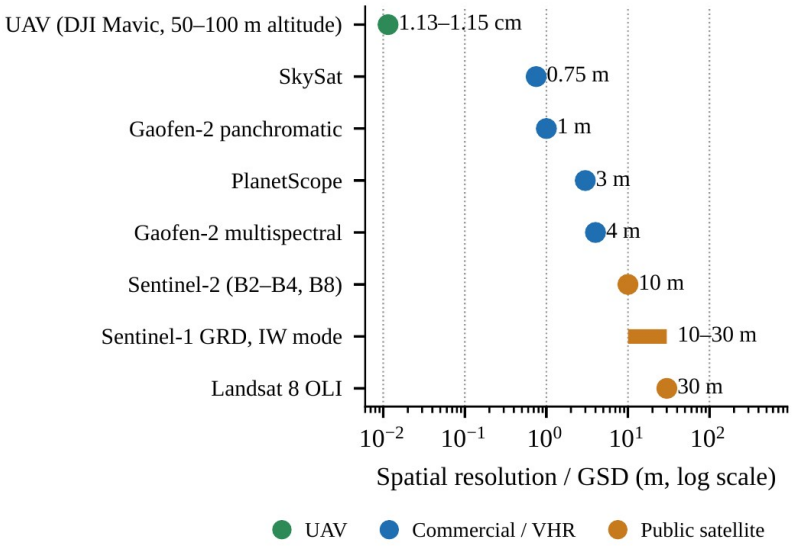


Fig. 1. Spatial resolution (ground sample distance) of data sources as reported in the reviewed studies: UAV and SkySat/PlanetScope [3], Gaofen-2 [7], Sentinel-2 [5], Sentinel-1 [2] and Landsat 8 [6]. Values are quoted from the sources; resolution alone does not determine detectability.

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Table I. Data sources in the reviewed studies

Source	Role in reviewed work	Reported limitation
Landsat 8 / Sentinel-2	Index mapping, segmentation [5], [6], [8]	Cloud; pixel size hides small features [6]
Sentinel-1	Boat detection, InSAR subsidence [2], [4], [9]	Hard to identify single vessels [2]
PlanetScope, SkySat	Dating of extraction, label aid [2], [3]	Need cloud-free scenes [3]
Gaofen-2	Segmentation of sand-mining areas [7]	Only five image products used [7]
UAV	Volumes, DSM differencing [3]	Battery, weather, rules, small area [3]
VGI	Citizen reporting [4]	Participation imbalance [4]

Literature Review

A. Scope

The review covers twelve application studies from 2019 to 2025 that were selected for the seminar project because they use satellite, drone, GIS or learning-based methods for sand mining or for closely related mining and riverbank processes, plus two reviews of deep-learning change detection [10], [11]. Three studies (marked † in Tables II and III) were summarised from their abstracts or public descriptions only. The selection is not an exhaustive survey of the field, and the statements below describe only the cited studies.

B. Spectral-Index and Geospatial Approaches

Mukherjee [6] detects river sandbanks without labelled data in two steps. Water bodies are found with the modified normalised difference water index,

$$MNDWI = \frac{\rho_{Green} - \rho_{SWIR1}}{\rho_{Green} + \rho_{SWIR1}}, \quad (1)$$

then dilated, thinned and filtered by connected-component size so that long, river-like structures remain; high-mineral surfaces are then found by thresholding a coal mine index, and only those near a river are kept. On Landsat 8 scenes of the Damodar River, India, the average accuracy, precision and recall were 90.75%, 85.47% and 73.5%, with lower accuracy and F1 in March and May, which the author links to soil-moisture variation in dry months [6]. The method detects sandbanks rather than illegal mining.

Singh et al. [1] combined NDWI and MNDWI shoreline extraction from Landsat and Sentinel-2A imagery (1990–2020) with the Digital Shoreline Analysis System to quantify erosion and accretion at illegal mining sites on the Chambal River. Erosion occurred at all illegal sites, with a maximum of 1.26 m/year, compared with −0.18 and 0.19 m/year at unmined sites [1]. Duan et al. [12]† used MODIS, Landsat and VIIRS day/night-band data to monitor illegal dredging in Lake Hongze, finding night-time light data suitable for tracking night-time dredging vessels and relating dredging stages to suspended-particulate trends. These approaches are transparent and need little training data, but they describe past activity.

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C. Deep-Learning Detection and Segmentation

Boat-based detection. Kumar et al. [2] trained a YOLOv5l detector on 665 Sentinel-1 scenes of the Vietnamese Mekong Delta, with 1,111 annotated patches containing 11,338 labelled boats. The model reached 96.1% mean average precision (mAP) over three boat classes and 98.4% for the sand-dredging barge class at an IoU threshold of 0.5, and counts of barges were converted into extraction budgets (about 366 Mm^3 in 2015–2022) by regression against riverbed incision [2]. Vu et al. [9] reused this idea on the Bassac River, detected 386 barges in 2014–2023, and coupled the counts with Delft3D-FLOW simulations, concluding that mining contributed 41.0–56.4% of total riverbed incision. These methods target dredging vessels and do not cover bank or bar mining.

Area segmentation. Zhang et al. [7] proposed a lightweight multi-scale network (LMS Net) for riverbank sand-mining areas in Gaofen-2 imagery. On their benchmark it reached 98.07% overall accuracy and 88.24% mIoU with 1.36 M parameters, against 98.33% and 89.83% for U-Net [13] with 31.03 M parameters (about 96% fewer, computed from the reported counts). The dataset was drawn from five image products, and augmentation was applied before the 8:1:1 split [7]; near-duplicate patches may therefore appear in both training and test sets, which could make the scores optimistic.

Saputra et al. [8] compared five segmentation architectures on 37 mine sites across climate zones. A feature pyramid network with an ImageNet-pretrained DenseNet-121 encoder gave the best mIoU (0.7271), ahead of U-Net (0.7159) and DeepLabV3+ (0.7082), while a Transformer model (SegFormer, 0.2759) and a geospatial foundation model (Prithvi, 0.0872) performed far worse, which the authors attribute to the small dataset. Red, green, blue and near-infrared inputs worked best, and adding NDVI reduced accuracy. The non-mining class made up 83.55% of training pixels, mining disturbance was the hardest class (mIoU 0.5303), and performance varied by climate (0.811 tropical, 0.555 cold) [8]. Hejmanowska et al. [5] compared U-Net on Sentinel-2 with Random Forest, SVM and CART in Google Earth Engine for a Polish mining region and obtained an overall accuracy of 94.60% for U-Net against 80.00%, 78.57% and 76.79%; they also stress that averaged per-class accuracy can overstate performance (94.84% against 76.79% overall for CART) [5].

D. UAV Monitoring and Verification

Diaconu et al. [3] combined repeat UAV surveys with satellite dating. In Romania, excavations were found by visual comparison of consecutive images, dated to 5–17 February 2022 from PlanetScope, and measured in the field (maximum removed volume 314 m^3). In Greece, differencing of two UAV-derived DSMs (August and October 2022) gave 5,913.57 m^3 of net loss and 1,032.91 m^3 of fill, so that 4,880.66 m^3 were removed [3]. The authors note that floods can erase traces of mining and that satellite resolution and weather limit the approach. No learning-based detector is used. The IIT Kanpur–NMCG project† combined high-resolution satellite data, drone surveys and modelling to study geomorphic and ecological effects of sand mining in large rivers [14].

E. Change-Detection Reviews

Because mining is a temporal process, change detection is relevant. Shafique et al. [10] review supervised, unsupervised and semi-supervised deep change detection for SAR, multispectral, hyperspectral, very-high-resolution and heterogeneous imagery. Wang et al. [11] organise the field by learning paradigm and identify

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incomplete supervision, self-supervised and few-shot learning, foundation models and multimodal data as promising directions, which is relevant where labelled mining sites are scarce.

F. Prediction-Oriented Work

The only forward-looking model among the reviewed studies, by Nguyen and Nguyen [15]†, uses AdaBoost, CatBoost, gradient boosting and Random Forest with 16 conditioning factors (topography, climate, hydrology, human activity) and erosion points extracted from Landsat OLI images of 2010, 2015 and 2024 to map riverbank erosion susceptibility along the Mekong River. It shows that ensemble models on remote-sensing-derived variables are a workable way to produce susceptibility maps, but the prediction target is erosion rather than illegal extraction. The process-based simulations of Vu et al. [9] estimate the morphological impact of mining that has occurred rather than the location of future mining.

G. Synthesis and Research Gap

Table II lists the studies and Table III shows which data and method types each reports. Only two use UAV data, none is reported to combine UAV imagery with a learning-based detector, five use deep learning, and the single predictive model targets erosion. This is a statement about the studies reviewed here, not about the whole literature. The gap can be summarised as follows:

1) G1: detection and monitoring dominate; predicting future high-risk locations is rarely the main goal;
2) G2: satellite coverage and UAV detail are seldom combined within one learning-based workflow;
3) G3: historical detections and geographical context are not systematically exploited for hotspot prediction;
4) G4: few studies connect detection outputs to permit data and a decision-support interface, with [5] and [4] as partial exceptions.

Table II. Summary of the reviewed application studies (results as published; datasets differ, so values are not comparable)

Ref., year	Area	Data	Method	Reported outcome	Limitation w.r.t. prediction
[12]†, 2019	Lake Hongze, China	Landsat, MODIS, VIIRS night lights	Detection of dredging vessels and turbidity trends	Night-light data suited to night dredging	Detection and impact only
[6], 2023	Damodar River, India	Landsat 8; Sentinel-2A tested	MNDWI, morphology, mine-index threshold; no labels	Precision 85.47%, recall 73.5%, accuracy 90.75%	Sandbanks, not illegality; 30 m pixel; dry-month drop
[1], 2023	Chambal River, India	Landsat, Sentinel-2A, 1990–2020	NDWI/MNDWI shorelines, DSAS	Erosion up to 1.26 m/yr at illegal sites	Historic rates; no learned forecast

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Ref., year	Area	Data	Method	Reported outcome	Limitation w.r.t. prediction
[3], 2023	Buzău River (Romania); Kallifitos torrent (Greece)	UAV, PlanetScope, SkySat	Repeat UAV, DSM differencing, permit check	314 m³; 4,880.66 m³ removed	Small sites; manual comparison; floods erase traces
[4], 2024	Gadar River, Iran	Sentinel-1, VGI reports, QuickBird basemap	Web GIS, PSI/SBAS InSAR	359 reports, 338 correct; max subsidence −10.1 cm	Reactive; participation imbalance
[2], 2024	Vietnamese Mekong Delta	Sentinel-1 (665 scenes); PlanetScope for labels	YOLOv5l boat detection, budget regression	mAP 96.1% (barges 98.4%)	Dredging barges only
[9], 2025	Bassac River, Vietnam	Sentinel-1	YOLOv5l and Delft3D-FLOW	386 barges; 41.0–56.4% of incision	Impact of past mining
[7], 2025	Jilin, Hunan, China	Gaofen-2	LMS Net segmentation	OA 98.07%, mIoU 88.24%, 1.36 M parameters	Segmentation only; five image products
[8], 2025	37 mines worldwide	Sentinel-2, Landsat	FPN with DenseNet-121	mIoU 0.7271	Not river sand; imbalance; climate effects
[5], 2025	Poland	Sentinel-2 L2A	U-Net vs. RF, SVM, CART; permit overlay	OA 94.60% vs. 80.00% (RF)	Mineral extraction, not forecast
[15]†, 2025	Mekong River, Vietnam	Landsat OLI, 16 factors	AdaBoost, CatBoost, GB, RF	Erosion susceptibility maps	Target is erosion
[14]†, 2025	Large Indian rivers	High-res. satellite, drone	Geomorphic assessment, modelling	Final report, Sep. 2025	Assessment oriented

†Summarised from abstract or public description only. Abbreviations: OA, overall accuracy; GB, gradient boosting; RF, random forest.

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Table III. Data and method coverage of the reviewed studies (author's assessment from the cited works)

Study	Opt.	SAR	UAV	DL	ML	Fcst.
[12]†	•					
[6]	•					
[1]	•					
[3]	•		•			
[4]	◦	•				
[2]	◦	•		•		
[9]	◦	•		•		
[7]	•			•		
[8]	•			•		
[5]	•			•	•	
[15]†	•				•	◦
[14]†	•		•			

• reported; ◦ partial (optical used as base map or labelling aid; forecast of erosion, not mining); blank: not reported in the cited work. Opt., optical; DL, deep learning; ML, other machine learning; Fcst., forecast of future locations or risk. †Abstract or description only.

Proposed Conceptual Framework

A. Overview

Fig. 2 shows the proposed five-layer framework. It is a design derived from the literature above; it has not been implemented, and its components are candidate choices to be tested. Satellite data provide wide, repeated coverage, UAVs provide detailed verification of selected sites, learning-based detectors convert imagery into mining maps, a risk model converts the accumulated record into a forward-looking map, and a GIS layer presents the results to inspectors. Table IV lists the layers with their inputs, candidate techniques and the evidence from the reviewed work.

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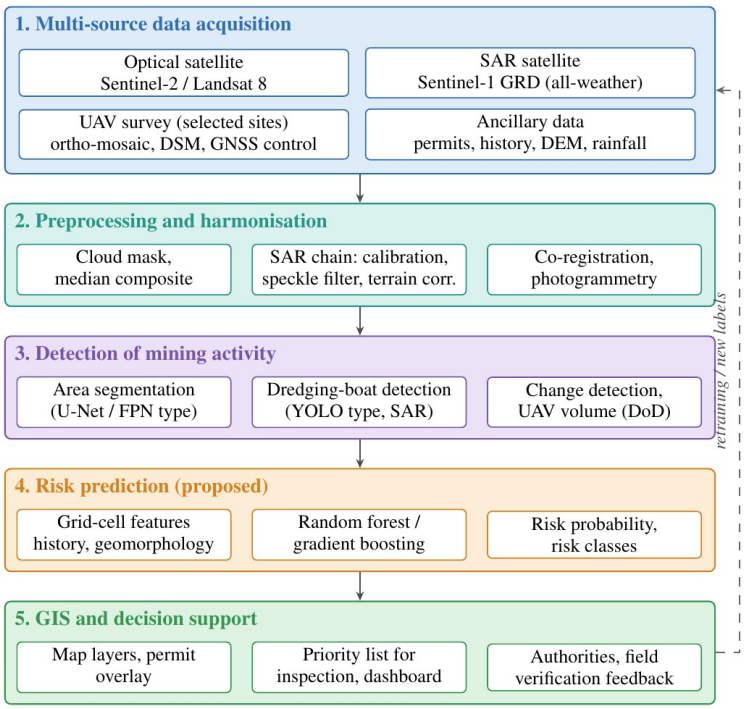


Fig. 2. Proposed five-layer conceptual framework for detection, risk prediction and GIS-based decision support (author's design; not an implemented system).

Table IV. Layers of the proposed framework and their evidence base

Layer	Candidate techniques	Supporting evidence
1 Acquisition	Sentinel-2/Landsat 8, Sentinel-1, PlanetScope/SkySat where available, UAV, permits, history	Multi-source use in [2], [3], [5]
2 Preprocessing	Cloud masking and median composites; SAR calibration, speckle filtering, terrain correction; UAV orthomosaic and DSM with GNSS control	Workflows in [2], [3], [8]
3 Detection	Encoder–decoder segmentation; YOLO-type boat detection on SAR; bi-temporal change detection; index rules as a label-free baseline	[2], [5]–[11]
4 Risk prediction	Grid-cell features; random forest and gradient boosting; spatial and temporal validation	Ensembles in [15], [16]; classical classifiers in [5]
5 GIS and decision support	Layers, permit overlay, priority list, dashboard, field feedback	Web-GIS design in [4]; permit overlay in [3], [5]

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B. Detection Layer: Choice of Models

The reviewed evidence supports a modular rather than a single-model design. For sand-mining areas, encoder–decoder CNNs are the best-supported option: U-Net outperformed classical classifiers [5], a lightweight network came close to U-Net with far fewer parameters [7], and a feature pyramid network was best among five architectures when labelled data were limited [8]. Large Transformer and foundation models did not help in that small-data setting [8], so they should not be assumed to be better. For in-channel dredging, single-stage detectors on SAR data are proven [2], [9]. Where no labels exist, index-based rules [6] give a baseline and a way to generate candidate labels. Temporal comparison of epochs follows the change-detection literature [10], [11].

C. Risk Prediction Layer

We propose to divide each study river into cells i (for example, fixed-length reaches with a bank buffer) and to treat risk as the probability that mining is detected in a cell during the next epoch t+1, given features observed up to epoch t:

$$\hat{p}_i(t+1) = P(y_i(t+1) = 1 \mid x_i(t)) = f_\theta(x_i(t)), \quad (2)$$

where $y_i = 1$ if verified mining activity is recorded in cell i and f_θ is a classifier such as a random forest [16] or gradient-boosting model, implemented with standard libraries [17]. Table V lists candidate features and states which are motivated by cited work and which are hypotheses to be tested. Positives are expected to be rare, so class weighting and precision–recall metrics are preferable to overall accuracy, a point reinforced by the pixel imbalance reported in [8] and the accuracy discussion in [5]. Cell risks are mapped to classes according to the number of cells the authorities can inspect.

Table V. Candidate features for the risk model (proposed; to be tested)

Feature group	Examples	Basis
Detection history	Number and area of past detections; time since last detection	Hypothesis
Sandbank / geomorphology	Sandbank extent from index or segmentation; bank erosion or accretion rate	[1], [6]
Vessel activity	Density of detected dredging barges from SAR	[2]
Season and flow	Monsoon vs. dry season; rainfall or discharge	[3], [6]
Regulation	Distance to nearest licensed site	[3]
Access / exposure	Distance to roads and settlements	Hypothesis

D. Verification and Volume Estimation

Detections and high-risk cells feed a UAV task list. Following the repeat-survey approach of [3], the net excavated volume between two DSMs is obtained by cut–fill differencing,

$$V_{loss} = \sum_{k:\,\Delta z_k < -\tau} |\Delta z_k| A, \quad V_{fill} = \sum_{k:\,\Delta z_k > \tau} \Delta z_k A, \quad (3)$$

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with Δz_k the elevation change in pixel k, A the pixel area, and τ a minimum level of detection reflecting DSM uncertainty [18]. The net removed volume is $V_{\text{loss}} - V_{\text{fill}}$, as in [3]. Verified outcomes are returned as new labels (Fig. 4), which also provides the ground truth that the risk model requires.

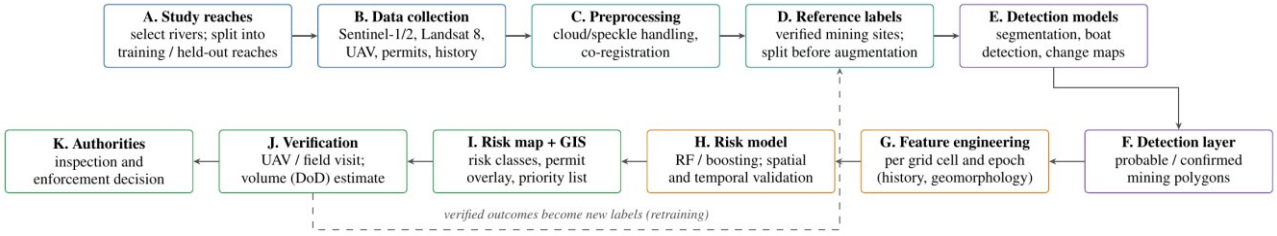


Fig. 4. Planned implementation workflow. Reaches are split into training and held-out sets before labelling and augmentation; verified outcomes feed back as new labels.

E. GIS and Decision Support

The fifth layer stores detections, risk cells, permit polygons and UAV products as map layers (Fig. 3). An open-source stack of the kind used in [4] (GeoServer, PostGIS and a web client) is one feasible implementation, and its report-checking procedure (telephone contact and site visits before use) suggests how citizen reports could be admitted as supplementary evidence. The expected users, taken from the seminar scope, are municipal and district authorities, mining and geology departments, pollution-control agencies, police, disaster-management authorities and, later, regulatory databases holding lease records. Predicted risk should be read as a screening aid for prioritising inspection, not as evidence of an offence.

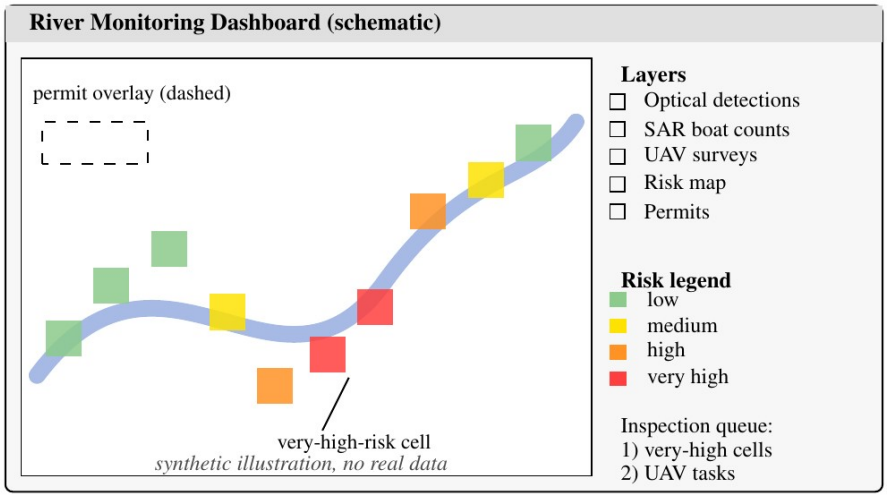


Fig. 3. Schematic of the planned GIS dashboard. The river, cells and labels are synthetic and illustrate the layout only; they do not represent results or real locations.

Proposed Evaluation Protocol

No evaluation has been carried out. The protocol below fixes how it should be done so that the results are not inflated. First, training, validation and test data should be separated by river reach and by date before augmentation, because augmenting first can place near-identical patches on both sides of the split [7].

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Second, the diversity of climate and mining type matters, as shown by the large spread of results across climate zones in [8], so held-out reaches should differ from training reaches. Third, reporting should be class-wise: overall accuracy can hide poor minority-class results [5], [8].

For segmentation, precision, recall, F1 and intersection over union are computed from pixel counts as in [7], e.g., IoU = TP/(TP + FP + FN) and F1 = 2TP/(2TP + FP + FN). For the risk model, the model is trained on epochs up to t and tested on epoch t+1, using held-out reaches. Table VI lists the dimensions. Because published scores are not comparable across datasets, any comparison should use the same data and splits.

Table VI. Proposed evaluation dimensions

Dimension	Measure
Segmentation quality	Class-wise precision, recall, F1, IoU on held-out reaches [7], [8]
Boat detection	Precision, recall, mAP at IoU 0.5 [2]
Risk ranking	Precision–recall AUC; precision and recall among the top-k cells for an inspection budget k
Calibration	Agreement of predicted probability with observed frequency
Generalisation	Results by climate zone, river type and season [8]
Volume accuracy	Agreement of DSM-derived volumes with field measurement [3]
Baselines	Index rules [6]; random forest vs. boosting; history-only model
Operational value	Share of inspected cells with confirmed mining

Discussion and Limitations

Data scarcity and labels. Labelling is the main bottleneck: a six-month full-time effort was needed to harmonise labels for 37 mines [8], and one study notes that manually labelling small land classes is laborious and error-prone [6]. Few-shot and self-supervised learning [11] and label-free index baselines [6] are possible mitigations but untested here.

Resolution and visibility. Features smaller than a pixel are missed [6], vessels are hard to identify in SAR [2], floods may erase evidence [3], and boat counting does not capture bank or bar mining [2]. Detection of illegality ultimately depends on permit data.

Prediction target and circularity. Labels derived from past detections reflect where mining was observable, so a risk model may learn the visibility of mining rather than its occurrence. Cells with no recorded mining are not proven free of it. Risk estimates should therefore be validated prospectively against field outcomes.

Responsible use. Citizen reporting showed demographic imbalance [4]; false positives can burden inspectors and communities; and enforcement requires evidence that meets legal standards, for which UAV-based measurement with ground control is more suitable than model output [3]. UAV operation also carries registration and licensing duties [3].

Source inconsistencies. In [4], the reported completeness, correctness and quality (94.15%, 92.48%, 86.63%) do not follow from the stated counts and formulas: 338 true positives, 21 false positives and 27

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false negatives give 92.60%, 94.15% and 87.56% respectively. We therefore quote only the counts. In [3], one caption gives different survey dates from the text; we use the text.

Conclusion

This paper compared twelve studies on satellite-, UAV-, GIS- and learning-based monitoring of sand mining and related processes. They show that detection and segmentation are mature enough to be useful, that UAVs give reliable site-level volumes, and that forward-looking risk prediction and integrated satellite–UAV learning pipelines remain largely unexplored. We proposed a five-layer conceptual framework, a risk formulation, a verification loop and an evaluation protocol that avoids common sources of optimistic results. The framework is a design only: no model was trained, no accuracy is claimed, and all quoted values belong to the original studies. The next stage is to select study reaches, assemble verified labels and permit data, implement the detection baselines, and test whether the proposed features predict where mining is detected next, reporting held-out results and negative findings as well as positive ones.

References

1. S. Singh, G. Meraj, P. Kumar, S. K. Singh, S. Kanga, B. A. Johnson, D. K. Prajapat, J. Debnath, and D. Sahariah, “Decoding Chambal River shoreline transformations: A comprehensive analysis using remote sensing, GIS, and DSAS,” Water, vol. 15, no. 9, p. 1793, 2023.
2. S. Kumar, E. Park, D. D. Tran, J. Wang, H. L. Ho, L. Feng, S. A. Kantoush, D. V. Binh, D. Li, and A. D. Switzer, “A deep learning framework to map riverbed sand mining budgets in large tropical deltas,” GIScience & Remote Sensing, vol. 61, no. 1, p. 2285178, 2024.
3. D. C. Diaconu, P. D. Koutalakis, G. T. Gkiatas, G. V. Dascalu, and G. N. Zaimes, “River sand and gravel mining monitoring using remote sensing and UAVs,” Sustainability, vol. 15, no. 3, p. 1944, 2023.
4. M. Bayazidy, M. Maleki, A. Khosravi, A. M. Shadjou, J. Wang, R. Rustum, and R. Morovati, “Assessing riverbank change caused by sand mining and waste disposal using web-based volunteered geographic information,” Water, vol. 16, no. 5, p. 734, 2024.
5. B. Hejmanowska, K. Michałowska, P. Kramarczyk, and E. Głowienka, “The potential of U-Net in detecting mining activity: Accuracy assessment against GEE classifiers,” Applied Sciences, vol. 15, no. 17, p. 9785, 2025.
6. J. Mukherjee, “Detection of river sandbank for sand mining with the presence of other high mineral content regions using multi-spectral images,” arXiv preprint arXiv:2307.00314 [cs.CV], 2023.
7. H. Zhang, S. Liu, and H. Liu, “Lightweight multi-scale network for segmentation of riverbank sand mining area in satellite images,” Remote Sensing, vol. 17, no. 2, p. 227, 2025.
8. M. R. U. Saputra, I. D. Bhaswara, B. I. Nasution, M. A. L. Ern, N. L. R. Husna, T. Witra, V. Feliren, J. R. Owen, D. Kemp, and A. M. Lechner, “Multi-modal deep learning approaches to semantic segmentation of mining footprints with multispectral satellite imagery,” Remote Sensing of Environment, vol. 318, p. 114584, 2025.

BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
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Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

9. T. H. Vu, L. Backhaus, D. V. Binh, S. A. Kantoush, and J. Stamm, "Applying deep learning for boat detection and numerical modeling to assess sand mining impacts on river morphology: A case study in the Vietnamese Mekong Delta," Geomorphology, vol. 490, p. 110010, 2025.
10. A. Shafique, G. Cao, Z. Khan, M. Asad, and M. Aslam, "Deep learning-based change detection in remote sensing images: A review," Remote Sensing, vol. 14, no. 4, p. 871, 2022.
11. L. Wang, M. Zhang, X. Gao, and W. Shi, "Advances and challenges in deep learning-based change detection for remote sensing images: A review through various learning paradigms," Remote Sensing, vol. 16, no. 5, p. 804, 2024.
12. H. Duan, Z. Cao, M. Shen, D. Liu, and Q. Xiao, "Detection of illicit sand mining and the associated environmental effects in China's fourth largest freshwater lake using daytime and nighttime satellite images," Science of the Total Environment, vol. 647, pp. 606–618, 2019.
13. O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation," in Proc. Int. Conf. Medical Image Computing and Computer-Assisted Intervention (MICCAI). Munich, Germany: Springer, 2015, pp. 234–241.
14. Indian Institute of Technology Kanpur, "Geomorphic and ecological impacts of sand mining in large rivers," National Mission for Clean Ganga (NMCG), Ministry of Jal Shakti, Government of India, Final project report, Sep. 2025.
15. T. G. Nguyen and H. D. Nguyen, "Prediction of riverbank erosion susceptibility areas of the Vietnam Mekong Delta using machine learning and remote sensing in the context of geographical studies," Physical Geography, 2025, online first.
16. L. Breiman, "Random forests," Machine Learning, vol. 45, no. 1, pp. 5–32, 2001.
17. F. Pedregosa et al., "Scikit-learn: Machine learning in Python," Journal of Machine Learning Research, vol. 12, pp. 2825–2830, 2011.
18. J. M. Wheaton, J. Brasington, S. E. Darby, and D. A. Sear, "Accounting for uncertainty in DEMs from repeat topographic surveys: Improved sediment budgets," Earth Surface Processes and Landforms, vol. 35, pp. 136–156, 2010.