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Appraisal of Methods for Identifying, Mapping, and Modelling of Fluvial Erosion in a Mining Environment

F. F. Howard, I. Yakubu, C. B. Boye, J. S. Y. Kuma

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***Abstract*—**Natural and human activities, such as mining operations, expose the natural soil to adverse environmental conditions, leading to contamination of soil, groundwater, and surface water, which has negative effects on humans, flora, and fauna. Bare or partly exposed soil is most liable to fluvial erosion. This paper enumerates various methods used to identify, map, and model fluvial erosion in a mining environment. Classical, Artificial Intelligence (AI), and GIS methods have been reviewed. One of the many classical methods used to estimate river erosion is the Revised Universal Soil Loss Equation (RUSLE) model. The RUSLE model is easy to use. Its reliance on empirical relationships that may not always be applicable to specific circumstances or locations is a flaw. Other classical models for estimating fluvial erosion are the Soil and Water Assessment Tool (SWAT) and the Universal Soil Loss Equation (USLE). These models offer a more complete understanding of the underlying physical processes and encompass a wider range of situations. Although more difficult to utilise, they depend on the availability and dependability of input data for correctness. AI can help deal with multivariate and complex difficulties and predict soil loss with higher accuracy than traditional methods, and also be used to build unique models for identifying degraded areas. AI techniques have become popular as an alternative predictor for degraded environments. However, this research proposed a hybrid of classical, AI, and GIS methods for efficient and effective modelling of fluvial erosion.

Keywords—Fluvial erosion, classical methods, Artificial Intelligence, Geographic Information System.

I. INTRODUCTION

FLUVIAL erosion can be due to mining-related operations such as the removal of soils and plants, which results in increased fluvial erosion and the creation of significant volumes of waste (solid and liquid) with suspended sediment burdening downstream water bodies [36]. The degradation caused by fluvial erosion in a mine can be detrimental to people's health and safety as well as cause environmental harm (on-site and off-site repercussions) to fields and loss of soil fertility [60]. These eroded areas continue to exist due to climate change and poor land use management, which prevent soil formation and vegetation development [35].

In degraded and disturbed areas, evidence of lands indicating active fluvial erosion (Fig. 1) and its relative mass movement processes of sediment yield into water bodies are inequivalent signals of severe geomorphic activity [35], [36]. The intensity of fluvial soil erosion can vary greatly depending on the temperature, soil, topography, cropping, and land management at a given location [55]. According to published literature, this high activity is a result of human disturbance of an unstable geomorphic system, and good examples of these effects include deforestation and illegal mining [2], [35], [36].

F. F. Howard, Postgraduate Candidate, C. B Boye, Yakubu I.*, are with Geomatic Engineering Department, and J. S. Y Kuma is with Geological Engineering Department, University of Mines and Technology (UMaT), Tarkwa, Ghana (*e-mail: yissaka@umat.edu.gh).

Fig. 1 Fluvial Erosion in Construction/Mining Areas

II. CLASSICAL METHODS

There are few approaches for modelling fluvial erosion in mining environments in literature. In France, the "Talus Royal Method" was successfully applied to rock road cuts [23]. In the United States, the Rosgen technique has been frequently employed for periodic stream rehabilitation, including mined areas [46], [47]. In mining locations in the United States, Australia, Colombia, and Spain, the GeoFluv technique has proven to be effective [11]-[13].

The hydrology, erosive stability, and evolution of both conventional and geomorphic restoration techniques in mining zones can also be evaluated using a variety of methodologies, models, and software [45], [61]. Utilising conventional

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erosion models, such as the USLE [58], the RUSLE, and the Modified Universal Soil Loss Equation (MUSL) [43], [44], is a noteworthy technique for assessing the stability of mining-degraded sites. The geomorphic development of post-mining landscapes has been evaluated using the Dynamic Water Erosion Prediction Project (DWEPP), the Water Erosion Prediction Project (WEPP) [16], [20], [42], [57], and Landscape Evolution Models (LEMs), like SIBERIA or CAESAR-Lisflood, as well as the European Soil Erosion Model (EUROSEM) [21], [37], WATEM/SEDEM model, and the Limburg Soil Erosion Model [25]. When correctly calibrated, these models have yielded excellent results.

Reference [36] identified that topography, slope, and surface soil cover have an effect on the action of river erosion. The authors examined two surface soil covers (topsoil and subsoil) with two topographic profiles (linear and concave) throughout two hydrologic years. Sediment load, rill growth, and plant colonisation were the four profiles that were measured in the field. Their results showed that carbonate colluvium or topsoil cover on a concave slope produced more sediment than thick, uncompacted topsoil cover on a linear slope. The study also found a connection between topography and vegetation establishment, which is important for preventing river erosion. Fluvial erosion is exceedingly worse in tropical and hilly places due to sudden soil changes and excessive rainfall combined with land management, according to [36] and [56]. Lengthy precipitation events and snow gliding produce fluvial erosion and avalanches, which, in addition to geological, morphological, and anthropogenic variables, make certain locations more vulnerable [65].

To effectively manage fluvial erosion, the terrain, land cover, and vegetation must all be appropriately managed [52]. The available literature shows that topography and land cover management are critical components of mining operations [8], [36]. Additionally, efforts should be directed toward producing biologically functioning and stable soils that limit river erosion and promote post-mining land regeneration [8], [36].

III. AI Methods

In contrast to other traditional modelling techniques, the AI technique is a novel one with a flexible numerical structure capable of discovering complicated non-linear correlations between input and output data [4]. The AI techniques found in existing literature for identifying fluvial erosion include Kohonen Neural Network, multivariate adaptive regression splines, multivariate partial least square regression, variable importance projection statistics, random forest, support vector machine, least square support vector machine, random subspace algorithms, ANN-Bagging, AdaBoost, reducing pruning error tree, fractal rainfall disaggregation, boruta algorithm, naïve bayes trees, Fischer's linear discriminant, shuffled frog leaping algorithm, particle swarm optimization, fuzzy inference system, convolutional neural networks, object-based image analysis, and many others.

A. Review of Applications of AI Techniques for Fluvial Erosion Modelling

It is interesting that the use of various AI approaches to detect fluvial erosion is widespread in the literature. For instance, [32] quantitatively predicted soil loss from natural runoff plots using WEPP and neural networks. The scientists used information from 2,879 erosion events from eight different US locales. Eight input parameters were used to create neural networks for the data from each individual site, and ten parameters were used to create neural networks for the whole data set. The data demonstrate that neural networks outperformed the WEPP model in predicting event runoff volumes and soil loss amounts, with the exception of a small number of minor events where negative erosion predictions were physically impractical.

The linear correlation coefficient (R) for the neural network predictions that came as a result was found to be between 0.7 and 0.9. In sites where there is enough information from erosion monitoring, the acquired results point to the possibility of utilising neural networks to estimate soil erosion by water at the plot scale. For the purpose of simulating soil erosion, [57] employed five AI techniques: Fuzzy K-Nearest Neighbour (FKNN), Artificial Neural Network (ANN), Support Vector Machine (SVM), Relevance Vector Machine (RVM), and Least Square Support Vector Machine (LSSVM). In order to evaluate these models, a historical dataset with ten explanatory variables was used, and four alternative land-use management strategies were used to manage soil erosion on hillslopes in northern Vietnam. Randomly produced data samples representing both soil erosion and non-erosion totalled 236 (80% for training and 20% for testing) to assess the robustness of the five models.

To assess the performance of the five models, [55] used the Classification Accuracy Rate (CAR) and Area Under Receiver Operating Characteristic (AUROC) performance indicators. According to the results, the RVM model performs best during both the training (CAR = 92.22% and AUC = 0.98) and testing (CAR = 91.94% and AUC = 0.97) phases. The performance of the other four AI methods was strong. These findings unequivocally support the effectiveness of using AI algorithms to predict soil erosion. Both the training (CAR = 92.22% and AUC = 0.98) and testing (CAR = 91.94% and AUC = 0.97) phases demonstrated that the RVM model had the most impressive results. The performance of the other four AI strategies was likewise excellent. Therefore, these results strongly indicate the effectiveness of utilising AI techniques to anticipate soil erosion.

Reference [36] compared deterministic model-based erosion modelling approaches. For the research findings, both empirically-based and process-based models were applied. The ANN and Fuzzy Inference System (FIS) were used in the empirical modelling, which was based on statistics and AI methodologies. Physical process-based modelling (WEPP, EUROSEM, and CIHAM-UC) includes the calibration, validation, and testing of the model's constituent parts, such as the equations. The Chirgu River basin was used to gather the input and output data for the various models throughout both the rainy and dry (irrigation) seasons. The gathered data

Open Science Index, Geological and Environmental Engineering Vol:17, No:11, 2023 publications.waset.org/10013350.pdf

demonstrates that the AI-based techniques offer a respectable match with a r^2 coefficient of determination that is close to 0.7.

For soil erosion modelling, [65] used Object Image Analysis (OBIA) and a Convolutional Neural Network (CNN) based on the U-Net architecture. A collection of manually mapped erosion sites was used to train the algorithms. CNN performed well in object identification tasks, allowing researchers to determine the relevant qualities or traits that can be utilized to distinguish eroded locations from other places.

Reference [24] simulated soil erosion rates using ANN techniques. In order to show the spatial variations in the soil erosion rate, a Geographic Information System (GIS) was used as a pre-processor and post-processor tool in this work. The ANN technique was trained, improved, and verified using data from the Kasihain watershed in northern Iran. Field plots were used to calculate soil erosion values on the hillslopes. A Multi-Layer Perceptron (MLP) network was used to calculate the rate of soil erosion, with inputs including slope, air and soil temperature, rainfall intensity and amount, soil moisture, and vegetation cover. The study's findings demonstrate that the ANN can predict soil erosion with an r^2 of 0.94 and an arithmetic mean squared error of 0.04 with high levels of accuracy. The results also show that coupling ANN with GIS for soil erosion estimates and mapping has a lot of promise.

Reference [5] assessed the efficacy of ANN applications to forecast erosion risk using several simulations and produced accurate classification outcomes. One of Indonesia's most significant potential watersheds, the Serang Watershed in Kulonprogo, Yogyakarta, was used to test the model. The simulation results showed that the number of iterations had a significant impact on accuracy relative to other variables. ANN, which has a performance accuracy of 99.32% and a root mean square (RMS) error of 0.0001, is a possible technique for future erosion modelling.

Reference [7] used four AI techniques to predict the susceptibility of gully erosion: ANN, General Linear Model (GLM), Maximum Entropy (MaxEnt), SVM, and random sampling of training and validation data. The 50/50 random sample ANN was the most effective model in the examination of the research findings. For the Urseren valley (in the Central Swiss Alps), [49] mapped several erosion processes using high-resolution aerial pictures using OBIA and CNN with U-Net architecture. With increases in total degraded area of 167% and 201%, respectively, over the 16-year study period, the findings of this study show that OBIA and U-Net followed similar linear trajectories.

Additionally, CNN with U-Net design can be applied to spatially and temporally uncharted data, making it a method capable of efficiently and effectively capturing the temporal patterns and spatial heterogeneity of degradation in alpine grasslands. Additionally, U-Net was considered to be a strong and powerful tool for mapping erosion locations in a foresighted manner using a significant volume of fresh aerial imagery.

Reference [49] automated the identification of areas of soil degradation on agricultural land. The method is based on information from multitemporal remote sensing. Deep machine learning methods were used to choose appropriate remote sensing data scenes. An examination of 1028 pictures from Landsat 4, 5, 7, and 8 of 530 agricultural areas served as the foundation for deep machine learning. The findings of this work suggest that deep machine learning can be used to choose remote sensing data from a binary dataset.

Using extremely high spatial resolution photos from Google Earth, [22] used a mask region-based convolutional neural network (Mask R-CNN) to automatically delineate and categorise yardangs (wind-eroded areas). More than 90% of the found yardangs accurately identified and classified the change in landform, according to the results of manual validation on photos from additional research sites, resulting in an overall detection accuracy of 74%. The scientists came to the conclusion that Mask R-CNN is a trustworthy model for defining different kinds of multi-scale yardangs and for researching the morphological and evolutionary characteristics of landforms.

Using improved mask R-CNN and transfer learning, [54] automatically identified and dynamically monitored open-pit mines in Hubei Province. With values of 0.9718, 0.8251, and 0.0862, respectively, the IMRT model outperformed R-CNN in terms of pixel accuracy (PA), Kappa, and missed alarm, indicating that it was more effective at automatically identifying open-pit mines. The outcomes are also used to measure the environmental harm caused by mines. The evaluation's findings also indicate that level 1 (severe) land occupation and the loss of vital mining sites are responsible for 34.67% and 36.2%, respectively, of the damage to the topographic landscape.

Reference [38] employed CNN with U-Net architecture and a weighted cross-entropy loss function to detect rills on tailings dams. The final model produced promising results with precision scores of 83.3 percent, 72.0%, and 77.2%.

B. Importance of Using AI Techniques for Fluvial Erosion Modelling

It is critical to have a model that accurately depicts the real world since erosion modelling is a crucial measuring tool for both land users and decision makers to evaluate land cultivation [5]. The ambiguous data from various sources and the processing techniques make erosion models difficult. AI can be trusted to analyse complex, non-linear data, including that related to erosion [5]. The comparison of several cutting-edge machine learning methods is necessary for the complicated and dynamic process of modelling soil erosion [55]. AI has shown considerable promise and effectiveness in resolving challenging soil science issues. With the use of this cutting-edge technique, historical datasets may be used to create data-driven models that can be used to anticipate a variety of complicated phenomena, such as soil erosion.

Numerous studies in the field of fluvial erosion have been conducted to calibrate and evaluate the runoff and erosion elements with empirical models that are process-based models, as documented in the literature [14], [19], [28], [31], [39], [41], [49], [51], [54], [62], [63]. For evaluation, many of

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these empirical models demand significant data and good performance [36]. AI is being effectively applied in various areas linked to fluvial erosion modelling. It may provide a user-friendly alternative or supplement to sophisticated, physically based models [32].

AI's popularity has risen in recent decades and rapidly expanded into new application sectors. Because it can assess multi-source data sets, AI is considered a universal approximation [32]. In soil science and geoscience, AI can help deal with multivariate and complex difficulties [55]. Furthermore, AI predicts soil loss with higher accuracy than traditional methods [55]. Also, AI techniques can be used to build unique models for identifying degraded areas [55]. Due to the insufficiency of empirical predictors, AI techniques have become popular as an alternative predictor for predicting degraded environments.

Furthermore, AI can calculate hydrological parameters from field or observational data [24]. As a result, using AI techniques to estimate soil erosion can help reduce costs and study time. Furthermore, AI can estimate soil erosion in real-time at any location and at any moment [24]. The fundamental benefit of employing AI in fluvial erosion modelling is that it is data-driven and does not require any constraining assumptions about the basic model's structure [24].

AI models are black box models since they learn from the studied data and do not require reprogramming. The model must be trained, optimised, and tested as part of the AI modelling process. Selecting one model from a list of potential models is what training the network model entails. The process of modifying parameters to get an optimal set of parameters without breaching specific limitations is known as optimization. Any method used to measure a computer network's performance quantitatively is referred to as a network performance test [24].

IV. Geospatial Method for Erosion Mapping

The intensity of soil erosion and other aspects can be effectively mapped using GIS [24], [29], [34], [64]. Estimating and mapping soil erosion and sediment yield has been the subject of numerous studies in the past and present [10], [26], [30]. AI can estimate soil erosion with great accuracy and speed, but it will be challenging for other users to apply the results without a specific location [24]. It is therefore imperative to consider the use of GIS.

GIS is a potent technology that can be used to solve environmental issues and model soil erosion. Combining the AI model with GIS approaches is essential when creating a model to mimic soil erosion using AI techniques in a GIS setting. Thus, combining AI and GIS can produce findings that are accessible to all users and presented in a geo-referenced graphic format [18].

A. Application of Geospatial Techniques in Erosion Mapping

Geospatial techniques effectively assess and map regions susceptible to soil erosion hazards [50]. Reference [33] modelled a broad area's identification of its sensitivity to soil loss by implementing multi-criteria evaluation in a GIS framework. The model's validity was established by comparing the predicted soil erosion-prone locations with the field's actual erosion and depositional features. Reference [48] applied 2D and 3D visualization and spatial analysis of geographic data to support the environmental decision-making process, which is one of the most significant uses of GIS. Due to the location-based nature of 80% of decision-makers' data, the spatial analytic capabilities of GIS offered more accurate information regarding decision-making circumstances. With the overlay procedure in GIS, the decision-maker locates a list that meets a predetermined set of criteria.

Another approach for mapping erosion is an index model. Instead of a simple yes or no, [48] used an index model to generate an index value for each unit area. The process for calculating the index value was the main factor considered while creating an index model, whether vector-based or raster-based. Reference [48] expressed the weighted linear combination approach as being the most popular technique for determining the index value for each unit area and creating a ranking map based on the index values. The index model is best suited when there is a risk of information loss and the threshold value may not be precise. GIS software was used to diagnose the spatial distribution of soil erosion and soil nutrient variations under different land uses in two agro-ecological zones of southern Mali by [50]. The discussion of the effect of soil erosion on agricultural land productivity emphasised the importance of the empirically derived relationship between the RUSLE, in-situ soil data measurement, and satellite products.

The RUSLE is a computer-based model that has greatly profited from the rise in computer processing power, and much more so with the development of GIS and remote sensing technology. As described by [40], although significant obstacles still exist despite these technical developments, earlier research has proven that these geospatial technologies make determining soil erosion and its spatial distribution possible at affordable costs and with acceptable accuracy. The RUSLE has considerably benefited from recent geospatial technology advancements in GIS and remote sensing [40]. The RUSLE has expanded the variety of circumstances in which it can be used, such as disturbed landscapes, rangelands, and forests [3]. Due to the intricate interactions of numerous elements, including climate, land cover, soil, topography, and human activities, estimating soil erosion loss is frequently challenging [33]. Reference [3] cited erosion models as a tool for forecasting and reasonable prediction that can help comprehend natural events like the transport and deposition of silt by overland flow. The RUSLE was first created to estimate cropland soil erosion with gently sloping topography. While satellite remote sensing is becoming a more important data source for all RUSLE characteristics, GIS is still primarily used to calculate individual RUSLE parameters [40]. Application of the RUSLE model is common among agricultural engineers, hydrologists, geomorphologists, and soil scientists [26]. Reference [1] employed a developed simplicity model in the GIS environment to estimate existing

Open Science Index, Geological and Environmental Engineering Vol:17, No:11, 2023 publications.waset.org/10013350.pdf

and projected soil erosion as influenced by long-term changes in LULC [3]. To examine the links between soil erosion risk and LULC distribution, [33] created a soil erosion risk map with five classifications (very low, low, medium, medium-high, and high) based on the simplified RUSLE within the GIS context. Reference [35] created a RUSLE model that evaluated the risk of soil erosion in the Tensift watershed using remote sensing (RS) and GIS techniques. RUSLE elements like cover management (C), conservation practices (P), slope length and steepness (LS), soil erodibility (K), and rainfall erosivity (R) help determine how slope, elevation, geology, and soil erosion relate to LULC.

Soil erosion prediction and assessment has been a challenge to researchers since the 1930s, and several empirical, conceptual, and physical process-based models have been designed for specific sets of conditions in particular areas. Most of these models need information related to soil type, land use, landform, climate, and topography to estimate soil loss [48]. To assess the sensitivity to soil erosion, multi-criteria analysis was applied when producing and combining spatial data for describing the causal factors. Analytical Hierarchy Process (AHP) Pairwise Comparison Methods are used through the Weighted Linear Combination (WLC).

Reference [6] evaluated the uses of GIS in estimating soil erosion, talked about the challenges and restrictions of earlier studies, and concluded that GIS offered enormous promise for enhancing soil erosion estimation. In order to estimate soil erosion loss using geostatistical techniques (i.e., collocated co-kriging and a joint sequential co-simulation model), [33] used a sample ground dataset, Thematic Mapper (TM) images, and DEM data. They showed that such methods provided significantly better results than traditional methods. Reference [48] assessed the sites vulnerable to soil erosion based on multi-criteria evaluation in the upper catchment of the Markanda River. GIS was used for the derivation, integration, and spatial analysis of the geographic layers of each theme.

The identification of sediment source locations and the forecasting of storm sediment yield from catchment areas have both been addressed using a GIS-based methodology that has been proposed and validated [8]. The goal of this study was to use GIS to discretise catchments into tiny grid cells and calculate their physical characteristics, including slope, land use, and soil type, all of which have an impact on the processes of soil erosion and deposition in various catchment sub-areas [8]. Further, GIS methods were also used to partition the sub-areas into overland and channel types, to estimate the soil erosion in individual grid cells, and to determine the catchment sediment yield by using the concept of sediment delivery ratio. Grid-based discretisation is found to be the most reasonable procedure in both process-based models as well as in other simple models [9]. The Integrated Land and Water Information System (ILWIS) GIS was used for discretising the catchments into grid cells, and the Earth Resources Data Analysis System (ERDAS) Imagine image processor was used for processing satellite data related to land cover and soil characteristics.

B. Advantages of Geospatial Techniques over Classical Methods

According to [40], empirical erosion models like the RUSLE offer a reasonably straightforward yet thorough framework for evaluating soil erosion and its contributing components. According to RUSLE, significant influences on soil erosion include rainfall (R), topography (LS), soil erodibility (K), cover management (C), and support practices (P). According to reports, the utility of RUSLE has benefits, including the availability of quantitative data that can be compared with qualitative evaluations in erosion studies and the fact that the data needed to execute RUSLE are simple to get and compatible with GIS, thereby making it easy to implement and understand [1].

For monitoring and planning land use that will prevent land degradation, [33] methodologies and results discussed how effective a combination of RUSLE, Remote Sensing, and GIS is for understanding the relationship between soil erosion risk and LULC classes. The outcome of the model of [50], which was based on a multi-criteria GIS evaluation, shows that it is necessary to identify places susceptible to soil erosion. Such model-based integrated maps can assist us in making forecasts, planning the implementation of preventative and restorative measures, and prioritising the region based on the degree of erosion. Physical survey is the foundation of traditional methods for locating erosion potential areas, but when the erosion problem is widespread, this process can be challenging and time-consuming. As a result, GIS-based spatial modelling generates helpful data for solving complicated problems by rationally establishing relationships among diverse dependent geographic characteristics [15], [48].

Reference [59] indicated that using remote sensing and GIS technologies for erosion risk mapping, based on the methodology implemented in the Coordination of Information on the Environment (CORINE) model, resulted in an effective and accurate assessment of soil erosion in a considerable short time and at a low cost for large watersheds; therefore, the model can provide decisionmakers with the areas with erosion risk so that they can develop soil and water conservation plans in general and generate detailed erosion studies for the regions of high erosion risk.

The key benefit of using GIS technology is that it can quickly provide information on the anticipated cost of soil loss for any area under investigation [27]. The main reasons for using a GIS are that runoff and soil erosion processes vary spatially, so that cell sizes should be used that allow spatial variation to be taken into account. Also, the data for the large number of cells required are enormous and cannot easily be entered by hand, but can be obtained by using a GIS [17]. The possibilities of rapidly producing modified input-maps with different land use patterns or conservation measures to simulate alternative scenarios, the ability to use very large catchments with many pixels, so the catchment can be simulated with more detail, and the facility to display the results as maps are further advantages of using a GIS [17].

GIS has a good ability for erosion control through land use modelling. Land use management provides a good alternative way for long term erosion control [53].

The techniques for calculating soil loss based on erosion plots have significant drawbacks in terms of the cost, representativeness, and accuracy of the data they produce. Due to the restriction of small samples in complex ecosystems, they are unable to offer a spatial distribution of soil erosion loss [33]. So, mapping soil erosion in large areas is often very difficult using these traditional methods [33]. The ability to estimate soil erosion and its spatial distribution with acceptable prices and improved accuracy across wider regions is made possible by the use of remote sensing and GIS techniques [33].

V. Conclusions

It is evident that fluvial erosion has been and will continue to be the subject of numerous research efforts. Appraisal of the numerous methods by various researchers reveals that several classical, Geospatial, and AI methods have been used to identify, map, and model fluvial erosion. However, the researchers recommend a hybrid of classical, AI, and geospatial methods for effective and efficient modelling of fluvial erosion.

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