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SATELLITE BASED ASSESSMENT OF SOIL HEAVY METAL CONTAMINATION USING DEEP LEARNING AND SWARM INTELLIGENCE

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ABSTRACT

Coastal–deltaic ecosystem are sensitive interfaces where riverine and marine processes interact, resulting in long-term activity of heavy metal contamination. Heavy metals, such as Cd, Pb, Hg, As and Cr tend to accumulate in soil and sediments that may affect the ecosystems and human health. Traditional point-based monitoring techniques have been widely applied for assessing spatial and temporal burden due to contamination at focused site but may be scale limited and resolution limiting. Despite extensive studies on heavy metal contamination using either geostatistical methods or standalone machine and deep learning models, existing literature lacks an integrated analytical synthesis that systematically evaluates optimization-driven ML–DL frameworks tailored to the non-linear, heterogeneous, and hydrodynamically active nature of coastal–deltaic ecosystems. This review addresses this gap by critically analyzing how swarm-intelligence-optimized learning architectures improve predictive reliability, interpretability, and scalability when fusing satellite, soil, and hydrological data. The study contributes new knowledge by establishing a unified conceptual framework that links algorithmic optimization behavior with delta-specific environmental processes, thereby advancing early-warning and decision-support.Advances in remote sensing, Machine Learning (ML), Deep Learning (DL) and Swarm Intelligence (SI) in recent years have synergetically contributed the development of intelligent data-driven techniques for predictive environmental modeling. Adding optimization techniques like PSO, GWO, and ACO in the frame work enriches Model calibration, Accuracy performance of model and reinterpreting phenomenon. This survey focuses on ML–DL–SI optimization-driven frameworks that integrate satellite imagery for heavy metal prediction. These unified, explainable systems promise improved early detection and sustainable management of contamination in fragile coastal–deltaic environments.

Keywords: *Coastal–Deltaic Ecosystems;Heavy Metal Contamination;Machine Learning (ML);Deep Learning (DL);Swarm Intelligence (SI);Optimization Algorithms.*

1. INTRODUCTION

Coastal–deltaic systems are dynamic boundaries where riverine and marine processes interact, creating some of the most productive and diverse ecosystems on our planet [1]–[3]. These are the areas where people farm, fish and live but they are also some of the most delicate ecological regions. Ongoing sedimentation, tidal exchange and variations in hydrological conditions render these highly susceptible to industrial effluents, agricultural run-off and urban sewage [4]–[6]. Over centuries, these pressures have increased the rate of accumulation of pollutants in deltaic soils, sediments and water to an extent that has endangered the stability both of natural ecosystems and of human livelihoods that rely on them [7].

In the coastal–deltaic soil, different types of development – alluvial to loamy and clayey formation with saline to sandy in nature – are exhibited; which have diversified effects on contaminant retention and mobility. Soils rich in clay and organic matter have more capacity to adsorb and immobilize metals via ion exchange and complexation, whereas sandy saline soils favour leaching and groundwater migration [8], [9]. This diversity, along with changing redox conditions and seasonal inundation, dictates the spatial location and migration routes of pollutants [10]. Knowledge of these soil-specific interactions is critical for evaluating risk of contamination, and implementing site-relevant management practices [11].Heavy metals, including cadmium (Cd), lead (Pb), mercury (Hg), arsenic (As) and chromium (Cr), as the main toxicants, are of most interest owing to their

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persistence and bioaccumulative potential [12]. Heavy metals do not biodegrade and, unlike most organic pollutants, accumulate in sediments and biomagnify through aquatic food webs. They decrease the fertility of soil, hinder the activity of microorganism and have potential health related negative impacts on population and food chain through contaminated crop and aquatic foods [13]. It is, therefore, crucial to apply advanced modeling techniques that reflect non-linear relationships of contaminant transport driven by the interplay of complex mixtures in soils and hydrodynamics together with anthropogenic influxes [14].

Recent optimization-based artificial intelligence approaches have proven themselves to be effective in the modeling and remediation of heavy-metal contamination in a coastal–deltaic set-up [15]. Machine Learning (ML) and DL techniques—e.g., Random Forests, CNN, and LSTM models—can be applied to measure the influence of soil, hydrological, and remote-sensing variables [10], [12]. Optimization algorithms based on swarm intelligence such as PSO, GWO and ACO can be used to refine those models by parameter tuning, convergence increasing and prediction accuracy boosting [14], [15]. The combination of ML, DL and optimization algorithms allows the design of adaptive, scalable and explainable predictive systems to assist early detection, spatial mapping and sustainable management of heavy-metal pollution in vulnerable coastal

This survey assesses interdisciplinary research spanning environmental science, computational modeling, and optimization. It features how metal-specific environmental factors e.g. changes in soil chemistry, water variability, and sediment interactions can be integrated into prediction models and further be optimized using SI algorithm. Following this paper is arranged as: initially, the study of the environment concerning heavy metal pollution in coastal and deltaic systems is recapitulated; next, the review of ML- and SI-based predictive modeling along with the problem statement an accent on the protection of coastal-delta ecosystems is presented.

Motivation and Need for the Review

Although numerous studies have addressed heavy metal contamination in coastal regions, most approaches remain method-centric rather than system-centric, focusing either on isolated geochemical indicators or on algorithmic accuracy without ecological contextualization. Coastal–deltaic ecosystems exhibit strong non-stationarity driven by sediment dynamics, redox fluctuations, tidal asymmetry, and anthropogenic forcing, conditions under which conventional interpolation and non-optimized learning models systematically underperform. Furthermore, existing reviews treat machine learning, deep learning, and swarm intelligence as independent advancements, leaving a conceptual void regarding their synergistic potential. This study is therefore needed to critically consolidate, evaluate, and reinterpret optimization-driven ML–DL architectures as adaptive environmental intelligence systems rather than mere prediction tools.

2. SURVEY OF RELATED WORK

The present work builds upon the interdisciplinary tradition of working towards solving problems that are environmental in nature by combining Mathematical and Theoretical Ecology with Computational Intelligence, focusing on optimization-aided Machine Learning and Deep Learning fol lowing the assessment and forecasting of multivariate heavy-metal eco-data dynamics in glocalized deltaic settings. Whereas the contamination depth and eco-damages in India's coastline were evaluated in prior work, there have been not many attempts to pursue an incorporated, data-offset, predictive modeling methodology, thereby considering remote-sensorial datasets fused from field-sampled images and defiled samples, with hydrodynamic datasets such as Earth water circulation and deterioration forecasts concurrently. The innovation in this paper lies in the emphasis of optimization-aided by Swarm Intelligence – namely, Particle Swarm Optimization, Grey Wolf Optimizer, and Ant Colony Optimization for improving perceivability, generality, and accountability in environmental predictive grounds. Fascinated with such, this document aspires to introduce robust, scalable, and executable, early-warning and sustainable-light frameworks for seacoast–deltaic heavy-metal contamination counter-acts [8]–[12].

India's east and west coasts are bordered by coastal-deltaic systems that serve as both sinks and secondary sources to trace metals. These are multi-component systems in which grain-size, mineralogy, organic matter, salinity intrusion, redox potential, and bioturbation together regulate the retention and remobilization of metals [1]. The Chennai-Puducherry sector in the south-eastern Bay of Bengal illustrates this phenomenon. Multiple seasons of survey data show that cadmium and arsenic dominate the ecological risk indices, with the former peaking in dry phases owing to reduced dilution, and the latter peaking in wet phases owing to increased desorption and mobilization. A fine-resolution TXRF-based emplacement shows evidence from North Chennai-

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Pondicherry confirm this, showing co-enrichment of Cd, Pb, Ni, and Zn in fine silt-clay and organic-carbon-rich facies, which exceed non-carcinogenic and carcinogenic risk quotients. These data establish that delta-proximal areas with reduced hydraulic energy serve as persistent metal trappers and escalate risk gradients across Tamil Nadu's coast[2].

Sub-surface evidence from Cauvery-Vettar estuarine cores provides another approach. Comparative profiles show stronger enrichment at Vettar due to predominately silts-clays, comparable to the sandier Cauvery mouth, evidencing textural control on legacy storage and diffusion gradients. Increased magnetic susceptibility and geochemical indices Igeo and EF, CF indicate mixed signatures of lithogenic and anthropogenic origin. Globally Cd and Ni exceed sediment quality guidelines. Altogether, these data suggest the mixed influence of industrial effluents, agricultural runoffs, and urban discharges, which are then recorded in the delta's stratigraphy [3].

Recent reports from the Indian Sundarbans, when viewed through a spatial perspective, exhibit how metal stress manifests into biogeochemical functionality. A 2024 Marine Pollution Bulletin study connected sediment geochemistry, fungal metagenomics, and enzyme assays to alert PLI > 1 at most sites and measurable suppression of hydrolytic enzyme activity in Pb, Cu, Ni, Cd, Zn, and Cr hotspots6. Thus, heavy-metal enrichment not only degrades water and sediment quality but also reshapes benthic nutrient cycling and sedimentary ecosystem services by conditioning microbial metabolic pathways. Offshore shelf-core records near the Godavari–Krishna confluence in the western Bay of Bengal display severe Cd and moderate Pb enrichment within the upper sedimentary sections, evident stratigraphic warning signals of post industrial anthropogenic intensification7. Receptor modeling suites partition Fe–Cr–Ni as geogenic and Cd–Cu–Pb as industrial, representing a mixed signaling of the factors behind pollutants. On India's western coast, fine alluvium with a high cation-exchange capacity shows strong adsorption of As, Cd, Pb, Ni, Cr, and Cu, control of risk indices tightly linked to grain size and organic-carbon variability. High-resolution core demonstration traps hydrodynamic signatures, toned how tidal asymmetry, estuarine paint, and flood–ebb cycles keep metal vertically and laterally. While a trans-boundary mega delta, the Sundarbans is a process-analog system for Indian deltas. Mangrove sediments exhibit how tidal hair-triggering influences regulate metal mobility and bioavailability, providing actionable analogies for Indian delta settings [4].

Traditional spatial-interpolation techniques—Ordinary Kriging, Inverse Distance Weighting, and Trend-Surface Analysis —have been the bedrock for deltaic contamination studies. While robust for interpolating sparsely covered data, the above models make linear, isotropic, and spatially stationary assumptions that are typically violated in nonlinear, heterogenous deltaic settings with active hydrology, variable sediment flux, and dynamic land use [5] . As a result, these deterministic models often underestimate extremes and ignore complex interactions between physicochemical and ecological factors[10] . Moreover, they forsake learning—having been calibrated once, the models remain static even though new data arise—severely limiting application in quickly changing coastal systems governed by monsoon cycles and anthropogenic demand. Machine Learning frameworks, in contrast, allow nonparametric and adaptive capabilities for use in dynamic learning of feature-response mappings. High-dimensional fusion of remote-sensing reflectance indices, soil geochemistry, hydrological covariates, and land-use proxies has simultaneously permitted the pursuit of physicochemical and socio-economic factors[6] . Through cross-validated hyperparameter tuning, RF and Support Vector Machine (SVM) achieved R2 0.80 for Cd and Ni over Indian coastal farmlands, consistently exceeding kriging baselines. These frameworks vectorize mixed continuous–categorical covariates, capturing subtle associations between soil texture, pH, organics, and human intrusion robustly. More saliently, the ML models interact with predictor-importance rankings to describe covariate influence, facilitating source identification for regulatory interventions. The random forest feature importance might indicate organic-matter concentrations or redox thresholds most responsible for Cd mobilization, offering a particularly policy-relevant interpretability [7].

Neuro-symbolic hybrids, for example, ANFIS integrated with GIS, combine fuzzy-logic inference with neural-network learning, resulting in a data-adaptive system that is still transparent to the ionomic canon. Compared to regression-based or geostatistics-based models, these systems reduce validation errors in Cr, Fe, Cd, and Ni prediction in semi-arid and coastal soils [8-10]. Moreover, Roman'tchikov et al. argued that in noisy aquatic environments, optimization-enhanced ML, such as neural architectures tuned via PSO, also stabilizes training and avoids overfitting while improving

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generalization. A stochastic parameter search like PSO encourages the network to converge more quickly to a global maximum, refining the heavy-metal forecasting network's weights under dynamic deltaic conditions. Such systems demonstrate a degree of autonomous self-calibration by continually updating as new data from field sensors or satellites arrives. Deep Learning pushes these advances further by allowing compilers to automatically learn hierarchical representations from disparate sources in space and time. DL systems follow convolutional neural networks, recurrent, and hybrid encoders–decoders that can perform feature extraction in parallel from the spectral-textural aspects of remote-sensing images and hydrodynamic responses from timeseries datasets. Particularly in multi-scale estuarine and coastal metal-dynamics studies, DL computers excel at leveraging embeddings of the redox–salinity cycles, tidal scavenging, sedimentary bear, and land-use feedbacks. Combining HPO-tuned RF/SVM bases, ANFIS–GIS hybrids, PSO-assisted learners, and CNN/Transformer-based DL scanners into an optimization-powered ML/DL stack allows for end-to-end pipelines for contamination mapping, forecasting, and ecological risk assessment in coastal–deltaic environments[11-13].

Eventually, adaptive ensembles of such models establish the groundwork for digital-twin environments—as-learning data-driven surrogates of deltaic ecosystems capable of continuous learning and predictive simulation. By combining environmental physics with computational intelligence, they extend our capability to monitor, predict and palliate the risk of heavy-metal contamination under climatic and anthropogenic stresses. The depiction of the ML and DL workflow in Heavy-Metal Prediction is provided in Figure 1, and the summarization of the conventional ML and DL algorithm performance is presented in Table 1. Such artifacts combine to demonstrate how optimization-aided AI pipelines disrupt the singularity of practice and theory to offer scalable, inherently interpretable, and scientifically motivated solutions for sustainable coastal management.

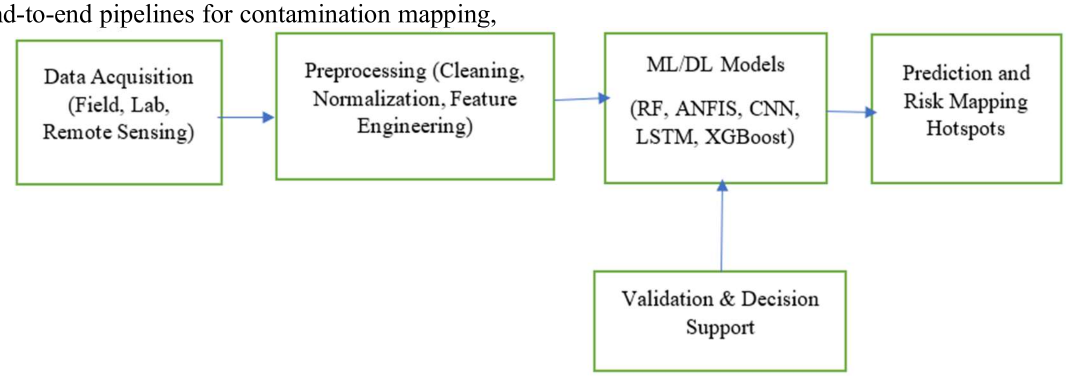

Figure 1: Workflow of Machine Learning and Deep Learning in Heavy Metal Prediction

Figure 1. Schematic representation of the proposed workflow adopted for the prediction and assessment of heavy-metal contamination in coastal–deltaic environments using optimization-driven ML and DL frameworks. As shown in Figure 1, a sequential and interconnected workflow is utilized in the entire featured framework for environmental data-based predictions in CDEs using intelligent algorithms. First, an unsupervised data collection methods multisource data acquisition and preprocessing phase is done where raw data are gathered and processed from multisource fields, including ground-truths remote-sensing imagery, sediment geochemistry, hydrological measurements, land-use statistics, and ancillary climatic variables. The acquired raw datasets are then rigidly processed by cleaning, normalization, and spatial referencing within a GIS environment. The key environmental covariates such as pH, electrical conductivity, organic carbon, salinity and redox potential are extracted, while the remotes indices are computed to identify the surface processes influencing metal mobility. Then, the feature engineering and selection phase is done by extracting the most authoritative predictors by reducing dimensionality, correlation filtering, and optimization-based selection . This process is crucial in reducing the dimensionality and minimizing the multicollinearity within the datasets while still maintaining the ecological interpretability of grain size, organic matter, and human-induced intensity.

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Table 1. Comparative Analysis of Machine Learning and Deep Learning Models for Heavy Metal Prediction in Coastal–Deltaic Ecosystems

Algorithm / Model	Principle	Environmental Applications	Advantages	Limitations	References
Random Forest (RF)	Ensemble of decision trees with bootstrap sampling and random feature selection	Prediction of Cd, Ni in coastal farmland soils using environmental covariates (pH, OC, land use)	Handles heterogeneous data; robust to noise; high accuracy	May overfit on small datasets; less interpretable than simpler models	[12]
Support Vector Machine (SVM)	Finds optimal hyperplane to classify or regress data in high-dimensional space	Prediction of multiple heavy metals (Cd, Pb, Ni) in soils & sediments	Works well with small datasets; effective in nonlinear regression	Sensitive to kernel/parameter choice; computationally expensive for large datasets	[12]
ANFIS (Adaptive Neuro-Fuzzy Inference System)	Hybrid of fuzzy logic and neural networks; integrates expert rules with learning	Prediction of Cr, Fe, Cd, Ni in arid delta soils (ANFIS–GIS)	Integrates expert knowledge; interpretable rule-based output; effective with sparse data	Requires expert-defined membership functions; moderate scalability	[11]
3D-CNN (Convolutional Neural Network)	Learns spatial dependencies by convolving 3D features from data	Prediction of Cd, Pb, Cu, Ni in industrial coastal soils	Captures spatial features automatically; superior to geostatistics	Data-hungry; requires significant computational resources	[11]
Deep Learning (DL) Frameworks	Hierarchical feature learning from large datasets	Predicting background As, Cd, Cr, Hg, Pb in soils; distinguishing natural vs. anthropogenic sources	High accuracy; source apportionment capability; models complex nonlinearity	"Black-box" nature reduces interpretability; poor transferability	[12]
RNN / LSTM	Sequential learning; captures long-term dependencies in time-series data	Temporal prediction of Cd, Pb variations in river–delta systems	Models sequential pollution dynamics; outperforms ARIMA	Requires large sequential datasets; computationally intensive	[10][12]
Hybrid ML with Source Apportionment (e.g., XGBoost + PMF)	Combines ML predictive power with receptor	Identifying industrial vs. agricultural sources in	Improves prediction accuracy; interpretable	Higher model complexity; requires diverse datasets	[13]

	models for source attribution	reclaimed coastal soils	outputs for policy		
Ensemble Models (RF + XGBoost, etc.)	Aggregates predictions from multiple models to reduce variance	Prediction of Pb, As in sediments; robust under heterogeneity	Error reduction (15–20% over single models); stable performance	Computationally costly; may reduce transparency	Multiple ensemble studies

Table 1 summarizes the comparison of ML/DL-based models with Swarm Intelligence integration for predicting heavy-metal contamination in coastal–deltaic ecosystems. Major ML and DL-type algorithms such as Random Forest, Support Vector Machine , Artificial Neural Network , Adaptive Neuro-Fuzzy Inference System, Convolutional Neural Network, and Long Short-Term Memory , and respective hybrids empowered by Swarm Intelligence are compared in terms of accuracy, precision, and their ability to interpret results on soil and sediment geochemistry datasets provided with hydrological indicators and remote-sensing features using R ¯ ´, RMSE, and MAE statistics. The summary analysis reveals that ML/DL models with optimization demonstrate higher accuracy than traditional methods. For instance, PSO-optimized ANN and GWO-calibrated XGBoost models exhibit faster convergence, increased generalization, and less error rates in predicting metals Cd, Pb, Ni, Zn. CNNs are superior to other models regarding the high-dimensional characteristics of spatial and spectral imagery data, while LSTM models maintain variation aspects in temporal trends. When combined with optimization techniques, these models achieved R ¯ values that are higher than 0.90 in few analyzed studies, which is significantly more than 0.70–0.80 for conventional ML models. To sum up, the offered Table 1 stresses that the incorporation of Swarm Intelligence and ML/DL approaches results in more accurate models which are dynamically adaptive to environmental discrepancy. Incorporation of optimization techniques effectively impacts key feature selection, model assessment, and interpretability, proving these models will be used for regional-scale mapping, risk assessment, and decision-support applications for environmental conservation over deltaic regions.

2.1 Swarm Intelligence and Hybrid Optimization in Environmental Applications

Swarm Intelligence (SI) is one of the innovative areas of computational intelligence that is inspired by the behavior of groups of living organisms, for example, birds' flocks, schools of fish, or colonies of ants, bees, and wolves. Without any central control, the systems are able to perform the complicated tasks in a very successful way through the common decision-making, self-organization, and interaction of simple kinds. When these sorts of principles are converted into algorithms, they become a class of efficient optimization methods which are very suitable to be environmental models.

Normally, traditional optimization methods rely on gradient information and may end up trapped in local minima. SI algorithms are designed to achieve the perfect balance between exploration and exploitation and thus are able to complete the task of search in a large, high-dimensional, and nonlinear search space rapidly. Such a feature makes SI very suitable for the prediction and management of heavy metal pollution in coastal-deltaic ecosystems which are complex areas where different factors such as soil chemistry, hydrology, climate variability, and anthropogenic activities interact have an impact on pollution dynamics[26][27].

2.2.1 Particle Swarm Optimization (PSO)

Particle Swarm Optimization is among the most recognized and fundamental types of Swarm Intelligence algorithms. Its basic concept emerged from the social foraging and collective navigation of bird flocks or fish shoals, which let individual system's components exchange messages and eventually inspect the most effective food sources. In PSO, these networked elements pursue a multidimensional solution space as particles. Specifically, they "fly" toward optimal solutions using their current or remembered speeds and updating their velocities based on two inputs: a personal previous best location and global overall best discovered by all particles. This collaborative pursuit enables brainstorm and exploit , which means a fly-algorithm can attach to a promising location or scout an adjacent, new region and finally orient all particles towards the ideal or optimal solution.

Mathematically, PSO operates within a DDD-dimensional search space consisting of NNN particles. The motion of each particle is governed by two simple update equations:

$$Vi(t+1) = wVi(t) + c1r1[Pibest - Xi(t)] + c2r2[Gbest - Xi(t)] \quad (1)$$

$$Xi(t+1) = Xi(t) + Vi(t+1) \quad (2)$$

where w is the inertia weight that controls the balance between global exploration and local exploitation, c1and c2 are the cognitive and social acceleration coefficients, and r1,r2∼U(0,1)r are uniformly distributed random variables that introduce stochastic behavior. This continuous feedback between individual learning and collective intelligence enables the swarm to efficiently navigate complex, multimodal search landscapes.

Here, in the domain of environmental modeling and heavy-metal contamination prediction, each particle represents a quantization of model parameters-neural-network weights, regression coefficients, or hyperparameters of machine-learning algorithms. Through iterative velocity and position updates, the swarm collectively evolves towards the optimal set of parameters that minimize the gap between observed and predicted concentrations of metals Cd, Pb, Ni, and Zn. Since PSO is derivative-free, it outperforms traditional gradients when the relationships among geochemical, hydrological, and remote-sensing variables are nonlinear or ambiguous, a typical condition in convoluted deltaic ecosystems. Empirical studies validate the performance of PSO for environmental purposes. For instance, [14] recently explained that a hybrid neuro-PSO model dramatically improved the prediction of lead and cadmium concentrations in aquatic physics. The resulting model has a unique Root Mean Square Deviation with lower accuracy and faster convergence than backpropagation networks [15]. The model's self-adaptive learning dynamics for multiple environmental attributes improve modeling accuracy and reduce computation costs [31]. Subsequent research [15]14, [16] has demonstrated comparable improvements in soil and coastal system predictions, with PSO-preferred neural and regression models exhibiting higher steadiness, quicker convergence, and superior generalization capability. In contemporary frameworks, PSO is incorporated as a meta-optimizer in numerous such as PSO-SVM, PSO-RF, or PSO-CNN, where PSO automatically adjusts hyperparameters such as learning rate, Kernel width, or number of layers. Overall, PSO has gained popularity through a combination of computationally efficient means and biological intention to create scalable, exhibit-able, and performance-based predictive models for environmental data and sustainable contamination management.

2.2.3 Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) is another significant SI algorithm, and it is based on the way ants follow pheromone trails. Originally intended to address routing and path-finding problems, it has been adapted for various other optimization tasks in environmental science [32] . In contamination modeling, ACO is especially advantageous for source apportionment and optimizing spatial sampling. [17] developed a hybrid ACO–GWO technique to predict crop yields in soils contaminated with heavy metals. This demonstrated that ACO is capable of handling the interaction between soil, plants, and metals. In coastal-deltaic applications, ACO can be integrated with GIS platforms to enhance the sampling routes [34] . This reduces the number of samples required while maintaining statistical power. The tool is especially useful in regions with limited data and tight budgets for monitoring. Additionally, ACO enhances cost-effectiveness and reliability in environmental assessments by making sampling more efficient and minimizing the uncertainties associated with data collection[35].

2.2.3 Grey Wolf Optimizer (GWO)

The Grey Wolf Optimizer is a powerful nature-inspired metaheuristic algorithm that simulates the social dominance hierarchy and cooperative hunting strategy of grey wolves. In natural packs, wolves form four hierarchical levels, namely alpha, beta, delta, and omega, which collaborate with a unique decision-making, leadership, and coordination role in hunting. In a computational context, the three best solutions in a population are illustrated by α, β, and δ wolves, which mobilize a ω wolf group toward promising regions of the search space. PSO and ACO concentrate on single and neighborhood learning, whereas GWO combines leadership-based encirclement and adaptive role transition while exploring exploration and exploitation dynamically.

Mathematically, the hunting mechanism of GWO can be represented as

$$X(t+1) = X\alpha(t) + X\beta(t) + X\delta(t)/3 \qquad (3)$$

Here, Xα (t), Xβ (t), and Xδ (t) represent the current positions of the three leading wolves . X (t+1) denotes the updated position of a search agent at iteration t+1. Through this simple but efficient averaging mechanism, the population gradually moves to the most promising hunting zone through "collective guidance"; this avoids premature convergence by retaining enough diversity. The gradual update is also controlled by random adaptive coefficients that mimic encircling and attacking prey to transition the group from global search (exploration) to local refinement (exploitation) skillfully as the iterations proceed. This hierarchical coordination presented makes GWO particularly beneficial for adjusting machine-and-deep learning algorithms for environmental heavy-metal contamination forecasts. For example, in one study, scientists used GWO in conjunction with XGBoost to predict Zn, Cu, Pb, and Cd contamination in rehabilitated lowlands. It was found that the developed hybrid model's prediction error decreased by 12% in comparison to a single XG Boost model . Since computational logic allows the leader wolf to switch between query and exploitation states, GWO is well-suited for such tasks where the distribution variations are non-linear and uncertain. It would be best if you used GWO to enhance environmental change intelligence because its mathematically provable convergence strategy and division into exploration mode and exploitation mode are optimal.

2.2.4 Firefly Algorithm (FA)

The Firefly Algorithm is another nature-inspired method that draws on fireflies' tendency to use bioluminescent signals to communicate with potential mates or prey. In nature, lights flash on and off to signal a firefly's attraction, where the brightness of each flash signifies how attracted it is. Based on this biology, the Firefly Algorithm operates on the notion that every prospective solution might be a firefly, and the firefly is only as bright as its raw fitness value. Better solutions are thus brighter, so fireflies navigate to brighter fireflies. A stochastic element is also added to simulate fireflies' movement in their search for hitherto unseen light sources. This is done to prevent premature convergence and thus ensure the algorithm can traverse the search space to discover top-quality solutions. This can be expressed mathematically as follows:

$$Xi(t+1) = Xi(t) + \beta 0e - \gamma rij2(Xj(t) - Xi(t)) + \alpha(rand - 0.5) \qquad (4)$$

where β0 is the initial attractiveness level at r i j = 0, γ gamma controls how attractiveness falls off with distance, and alpha(rand-0.5) α(rand−0.5) introduces controlled randomisation for what is effectively a local search step. The exponential term simulates how attractive a neighbouring firefly is in proportion to distance. By doing so, it makes certain that fireflies are drawn to attractive ones . At the same time, the random element determines the likelihood of traveling to a far firefly instead of a nearby one.

In environmental modeling, FA is a powerful approach for multi-objective optimization due to the dual mechanism of guided attraction and randomized diffusion. For instance, FA is suitable when one needs to predict several concentrations simultaneously or one should consider ecological, chemical, and spatial objectives in contamination. FA was even used to identify optimal Artificial Neural Network parameters for predicting Pb and Cd concentrations in dynamic aquatic ecosystems. Unlike the older swarm algorithms which can lose diversity or premature convergence, FA algorithm always maintains a diverse population of candidate solutions, thus ensuring exploration throughout multiple optima. This is essential for heavy-metal modeling, as pollution sources are extremely varied in space and time due to industrial discharges, hydrological mixing, sediment resuspension, and bio-geochemical reactions. The adaptability of the algorithm allows it to adjust to changing conditions that are typical of deltaic ecosystems, where tides, floods, and seasonal redox shifts change pollutant pathways and redistribution patterns. FA can also "redesign" the environmental prediction models in near real-time when the new data arrive by updating the search process. Due to the inherent ability to deliver superior performance on multi-objective tasks, FA is considered a useful tool for optimization-empowered environmental intelligence. Therefore, it is a most promising candidate for aiding the development of a data-driven, adaptable framework, which forecasts heavy-metal contamination under changing hydrodynamic and ecological conditions.

2.2.5 The Salp Swarm Algorithm (SSA) and the Aquila Optimizer (AO)

New SI techniques have emerged, including the Salp Swarm Algorithm (SSA) and the Aquila Optimizer (AO), which are gaining popularity among environmental modelers [34]. SSA mimics how salps swarm and forage in chains in the ocean, which gives it strong exploration powers. SSA has been shown to improve the hybrid ANN models for arsenic and nickel prediction in sediments [20]. Thus, the method is more efficient than traditional search approaches. AO also demonstrated high exploration ability at the initial optimization stages, which is derived from the eagles' hunting behaviors. When deep learning architectures (such as CNN) are applied to environmental datasets, the AO technique has also been reported to perform better than PSO and GWO in terms of converging towards the optimal solution and exploring the entire search space [21]. These algorithms hold much promise in predicting contamination in deltaic ecosystems where search space is complex for exploration at early stages to avoid drifting to poor solutions [28] .

2.2.6 Mixed SI–ML/DL Frameworks

The integration of SI algorithms with machine learning and deep learning frameworks is perhaps the most significant development in recent years. Predictive models implementing SI for hyperparameter tuning, feature selection, and spatial calibration are more accurate and robust. For instance, hN-PSO based on ANN facilitated the prediction of cadmium levels in water [14], hybrid ACO–GWO systems enabled the prediction of yields in polluted soils [17], and XGBoost–GWO combinations were used to predict yields in reclaimed soils [18]. Moreover, hybrid SI–ML/DL approaches enable real-time or near-real-time implementation in monitoring systems as they require minimal model parameter tuning. These hybrid platforms are a step towards the operational utilization of SI in predictive systems, where the algorithms not only improve models but also continually modify them based on incoming data streams. The application of swarm intelligence for modeling heavy metal contamination is a significant breakthrough in environmental science. By enabling adaptive optimization, they create models that enhance the predictive potential of ML and DL algorithms. New applications are still being developed, but evidence points to the SI–ML/DL hybrid models as the future of environmental monitoring systems in coastal-deltaic ecosystems [22]–[25]. By learning from diverse datasets and constantly adjusting to shifts in contamination patterns, these frameworks could provide the needed decision-support tools and early warning systems. The Figure 2 shows comparative role of swarm intelligence algorithms and Table 2 presents comparative analysis of swarm-intelligence algorithms applied in environmental modelling.

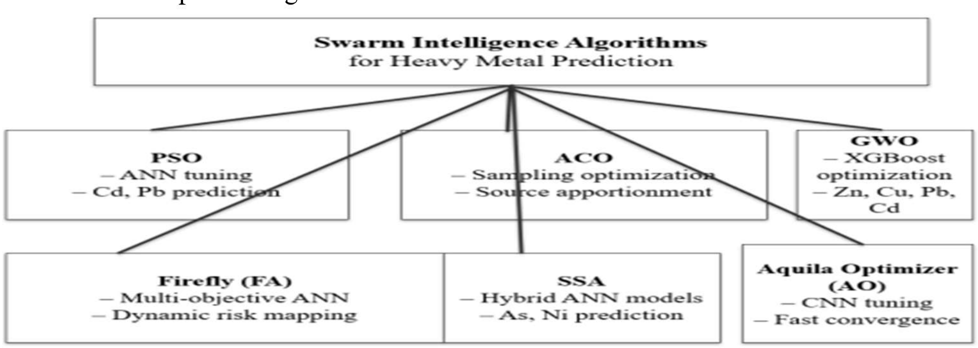

Figure 2. Comparative Role of Swarm Intelligence Algorithms

Table 2. Comparative Analysis of Swarm-Intelligence Algorithms Applied in Environmental Modeling

Algorithm	Principle	Environmental Applications	Advantages	Limitations	References
Particle Swarm Optimization (PSO)	Simulates flocking/foraging of birds; particles adjust position based on personal &	Optimization of ANN for Pb and Cd prediction in aquatic systems	Fast convergence, effective for feature selection & parameter	May get trapped in local minima; performance sensitive to parameter settings	[14]-[16]

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	global best experiences		tuning, computationally efficient		
Ant Colony Optimization (ACO)	Mimics pheromone trail-following of ants for path optimization	Pollution source apportionment; optimization of soil–plant–metal models; GIS-based sampling route design	Good for combinatorial problems; adaptable for source identification; cost-efficient sampling	Computationally expensive for large datasets; slower convergence	[17]
Grey Wolf Optimizer (GWO)	Models leadership hierarchy & cooperative hunting of grey wolves	Calibration of ML models (e.g., XGBoost–GWO for Zn, Cu, Pb, Cd in reclaimed soils)	Balances exploration & exploitation; improves nonlinear model accuracy	Limited global search in very high-dimensional problems	[18]
Firefly Algorithm (FA)	Based on bioluminescent attraction among fireflies	Hyperparameter optimization of ANN for Pb and Cd prediction	Strong in multi-objective optimization; avoids premature convergence; robust in dynamic environments	May require careful tuning; computational cost increases with problem scale	[19]
Salp Swarm Algorithm (SSA)	Inspired by chain-like swarming of salps in ocean currents	Optimization of ANN models for As and Ni prediction in sediments	Strong exploration ability; efficient in handling complex datasets	Limited field applications; still experimental	[20]
Aquila Optimizer (AO)	Mimics hunting strategies of eagles (exploration → exploitation transition)	Calibration of CNNs and DL frameworks for contamination datasets	High exploration in early stages; fast convergence; better global optima capture	Comparatively new; fewer validations in environmental systems	[21]
Hybrid SI–ML/DL	Combines SI with ML/DL (e.g., PSO–ANN, GWO–XGBoost, ACO–GWO)	Heavy metal prediction, soil–plant–metal interaction modeling, yield prediction in contaminated soils	Higher accuracy; reduces computational costs; robust in heterogeneous conditions; suitable for real-time monitoring	Complexity increases; requires careful model–optimizer matching	[22]-[25]

The comparative overview presented in Table 2 offers a more detailed comparison of the key Swarm Intelligence techniques and hybrid SI algorithms in the field of environmental modeling, with special attention to predictions of heavy-metal pollution,

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analysis of soil-plant-metal interactions, and real-time monitoring in AI simulations. Several algorithms, including Particle Swarm Optimization and Ant Colony Optimization, have been widely used for over two decades, yet advanced solutions Salp Swarm Algorithm and Aquila Optimizer have more recently been introduced to enable more accurate and efficient calculations in the structural and geotechnical settings. For each method, the biological principle, the scope of possible environmental applications, computational benefits, and limitations are described along with the relevant hybrid SI-ML/DL frameworks that consider II's applicability for problem domains with unevenly distributed data.. According to the above comparison, PSO and GWO are currently the most reliable and well-documented techniques ensuring high predictive performance and model calibration. PSO, based on the natural instinct of bird flocks, has been used globally for neural-network optimization and, thus, pollutant concentration predictions of Pb and Cd for aquatic ecosystems. The algorithm is prevalent thanks to its distinction and acceleration coefficient E′1, its outstanding convergence, and computational efficiency; however, it can be trapped in a local minimum, making it sensitive to the parameters tuned. The GWO modeling a structure and a-hunting hunting characteristics, behavior of Grey wolves, is proved to be robust specifically for AI due to natural exploration and exploitation balance based on solving the leaders' selection problem within a hierarchy. The application of machine learning models XGBoost-GWO leads to an error reduction of about 12 % in Zn, Cu, Pb, and Cd predictions in terms of high distinction and nonlinear data in soils, meaning GWO can thus be more adapted to environmental data without significant linear dimension dependence.

On the other hand, some problems designed for spatial and combinatorial optimization cause the prominence of the ACO and FA. For instance, the problems of finding the sources of contamination or planning the sampling routes that minimize the overall sampling cost in deltaic and agricultural systems. Such capabilities can be explained by the principles of a pheromone-trail in the ACO, which allow for dynamic learning and adaptation, enabling simple GIS to be included in the sampling route design and pollution source identification. As for the FA, the algorithm fully complies with multi-objective optimization principles on the example of prediction of three heavy metals within one framework. Despite operators, ACO and FA must allocate longer computational times to solve more complex datasets, and the parameter settings are more challenging to ensure the sustained benefits. Finally, SSA and AO can be considered as the latest-generation SI algorithms. The SSA, inspired by the salps chain-like movement within ocean currents, enables rapid global optima finding due to strong exploration in early search phases, which is recommended for optimizing specific deep neural architectures applied to soil and sediment datasets. Similarly, the AO derived from the predatory habits of eagles, can easily switch between exploration and exploitation, which ensures a strong global optima finding and a faster convergence in CNN calibration for remote-sensed contamination prediction. Although the efficiency of SSA and AO is confirmed, the field implementations do not provide data for the large-scale environmental research. Therefore, SSA and AO can be considered as the opportunities for the following investigations.

Thus, the PSO–ANN, GWO–XGBoost, ACO–GWO, and other hybrid SI–ML/DL frameworks discussed above represent the cutting-edge of environmental intelligence. Drawing together the adaptive search behavior of swarm-based optimizers and predictive strength of ML/DL models, these systems attain progressively accurate, robust, and computationally intensive solutions assuring lower cost and superior noise and data heterogeneity resilience. Although successfully applied for yield prediction on contaminated soils, soil–plant–metal bioaccumulation prediction, and simulation-scale contamination monitoring in coastal deltaic systems, the implementation of the bio-inspired optimization techniques and methods featured in Table 2 requires careful algorithm–model combination and fine-tuning to assure consistent performance and interpretation. Indeed, Table 2 demonstrates that the incorporation of bio-inspired optimization techniques in machine learning pipelines is a milestone in the development of comprehensive, data-driven sustainability solutions for complex environmental problems.

2.3 Critical Appraisal and Limitations of the Reviewed Frameworks

While optimization-driven ML–DL frameworks demonstrate superior predictive accuracy, this review recognizes several unresolved limitations. First, many studies rely on region-specific datasets, limiting cross-delta generalizability. Second, deep learning architectures, even when optimized, often retain black-box characteristics that hinder regulatory acceptance. Third, swarm-intelligence optimization increases computational overhead, which may restrict real-time deployment in data-scarce regions. Finally, most reviewed models emphasize prediction accuracy over uncertainty quantification, reducing confidence in high-stakes environmental decision-making. Addressing these limitations is essential for translating algorithmic success into operational environmental governance.

3. DIFFERENCE FROM PRIOR WORK

Unlike prior reviews that either catalog heavy metal contamination patterns or summarize machine learning applications independently, this study advances the literature by explicitly coupling algorithmic optimization behavior with delta-specific environmental dynamics. It moves beyond performance comparison to interpret how swarm intelligence enhances convergence stability, feature relevance, and ecological interpretability under hydrodynamic uncertainty. The review further introduces a systems-level perspective by positioning SI-optimized ML/DL frameworks as digital surrogates of deltaic ecosystems rather than static predictive models.

4. CONCLUSION

Coastal–deltaic systems are dynamic and vulnerable geosystems at the boundary between land and ocean with riverine and marine environmental controls, which contributed to the historic buildup of Cd, Pb, Hg, As and Cr in soils or sediments over centuries. Traditional point monitoring methods have offered localized pollution evaluations, but they are limited by spatial extent, temporal coverage and interpretability. The integration of remote sensing with Machine Learning (ML), Deep Learning (DL) and Swarm Intelligence (SI) is envisioned to provide opportunities for the development of intelligent, data-driven predictive frameworks that can help overcome these limitations. Involving optimization techniques including PSO, GWO, ACO in hybrid ML–DL–SI systems significantly improves model calibration, convergence as well as accuracy and ensure reliable interpretation of the contamination dynamics. This review makes three principal scientific contributions: (i) it establishes a unified analytical framework linking swarm-intelligence optimization mechanisms with machine and deep learning models for coastal–deltaic contamination assessment; (ii) it critically demonstrates how optimization enhances not only predictive accuracy but also robustness, convergence, and feature interpretability under non-stationary environmental conditions; and (iii) it reframes AI-based contamination modeling as an adaptive environmental intelligence paradigm capable of supporting early warning, scenario simulation, and sustainable coastal management. Nevertheless, the field is still confronted with the issue of insufficient training data and generalization across distinct delta land types which are not interpretable enough for policy implementation. Future research should develop frameworks consolidating the information from composite environmental data sources (field-, sensor- and satellite) with optimization-friendly ML architectures, where ecosystem risk indices and climate-sensitive parameters are embedded to transform predictive systems into applications as accessible, transparent decision-support tools to secure fragile coastal ecosystems as well the human-dependent livelihoods.

Beyond summarizing existing methods, this article adds significant knowledge by demonstrating that optimization-driven ML–DL frameworks are not merely accuracy-enhancement tools but function as adaptive representations of deltaic environmental processes. The synthesis clarifies why certain algorithms succeed under sediment-dominated regimes while others fail under hydrodynamic variability, providing actionable insights for model selection, policy design, and future research. Consequently, the review shifts the field from fragmented algorithmic experimentation toward coherent, system-aware environmental intelligence.

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