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ADVANCING SOIL EROSION PREDICTION IN WADI SAHEL-SOUMMAM WATERSHED ALGERIA: A COMPARATIVE ANALYSIS OF DEEP NEURAL NETWORKS (DNN) AND CONVOLUTIONAL NEURAL NETWORKS (CNN) MODELS INTEGRATED WITH GIS

Abstract: This study employs adaptive deep learning (utilizing DNN and CNN approaches) to accurately predict soil erosion, a crucial aspect of sustainable soil resource management. The goal is to develop fuzzy logic models for erosion forecasting in a large watershed with limited inputs, comparing them to predictions from the Revised Universal Soil Loss Equation (RUSLE). Integration of GIS enables analysis of satellite data, providing crucial details like land use, slope, rainfall distribution, and flow direction. This synergistic approach enhances erosion prediction capabilities and yields spatial erosion distributions. Producing precise erosion risk maps within GIS is crucial for prioritizing high-risk areas and implementing effective conservation methods in the Wadi Sahel watershed, Algeria. The assessment in the Oued Sahel-Soummam watershed involved overlaying five RUSLE factor maps using Arc GIS spatial analysis, resulting in an average annual soil loss of 4.22 tons per hectare. The DNN and CNN models were integrated with GIS for detailed calculation of annual average soil loss (tons per hectare per year) and mapping erosion risk areas in Wadi Sahel-Soummam watershed. Using the CNN model, estimated annual soil loss in Sahel-Soummam wadi was about 4.00 tons per hectare per year, while the DNN model estimated around 4.13 tons per hectare per year. This study employed two deep learning models for erosion prediction, with the DNN model featuring six hidden layers performing notably better than the compared CNN model.

Key words: soil erosion, deep neural network, convolutional neural network, modelling, GIS, RUSLE, watershed

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Introduction

Soil erosion is the most significant spatio-temporal phenomena, and the main environmental problems observed in the countries of North Africa. (Djeddou et al., 2019). Among the consequences of this phenomenon of erosion have been the degradation of land resources. Soil erosion is influenced by a variety of factors. Rainfall intensity and volume play a crucial role; intense and prolonged rainfall events increase the erosive force of water, resulting in more significant soil erosion (Anderson et al., 2021). Additionally, steep slopes are more susceptible to erosion as gravity accelerates the movement of water and sediment downslope (Sidle, 2006). Soil type and texture also play a role; soils with low organic matter content, poor structure, and coarse texture are more prone to erosion. Furthermore, vegetation cover, such as dense grasses and trees, acts as a natural barrier against erosion by slowing down runoff and stabilizing the soil. Changes in land use and land cover, including deforestation, urbanization, and the conversion of natural land to agriculture, can significantly increase erosion rates (Alawamy, 2021). Poor land management practices, such as overgrazing, improper tillage, and inadequate crop cover, can exacerbate soil erosion. Additionally, soil moisture content plays a critical role; dry, compacted soils are more prone to erosion compared to well-moistened soils that can absorb and retain water. Implementing erosion control practices like contour plowing, terracing, and buffer strips can effectively mitigate erosion (Panagos, 2015). This can lead to a decline in soil fertility, a series of negative impacts on environmental problems, and can threaten the storage capacity of dams, as well as agricultural production. The loss of biodiversity is another significant concern associated with soil erosion. Particularly in riparian zones, soil erosion can destroy habitats, leading to the loss of diverse plant and animal species. This disruption of ecological communities has cascading effects on the broader ecosystem (Montgomery, 2007). Additionally, soil erosion can exacerbate the risk of flooding and landslides. The sedimentation of water bodies increases the likelihood of flooding events, while the removal of stabilizing vegetation can lead to landslides, especially in areas with steep terrain (Favis-Mortlock et al., 2003). Soil erosion is not only an issue of physical disruption; it also contributes to air and water pollution. Eroded sediments can transport pollutants like pesticides, heavy metals, and pathogens. These contaminants pose significant risks to both water bodies and air quality, with potential impacts on human and environmental health (Lal, 2003). Lastly, soil erosion comes with substantial economic costs. Reduced agricultural yields, increased expenses for water treatment, and damage to infrastructure contribute to a significant financial burden. These costs can have widespread economic implications for affected regions (Nkonya et al., 2006). Geographical Information System (GIS) is a valuable tool in developing environmental models through their advance features of data storage, management, analysis, and display (Burrough et al. 1998). Generating accurate erosion risk maps in GIS environment is very important to locate the areas with high erosion risks for prioritization and to develop adequate conservation techniques (Vrieling et al., 2002). Soil erosion modeling is a complex dynamic process by which productive surface soil is detached, transported and accumulated over a distant place resulting in exposure of sub-surface soil, and siltation in reservoirs or natural streams (Verma et al., 1995). Jasrotia et al. (2002) indicated that modelling soil erosion can be used as predictive tool for:

- Assessing soil loss for conservation planning;
- Project planning;
- Soil erosion inventories and for formulating regulations.

Physical based mathematical models can predict where and when erosion is occurring, thus helping the conservation planet target to reduce erosion; Models can be used as a tool for understanding process and their interaction for setting research priorities.

Bonilla et al. (2009) used RUSLE in combination with GIS for evaluation of the effects of different combinations of vegetative cover on soil erosion rates for Santo Domingo County in Central Chile. The information was compiled in raster of 25 × 25 m cells. RUSLE parameter values were assigned to each cell and annual soil loss estimates were generated on a cell-by-cell basis. Soil loss estimated for the current and for three alternate scenarios of vegetative cover.

Under current cover conditions, 39.7% of the county is predicted to have low erosion rates (< 0.1 tons/ha/yr), 39.8% has intermediate rates (0.1 to 1.0 tons/ ha/yr), and 10.4% has high erosion rates (>1.1 tons/ha/yr). Under the recommended alternate scenario, 89.3% of the county was predicted to have low erosion rates, and no areas were affected by high soil loss, reduced soil erosion to a level that was not affecting long term productivity. RUSLE model and GIS techniques for determination of the soil erosion vulnerability of a forested mountainous sub-watershed in Kerala, India. The spatial pattern of annual soil erosion rate was obtained by integrating geo-environmental variables in a raster-based GIS method. The resultant map of annual soil erosion showed a maximum soil loss of (17.73 tons/ha/year) with a close relation to grass land areas, degraded forests and deciduous forests on steep side-slopes. Kamaludin et al. (2013) used RUSLE model to estimate the sediment losses, in the GIS environment within selected sub-catchments of Pahang River basin Malaysia.

Jaiswal et al. (2014) applied RUSLE model in Panchnoi river basin of North East India, which causes serious fluvial hazards in downstream areas. Values were assigned to different soil erosion parameters such as rainfall, soil types, relief, slope, and land use and land cover base on scientific principles to generate GIS layers using ArcInfo 9.3 software. The study disclosed the parametric impact of erosion parameters in the basin. It was found that soil types and vegetation cover played major role in soil erosion scenario of whole basin and rainfall has a great control over soil erosion. The study revealed that soil erosion risk in degraded hilly section was quite high and the area required soil conservation practices to attain sustainability in the region.

Kartic et al. (2014) used RUSLE model within GIS environment to investigate the spatial distribution of annual soil loss potential in the Kothagiri Taluk. Both magnitude and spatial distribution of potential soil erosion in the catchment were determined. GIS data layers including, rainfall erosivity (R), soil erodability (K), slope length and steepness (LS), cover management (C) and conservation practice (P) factors were computed for determining their effects on average annual soil loss. The resultant map of annual soil erosion showed a maximum soil loss of (27.11 tons/ha/year) with a close relation to built-up land areas, crop land and forest plantation on the steep side-slopes.

Recently, application of machine learning (ML) techniques (e.g., artificial neural network, adaptive neuro-fuzzy inference system and support vector machines) in environmental modelling, espeially hydrological processes have received much attention from the researchers (Mohammadi, 2021).

The objective of this research is to assess the susceptibility to soil erosion in the northeastern Algerian region of Wadi Sahel-Soummam. This will be accomplished through the application of a sophisticated deep learning model, utilizing both Deep Neural Network (DNN) and

Convolutional Neural Network (CNN) methodologies. The validity of these models will be confirmed by comparing their results with those obtained from the empirical RUSLE model.

Materials and Methods

Presentation of the study area

The catchment area of the Wadi Sahel-Soummam is located in the North-eastern part of Algeria between 3° 60' and 4° 70' of longitude Is and between 36° 00' and 36° 50' of Northern latitude. The catchment area of Wadi Sahel-Soumam extending according to a Northwestern axis. It is composed of area: plates of Bouira. It is limited:

In North: by the Large Kabylie's Mountains (Djurdjura Massif), in the East: by the Small Kabylie Mountains, in the South: by the Bibans and Mansourah's Mountains. in South-East by Hodna's mountains buttressing, and in the West: it is limited by the courses of Isser, and Sébaou. It presents a very irregular form Figure 1 and Table 1 (Mokhtari et al., 2017).

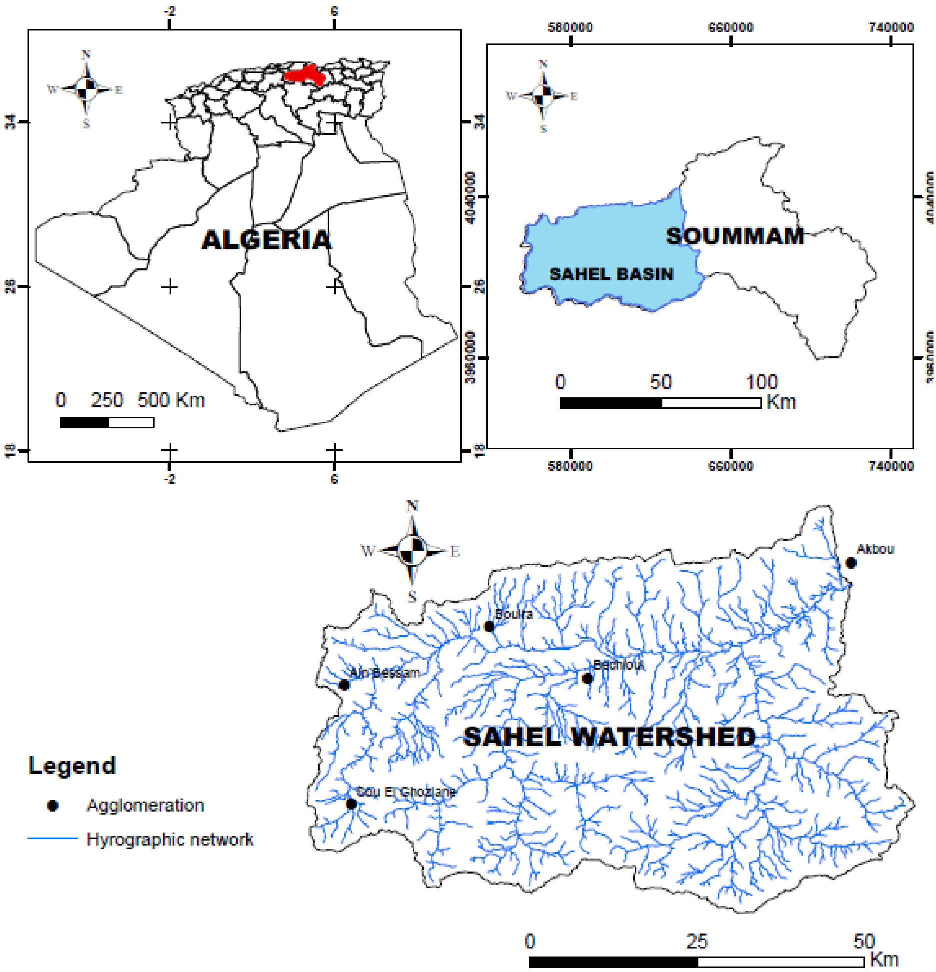


Fig. 1. Localization of the study area (Mokhtari et al., 2017)

Tab. 1. Morphometric characteristics of Wadi Sahel-Soummam watershed (Mokhtari et al., 2017)

Parameters	**Values**
Area	3736 km^2
Perimeter	360 km
Index compactness of Gravelius K_G	1.64
Maximum altitude	2308 m
Minimum altitude	173 m
Average altitude	783 m
Equivalent rectangle width l_e	41 km
Equivalent rectangle length L_e	91 km

The RUSLE model

The RUSLE is a standardized soil erosion prediction equation that can be used for many land use situations. The RUSLE model is based on the USLE erosion model structure which was developed by Wischmeier & Smith (1978) and improved and modified by Renard et al. (1997) as RUSLE model. The procedure for estimation of annual soil loss using RUSLE integrated with ArcGIS has been described by Soo Huey Teh (2011). The RUSLE has been widely used for both agricultural and forest watersheds to predict the average annual soil loss by introducing improved means of computing the soil erosion factors (Wischmeier & Smith 1978). This equation is a function of five input factors in raster data format i.e. rainfall-runoff erosivity, soil erodability, slope length and steepness, cover management and support practice. These factors vary over space and time and depend on other input variables.

$$A = R \times K \times LS \times C \times P \qquad (1)$$

Where:

A: is the computed soil loss per unit area, expressed in the units selected for K and for the period selected for R ; R: the rainfall and runoff factor, is the number of rainfall erosion index units, plus a factor for runoff from snowmelt or applied water where such runoff is significant; K: the soil erodibility factor, is the soil loss rate per rainfall erosion index unit; L and S are the slope length and steepness factors; C: the cover and management factor, (C thus ranges from a value of zero for completely non-erodible conditions, to a value of 1.0 for the worst-case); and P, the support practice factor, is the ratio of soil loss with a support practice like contouring, stripcropping, or terracing to that with straight-row farming up and down slope (Renard et al., 2011).

RUSLE has been formulated by data recording review from plot of land erosion of the unit that having a fix length of 72.6 feet (which is 22.1 m) and a fix slop of about 9% (or 5.14 degrees). L.S.C and factor P adjust real conditions compared to experimental plots conditions on the ground. These factors represent reports and are without dimension (Mokhtari et al., 2017).

The soil erosion intensity map generated had the values categorized using The Jenks optimization (the natural breaks classifcation method) into five soil erosion classes, i.e., very weak (<3), weak (3-6), moderate (6-9), strong (9-12), and very strong (>12).

Deep Neural Networks

A deep neural network (DNN) is an artificial neural network (ANN) that has multiple hidden layers between the input and output layers. DNNs, like shallow ANNs, can model complex non-linear relationships. An ANN's main goal is to solve real-world problems like classification by receiving inputs, performing calculations, and producing outputs. This research focuses on forward-feeding neural networks, which have an input, an output, and a sequential data flow. Deep learning can have a large number of hidden layers, which are mostly non-linear. The number of hidden layers in this study was set to 5 (Mokhtari et al., 2023).

The Deep Neural Network (DNN) is the fundamental architecture of neural networks, and it is modeled after the information processing capabilities of the human brain (Agatonovic-Kustrin & Beresford, 2000). DNNs are made up of neurons that improve as they learn. The layers are fully connected, which means that each neuron in a layer receives input from all neurons in the previous layer and serves as input to all neurons in the subsequent layers (Figure 2). DNNs have been used in regression analysis, classification, and unsupervised data clustering across many engineering fields due to their ability to analyze intricate data patterns (Agatonovic-Kustrin & Beresford, 2000).

The soil erosion intensity map generated had the values categorized using the Jenks optimization (the natural breaks classification method) into five soil erosion classes, i.e., very weak (<3), weak (3-6), moderate (6-9), strong (9-12), and very strong (>12).

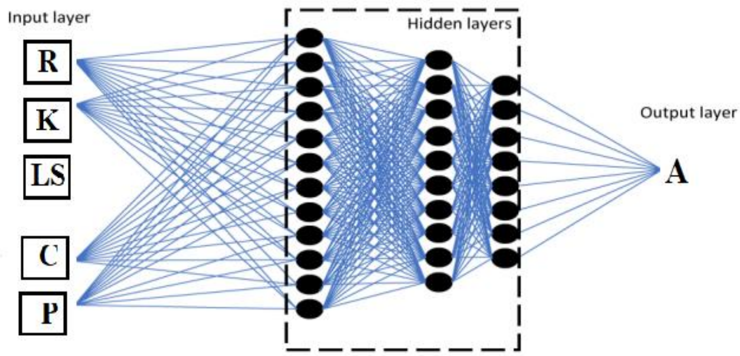


Fig. 2. Deep Neural Network. (Source: own elaboration)

Convolutional Neural Networks

Convolutional neural networks are a variety of feed-forward neural networks with multiple layers, some of which contain one or more convolutions (LeCun et al., 2015). Input, output, and hidden layers can be included. While the hidden layer frequently handles multiplication or dot product operations, the input and output layers serve the self-explanatory purposes. The network can be built with various layer types, including fully connected, normalizing, and pooling layers (Baek et al., 2020).

Through a simple but exact architecture, CNNs can efficiently map a large data set to an output (Figure 3). It performs better than DNNs, especially when analyzing visual images, thanks to its weight sharing structure and pooling techniques that allow for a reduction in the number of parameters. It's important to note that CNNs are spatially invariant, which means they cannot detect an object's position or orientation. Thus, CNNs may not be a good choice if data position is important. CNNs are now frequently used in a variety of water and wastewater treatment applications.

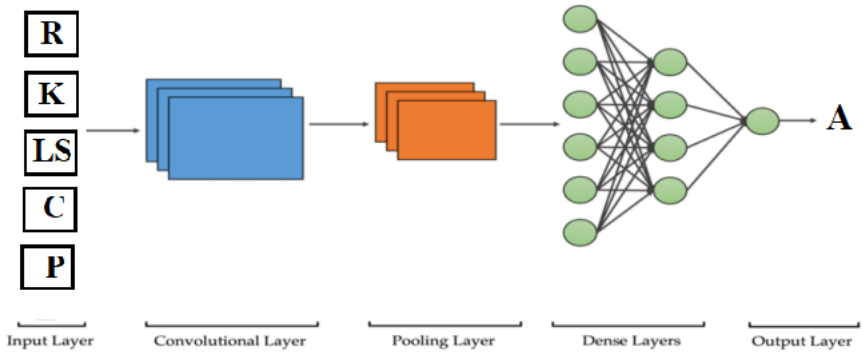


Fig. 3. Convolutional Neural Network (Source: own elaboration)

The Python-based Keras library, which offers an interface for deep learning, was used to build the models. Since mean-squared-error (MSE) is more sensitive to large errors than mean absolute error, it was chosen as the loss function. The CNN model was optimized using the Adam optimizer, and the RMSprop method was used to optimize the DNN model. The same 182 sample dataset from which both models were trained was randomly split into training and testing sets in the proportion of 70:30. The values of the chosen hyperparameters are shown in Table 2.

The soil erosion intensity map generated had the values categorized using the Jenks optimization (the natural breaks classification method) into five soil erosion classes, i.e., very weak (<3), weak (3-6), moderate (6-9), strong (9-12), and very strong (>12).

Tab. 2. Developed Models Description

	CNN model	DNN model
Input shape	(n, 5, 1)	(n, 5)
Number of layers	Total of 7	Total of 7
Batch size	8	16
Number of epochs	500	500
Loss function	MSE	MSE
Optimizer	RMSprop	RMSprop
Learning rate	0.001	0.005
Number of parameters	23041	6721

Results and Discussion

Annual soil erosion estimation using RUSLE model

In this study, the RUSLE model was integrated with GIS to conduct cell-by-cell calculation of average annual loss rate (tons/ha/year) and to identify and map soil erosion risk areas in the Wadi Sahel-Soummam watershed from different data sources (Mokhtari et al., 2017).

The erosion risk assessment in Wadi Sahel-Soummam watershed was performed by overlaying the five RUSLE factor maps using ArcGIS spatial analyst. The average annual soil loss in the Wadi Sahel-Soummam watershed was 4.22 tons/ha/year. As can be seen from the soil erosion map (Figure 4), the highest values of estimated soil erosion potential that were around 24 tons/ha/year occurred in the North eastern part of the watershed due to their high LS-factor values and an abrupt change in slope.

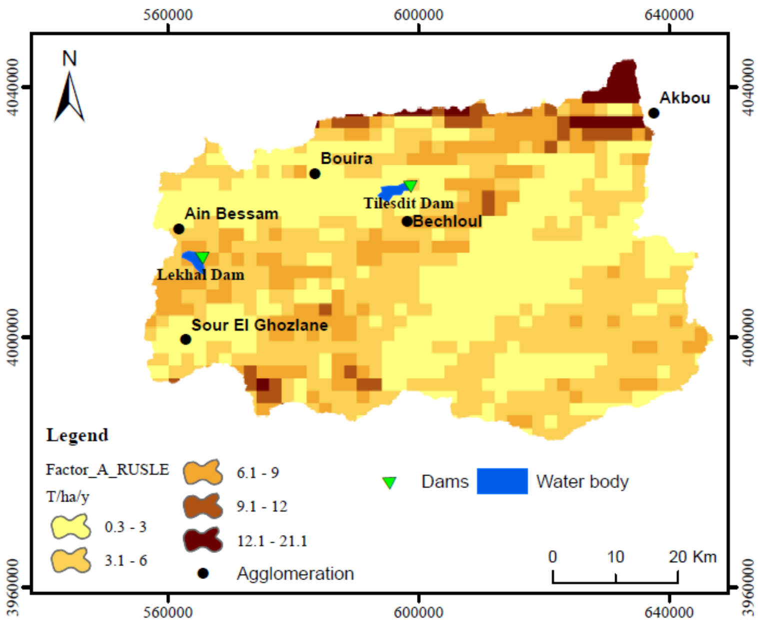
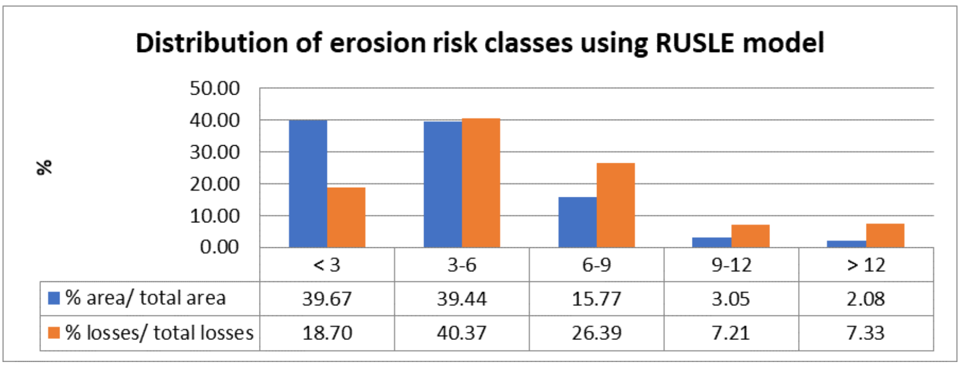


Fig. 4. The annual average soil loss map of the Wadi Sahel-Soummam watershed using RUSLE model

The estimation of soil erosion area coverage indicated that approximately 7773 ha (about 2.08%) of the study watershed showed strong water erosion and, consequently, high erosion risk. However, lower soil erosion occupied 14,858,364.88 ha (39.67%). The distribution of earth losses is not proportional to the areas as shown in Figure 4, as an indication 39.45% of the total watershed area contribute to 40.37% of total losses. The total annual losses of the basin are 1,494,698.57 tons/year (Figure 5).



	< 3	3-6	6-9	9-12	> 12
% area/ total area	39.67	39.44	15.77	3.05	2.08
% losses/ total losses	18.70	40.37	26.39	7.21	7.33

Fig. 5. Erosion risk classes of the Wadi Sahel-Soummam watershed using RUSLE model.

It was noticed that this analysis of soil erosion problems carried out by RUSLE approach provided important synthetic and systematic information on the nature, intensity, and spatial distribution of a phenomenon and therefore allowed identifying the most affected areas and the types of dominant erosion in the long term

Annual soil erosion estimation using DNN model

The data predicted by the developed DNN model was integrated with GIS to conduct cell-by-cell calculation of the annual average soil loss rate (tons/ha/year) and to identify and map the soil erosion risk areas in the Wadi Sahel-Soummam watershed.

The erosion risk assessment in Wadi Sahel-Soummam watershed was performed by using ArcGIS spatial analyst. The average annual soil loss in the Wadi Sahel-Soummam watershed was 4.13 tons/ha/year. As can be seen from the soil erosion map (Figures 6 and 7), the highest values of estimated soil erosion potential that were around 19.8 tons/ha/year occurred in the North eastern part of the watershed due to their high LS-factor values and an abrupt change in slope.

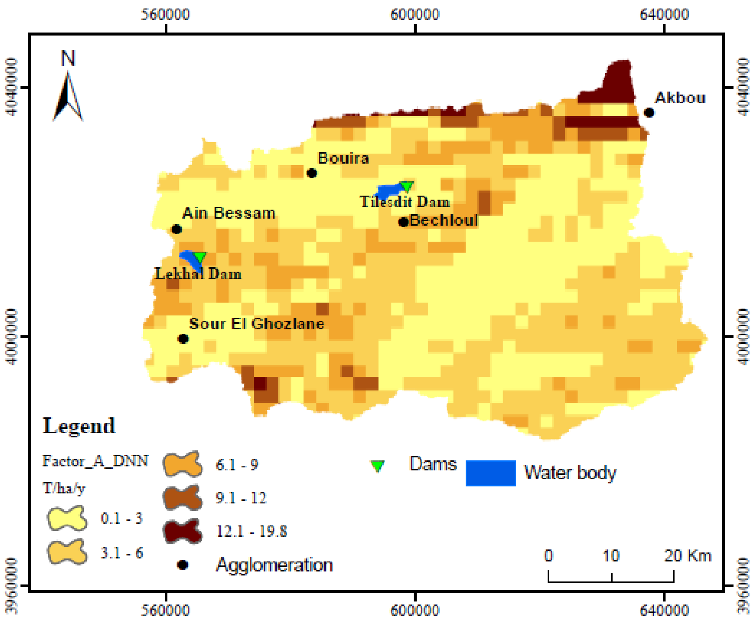


Fig. 6. The annual average soil loss map of the Wadi Sahel-Soummam watershed using DNN model

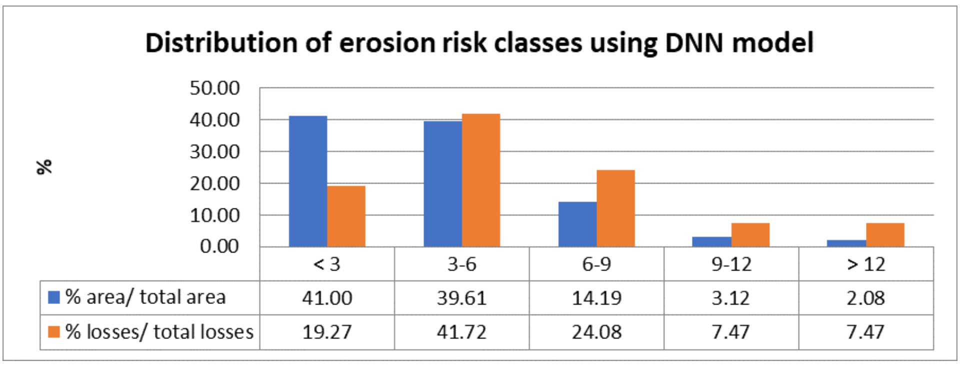


Fig. 7. Erosion risk classes of the Wadi Sahel-Soummam watershed using DNN model

Annual soil erosion estimation using CNN model

The data predicted by the developed CNN model was integrated with GIS to conduct cell-by-cell calculation of the annual average soil loss rate (tons/ha/year) and to indentifiy and map the soil erosion risk areas in the Wadi Sahel-Soummam watershed.

The erosion risk assessment in Wadi Sahel-Soummam watershed was performed by using ArcGIS spatial analyst. The average annual soil loss in the Wadi Sahel-Soummam watershed was 4.00 tons/ha/year. As can be seen from the soil erosion map (Figures 8 and 9), the highest values of estimated soil erosion potential that were around 14.9 tons/ha/year occurred in the North eastern part of the watershed due to their high LS-factor values and an abrupt change in slope.

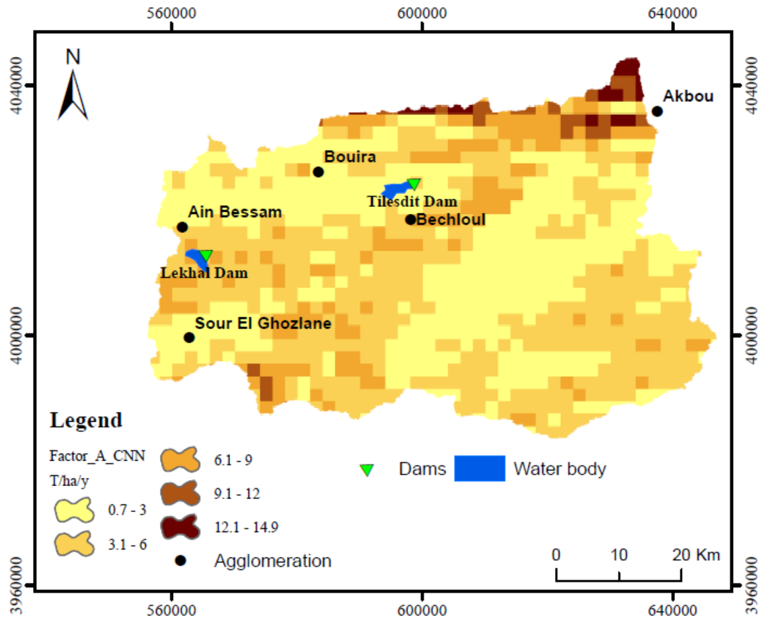
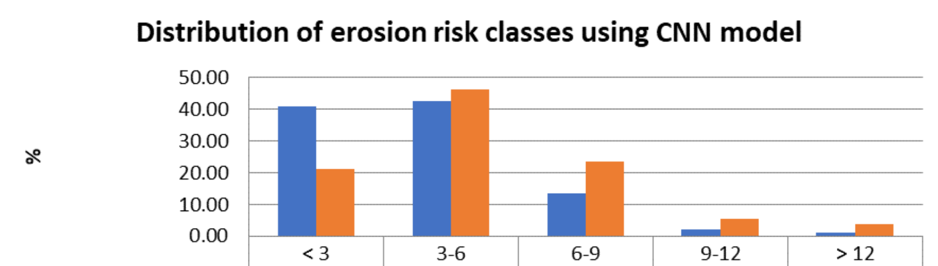


Fig. 8. The annual average soil loss map of the Wadi Sahel-Soummam watershed using CNN model



	< 3	3-6	6-9	9-12	> 12
% area/ total area	40.74	42.62	13.38	2.04	1.22
% losses/ total losses	21.23	46.22	23.33	5.32	3.90

Fig. 9. Erosion risk classes of the Wadi Sahel-Soummam watershed using CNN model

Comparative study of the annual soil erosion estimation

The RUSLE model was integrated with a GIS for a detailed cell-by-cell calculation of average annual soil loss, resulting in an estimation of 4.22 tons per hectare per year. This approach also identified erosion risk areas, highlighting approximately 7773 hectares, or about 2.08% of the watershed, exhibiting intense water erosion and consequently, a high erosion risk. On the other hand, a vast area of 14,858,364.88 hectares, or roughly 39.67% of the watershed, showed lower erosion rates. An interesting observation was that the distribution of soil losses did not correspond proportionally to the areas, indicating that 39.45% of the total watershed area contributed to 40.37% of total losses, emphasizing significant variations in erosion levels across different zones of the watershed. Overall, the RUSLE model provided crucial synthetic and systematic information, offering detailed insights into the nature, intensity, and spatial distribution of the phenomenon, as well as identifying the most affected areas and dominant erosion types in the long term. Regarding the DNN model, specific details regarding erosion risk areas and the distribution of soil losses are not provided in the text. However, it is noted that the DNN model estimated the annual soil loss at 4.13 tons per hectare per year, slightly lower than that of the RUSLE model. Similarly, for the CNN model, while the average annual soil loss was estimated at 4.00 tons per hectare per year, detailed information on erosion risk areas and the distribution of soil losses is not specified. Thus, while the DNN and CNN models offer slightly lower estimates for annual soil loss compared to the RUSLE model, additional details on erosion risk areas and the distribution of soil losses are necessary for a more comprehensive assessment of these two models.

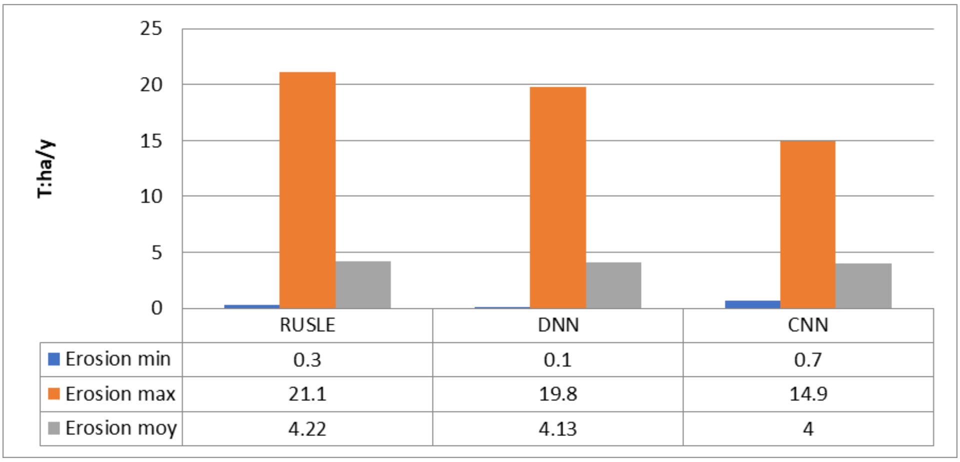


Fig. 10. Comparative study of the annual soil erosion estimation

Conclusion

This study indicated that using Deep Learning (DL) models and GIS technologies for soil erosion mapping resulted in accurate assessment of soil erosion for Wadi-Sahel Soumam watershed is necessary to soil management and water conservation measures at watershed scale in order to conserve the natural resources. Deep Neural Network (DNN) and a Convolutional Neural Network (CNN) were compared for prediction performance and ease of use. In the training phase, the results showed that both models could predict soil erosion accurately, with the DNN model being quicker. The testing results demonstrate that the DNN model outperforms the CNN model in terms of prediction accuracy. The CNN has a longer computation time and more training data requirements due to its greater number of parameters. Choosing the right input parameters, architecture, and hyperparameters is essential for producing accurate predictions; however, doing so may increase the CNN model's training data requirements and computation time.

The deep neural networks (DNN) model presented excellent capability in hydrological process modelling. Comparing DNN model with RUSLE model indicates that these models are very powerful tools to handle complicated problems. In this study, outcome data showed that ELM models are very capable of modelling soil loss rate, confirming the general enhancement achieved by using neural networks in many other hydrological fields.

This quantitative map can be an indispensable tool for the integrated management of soils, and gives relatively reliable results that can be of great help to the region's decision-makers and planners with the aim of simulating evolution scenarios and consequently targeting the priority areas that require conservation actions against erosion.

Conflicts of Interest: The authors declare no conflict of interest.

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