

AI Powered Remote Sensing for Soil Erosion Modeling: A Google Earth Engine Approach

Hoa Thi Tran¹[0000-0002-1742-0226], Dung Nguyen¹[0000-0003-4843-1160], and Ha Thanh Tran²

¹ Faculty of Information Technology

² Faculty of Surveying and Land Administration

Hanoi University of Mining and Geology

Emails: {tranthihoa, nguyenthimaidung, tranthanhha}@humg.edu.vn

*Corresponding author: Hoa Thi Tran (email:
tranthihoa@humg.edu.vn)

Abstract. Soil erosion is a natural process of the top soil gradual removal which is mainly driven by rainfall, winds and water flows. This process is also influenced by extreme climatic events like prolong droughts or intensive floods which lead to a potential of land degradation. Many research projects have been working on estimating and modeling this soil loss process, such as the USLE (Universal Soil Loss Equation) or its modified RUSLE (the Reverse USLE). Those traditional models, though, offer foundational insights of this process in a certain area, they are often limited by spatial resolution and static parameterization and a large computing volume. This study introduces an integrated framework that leverages freely remote sensed images, artificial intelligence (AI) algorithms and a cloud computing platform – Google Earth Engine (GEE) in predicting soil susceptibility across the study area. Three AI models of different complexities, Random Forest (RF), Support Vector Machine (SVM) and Long Short-Term Memory (LSTM) are examined and trained on key environmental factors. The results have shown that while RF works well in this project for presenting slowly changing erosion risk and no required extra tools, LSTM, which requires highly computing ability, is being expected to be a potentially choice for multi-year and seasonal predictions. SVM, in other word, is ineffective in handling large and complex datasets. Generally, the integration of GEE enhances computational scalability and allows to apply AI algorithms in modeling and predicting environmental and landscape changes.

Keywords: Soil Erosion, AI, Remote Sensing, GEE, Environmental Modeling.

1 Introduction

Soil erosion is a natural process of losing top soil from higher elevation to lower one due to the water runoff and gravity [1] leading to a challenge to agricultural practices and water sediment management. This environmental challenge is exacerbated by many factors such as characteristics of local topography, climatic

parameters (like precipitation) coupling with deforestation, intensive agriculture, and effects of climate change, posing risks to sustainable land use and food security[2, 3].

Traditional approaches like the Universal Soil Loss Equation (USLE) or Reverse Universal Soil Loss Equation (RUSLE) are commonly used to estimate soil loss by analyzing the characteristics of topography, climate, social economic conditions and land use practices of a desired area [4]. However, their reliance on manual parameter estimation and limited spatial scalability has restricted their effectiveness in dynamic and large scale environments[5].

Recent advancements in remote sensing have significantly enhanced abilities in monitoring and spatially mapping erosion-prone areas, aiding policymakers in targeting high-risk zones for intervention [6] by providing timely, cost-effectively and consistent earth observation data[7, 8]. Furthermore, the integration of artificial intelligence (AI), particularly machine learning (ML) algorithms has further revolutionized soil erosion modeling by enabling complex pattern recognition and predictive analytics[9-11]. Those ML algorithms have provided opportunities to study soil susceptibility based on conditions of input datasets, computing capacities of computers and programming abilities. For example, Random Forest (RF) is much suitable for observing slowly changing erosion risk while Support Vector Machine (SVM) is another option for handling small datasets[12]. Long Short Term Memory (LSTM), on the other hand, is designed for temporal or time series data which is more effective for monitoring and predicting erosion patterns over time[13, 14].

In parallel, Google Earth Engine (GEE) has emerged as a transformative platform for geospatial analysis, offering cloud-based processing of massive satellite images[15, 16]. GEE allows users to efficiently access, visualize, and analyze multi-temporal satellite datasets and terrain data, making it highly suitable for soil erosion assessment across diverse geographic scales[17, 18]. Besides, this web-based app eases the viewing constraint allowing all users (local communities, government or publicity) for faster and more intuitive data access[19]. Furthermore, collaborating with Google Colab which is a powerful python programming platform, AI models are much conveniently deployed and computed in GEE opening a potential for time and cost saving in soil erosion monitoring and predicting[20] have revolutionized the processing and analysis of large-scale environmental data[15, 16].

This study proposes an approach of AI powered remote sensing for soil erosion modeling using Google Earth Engine. By integrating various resolution images with ML algorithms (RF, SVM and LSTM) within GEE environment, we aim to: (1) examine remotely sensed data provided by GEE for contribution USLE parameters and map erosion severity; (2) examine performance of different ML algorithms in predicting soil erosion risk patterns; (3) develop an efficient, scalable, and automated method to map and predict soil erosion. Our proposed frameworks are expected to enhance the spatial accuracy of soil erosion estimation and to facilitate a reliable and potentially application of AI in environmental modeling.

2 Methodology

2.1 The USLE and its parameters

In learning and estimating soil loss, the idea of using a synthesized model was developed in 1960s with an introduction of a conventional equation – the Universal Soil Loss Equation or USLE. This equation is widely recognized as a foundation tool for monitoring soil erosion severity providing a reliable and effective method for soil conservation and land management, particularly in agricultural contexts.

The USLE involves five influential factors that contribute to erosion: rainfall and runoff (R), soil erodibility (K), slope length and steepness (LS), cover management (C) and erosion control practices (P)[21]. The formula of USLE was first introduced by Wischmeier and Smith in 1978, expressed as:

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

While

A is the annual soil loss (tons ha⁻¹ year⁻¹).

R is the rainfall and runoff factor (MJmm ha⁻¹ h year).

K is the soil erodibility (tons ha⁻¹ R unit⁻¹)

LS is the slope length and steepness factor.

C is the cover management (no unit but need standardized)

P is the control practices (no unit but need standardized)

Details about each factor are presented below.

The Rainfall and Runoff factor (R)

The factor R quantifies the potential of rainfall to cause erosion which is derived from historical rainfall data, such as precipitation intensity and frequency[22]. Otherwise, occurrence of storm events is also accounted as they result in surging the intensity of precipitation which then, increase the severity of soil erosion. In many regions, empirical formulas relate annual or monthly rainfall to erosivity. Records from stations though are accurate, they are not continuous data. Thus, rainfall raster datasets are an appropriate solution at a regional scale, such as TRMM (Tropical Rainfall Measuring Mission) dataset. Another possible option is CHIRPS (Climate Hazards Centre Infra-Red Precipitation with Station data) – an integration of satellite images and in-situ station. This type of dataset performs time series of precipitation for further analysis. R values typical range from 100 to 7000 depending on region, generally low in arid zones and high in tropics where rainfall is abundant.

The Soil Erodibility (K)

Soil texture, soil structure, organic matter and permeability also influence soil capacity of storing water and nutrients contribution the K factor or as known as the soil erodibility. K is estimated through an empirical model of soil particle size and texture (sand, silt, clay content), organic content and structure based the follow equation[23, 24]:

$$K = (0.2 + 0.3 \exp(-0.0256 \times Sand)) \times \left(\frac{Silt \times (Silt + Clay)^{0.3}}{100} \right) \quad (2)$$

Soil data are particularly provided by the Soil Survey Department, from Soil Map or FAO (Food and Agriculture Organization). K values are generally around 0.02 - 0.7.

The Slope Length and Steepness

LS depicts the landscape, which is involved the impact of topography (slope length and gradient) on soil erosion. In the study area, steep terrain has encouraged water runoff resulting in top soil removal. Typically, a Digital Elevation Model (DEM) of the preference area is applied to calculate slope and flow accumulation, which is expressed below[25, 26]:

$$LS = \left(\frac{Slope\ Length}{22.13} \right)^m \times (0.065 + 0.045 \times Slope + 0.0065 \times Slope^2) \quad (3)$$

LS values are positioned between 0.01 – 20, higher for steep or hilly terrain, however.

The Cover Management (C)

Cover management closely relates to the rate of vegetation cover or crop type which influence soil erosion by reducing exposure to rainfall impact. Land cover types are main sources to estimate the factor C. Areas with highly dense vegetation cover is inversely categorised as low C values, while C valued bare land or low-cover crops are typically low[4]. Satellite images like Landsat or Sentinel or existing land cover datasets can be used to generate C. The Normalized Vegetation Different Index based on formula (4)[27].

$$C = \exp \left(-\alpha * \frac{NDVI}{\beta} \right) \quad (4)$$

Commonly, $\alpha = 2$, $\beta = 1$ (can vary).

Based on land cover, C values can be obtained as following table 1:

Table 1. C values from landcover type

Land Cover	C values
Forest	0.001-0.05
Grassland	0.01-0.05
Cropland	0.2-0.5
Bare Soil	0.-1.0
Urban	0 (if fully impervious)

The Control Practices P

Management and conservation practices like contouring, terracing, or strip cropping are represented by the P factor to reduce soil erosion. Land use, soil conservation practice provided by local administrators or acquired from agriculture records or field observations are inputs for assigning values for the P factor[28]. For example, contour farming on moderate slope might have a P value of 0.5 while terracing could reduce erosion even more, with a P factor of 0.1[3]. P values are able to be generated based

NDVI assumptions. Lower values are often assigned where conservation practices exist. However, in this study, we use slopes (degree) which were computed from digital elevation model (DEM) to obtain P values. Table 2 provides ideas of P factor.

Table 2. P value factor for conversation practices categories

Slope (degree)	P values
0-2	0.6
2-5	0.5
5-8	0.5
8-12	0.62
12-16	0.7
16-20	0.8
>20	0.9

2.2 The Random Forest Algorithm

Random Forest (RF) is a widely used ensemble machine learning algorithm that has proven highly effective in environmental modeling, including soil erosion assessment. It operates by constructing a multitude of decision trees during training and outputs either the mode of classifications or the mean prediction in regression tasks[29]. RF handles high-dimensional data quite well, is robust to overfitting, and automatically ranks feature importance, making it particularly useful when dealing with diverse environmental factors such as rainfall, slope, vegetation cover, and land use. The algorithm's ability to model nonlinear relationships and manage missing or noisy data makes it ideal for integrating remote sensing inputs for erosion mapping in a spatially heterogeneous landscape[12].

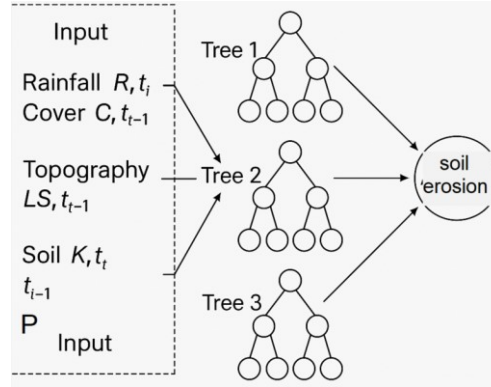


Fig 1. RF structure for soil erosion prediction at multiple time steps. It visually emphasizes how temporal patterns are handled through decision tree ensembles.

2.3 The Support Vector Algorithm

Support Vector Machine (SVM) is a supervised learning algorithm that excels in classification problems by finding the optimal hyperplane that separates different classes in a dataset. In the context of soil erosion modeling, SVM has been employed to classify land areas into erosion-prone and stable zones by analyzing input features such as vegetation cover, rainfall intensity, slope gradient, and soil type. Its effectiveness lies in the use of kernel functions to transform input data into higher dimensions, where complex relationships can be more easily separated[30]. SVM performs well with limited training samples and high-dimensional data, but can be sensitive to parameter tuning and computationally demanding when applied to large datasets.

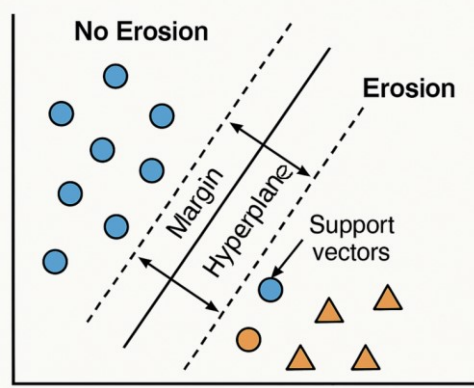


Fig 2. Applied SVM diagram for soil erosion prediction. Blue circles mean “No erosion” areas while orange triangles are “erosion” areas. Black hyperplane is decision boundary, dashed margins are maximum margin boundaries. Highlighter points are support vectors.

2.4 The LSTM Algorithm

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) designed to handle sequential data and capture long-term dependencies across time steps. In soil erosion modeling, LSTM can be used to predict changes in erosion risk by learning from temporal patterns in precipitation, vegetation indices (e.g., NDVI), and land surface dynamics. Unlike traditional models, LSTM networks are well-suited for modeling dynamic systems affected by seasonal or interannual variability, making them especially valuable in climate-sensitive areas[31]. Their application in remote sensing has grown rapidly, especially when integrated with platforms like Google Earth Engine for preprocessing and feature extraction, followed by external LSTM model training using frameworks such as TensorFlow.

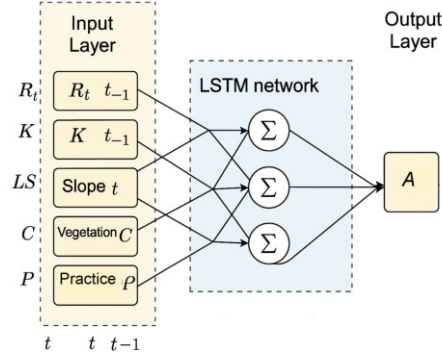


Fig 3. LSTM network diagram for time stepped inputs for USLE factors.

Each input (e.g., Rainfall R , Cover C) includes multiple time steps like t and $t-1$, representing temporal dynamics. The LSTM layer captures these sequences to model how erosion risk evolves over time. The output layer predicts A (Annual Soil Loss) for the current time step.

3 Results and Discussions

3.1 The Study Area

Our study area, Quang Nam, is one of the six largest provinces in Vietnam which is 10,754,86 km². The population is 1,519,400 resulting in the low population density of 144 people/km². Quang Nam is characterized by a variation of landscapes of coastal plains, hilly terrain to mountainous area from the East to West. Figure 4 represents the location of our study area - Province Quang Nam in the South coastal center area of Vietnam and its terrain data which contributes a characteristic of elevation change toward the coastline from about 2500m to below 50m. That leads to a greatly different height between the Eastern and Western region of the interested area. Because of spanning both lowland and highland regions, Quang Nam's ecosystem and biodiversity are rich and varied.

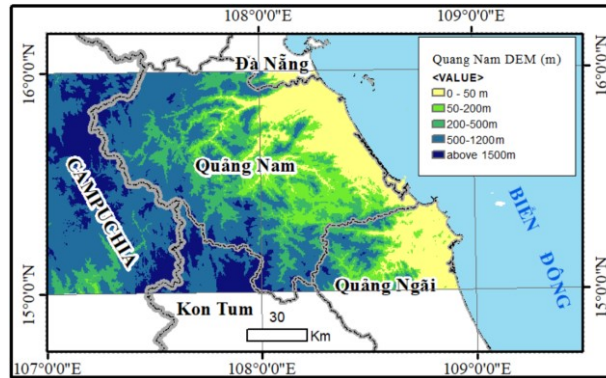


Fig 4. Study area and its digital elevation model

However, Quang Nam is increasingly affected by soil erosion, a pressing environmental issue exacerbated by a combination of topographical, climatic, and human factors. The province's steep slopes, seasonal monsoon rains, and deforestation from expanding agricultural practices heighten its vulnerability to erosion. These factors intensify soil loss, especially in mountainous and hilly areas, where soil is less stable.

Furthermore, the high rainfall intensity during the rainy season (more than 2500mm) causes increased surface runoff, further escalating soil erosion and degrading soil quality, affecting agricultural productivity and ecosystem stability[32]. Weathering is another additional factor for top soil removing in Quang Nam due to the fact of a coastal province. Nevertheless, wind speed records or other climatic factors aren't discussed in this study because it would contribute a more complex context that proposed model, USLE is unable to handle.

3.2 USLE Factors Generation

In the USLE analysis, we decided to examine a time observation from 2016 to 2024 which means covering 8 yearly USLE data. Results, then, were exported to raster files and added in GIS environment for map representation.

Figure 5 to 8 show the 2023 maps of each factor (R, K, LS, C, P and A respectively) and 2023 A soil erosion severity map in our case study in the GIS environment. A legend of 5 soil severity levels is defined at **Table 3**.

Table 3. The USLE categories [33]

Level	USLE (tons ha ⁻¹ year ⁻¹)
Very low erosion	0–1
Low erosion	1–5
Medium erosion	5–10
High erosion	10–50
Extreme erosion	> 50

In 2023, rain usually concentrated on the windward side facing to the ocean, resulting in higher intensive precipitation on that side which is appeared in dark blue. Soil erodibility K and landscape LS did not change significant during the time observation. It occurs that higher area are logical considered as lower K values (ability to store water and discrete texture) while the LS values are much higher at high elevation to steeper slopes.

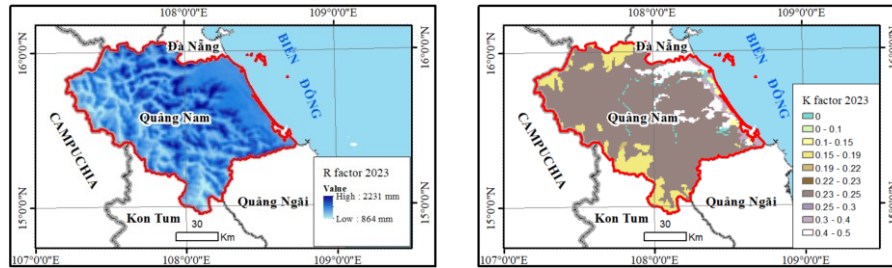


Fig 5. 2023 R factor (left and K factor (right) in 2023

Mountainous areas are mainly covered by dense vegetation while in coastal plains, infrastructure and bare land are dominant with sparse vegetation cover. This explains the low C values spatial distribution near the coastline and higher ones in the West and South West province. The P factor, on the other hand, is much higher in the coastal region due to the fact of advanced management land practices.

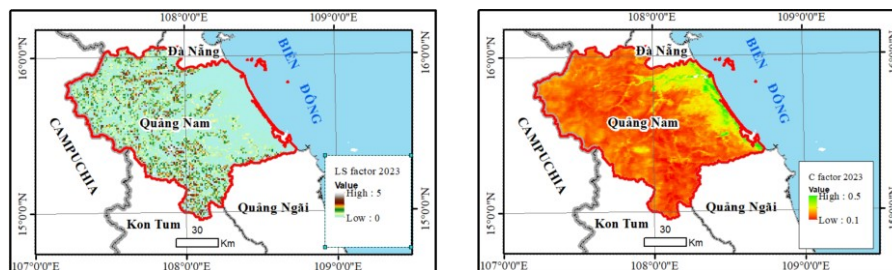


Fig 6. 2023 LS factor and C factor

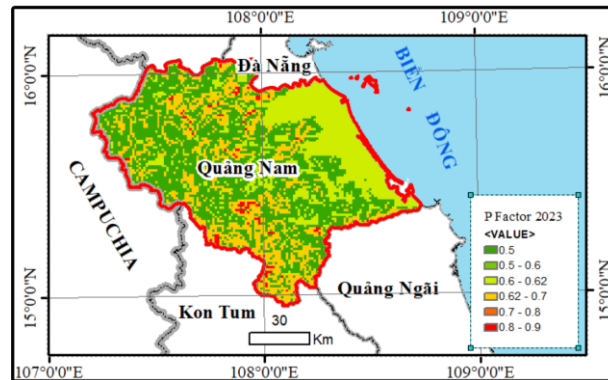


Fig 7. 2023 P factor

It appears that the variation of USLE factors have a major influence on variation of soil severity (figure 8). In the 2023 annual soil loss map, a vast majority of Quang Nam province is characterized from medium to extreme erosion.

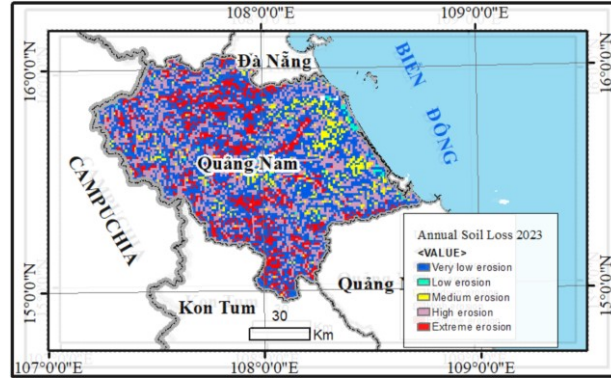


Fig 8. 2023 Annual Soil Loss (A) severity map

3.3 Soil Loss Prediction based AI Algorithms

Currently, we are examining parameters of the RF and SVM model for categorized non erosion and erosion risk across the study area. Since C and P are mainly connected to the NDVI. In the RF model, we took and trained data regarding the rainfall (for R factor), soil type – clay (for K), slope (for LS) and NDVI (for C and P) following the diagram in figure 1. Figure 9 illustrates spatial distribution of erosion areas (red color) and non-erosion (green) of 2023.

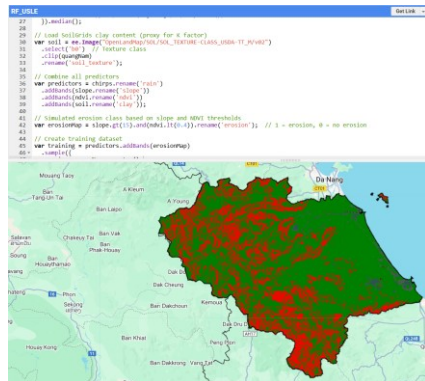


Fig 9. Random Forest soil erosion risk in GEE platform

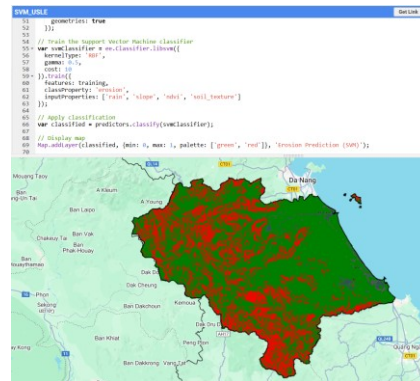


Fig 10. SVM soil erosion risk in GEE platform

Figure 10 presents the result of 2023 soil erosion risk generated by the SVM model. Sharing the same idea as the RF, results were categorized into non erosion and erosion area (green and red color on map, respectively).

For validating the results generated from the RF and SVM procedure, we exported those maps and performed the validation process with the 2023 soil erosion severity map in the GIS environment. Adhere, we examined the areas which were highlighted as “extremely eroded” since in the RF and SVM, we only focused on categorizing the

severe eroded ones. The values of accuracy and kappa parameters for RF and SVM are 80% and 0.6; 78% and 0.56 respectively which presents that the RF model's accuracy is fairly higher than the SVM one, though the accuracy of the SVM model can reach to "moderate agreement". However, since the Kappa is still low, there should be more model improvements or balancing data to boost the performance.

The LSTM, in the other hand, is more complicated to generate due to computing ability and language programming support in GEE. Thus, we decided to extract time series data from GEE (such as the NDVI, rainfall and slope) to *.csv format for further analysis (training and predicting). Predictions, then, will be reimported into GEE for visualization. For this model, we have taken opportunities to work on Google Colab to process the R and C factor which are subjects to change annually in our hypotheses while the LS, K and P factor are constant. There are many steps involved, such as: resizing the images, flattening and stacking all images based of rows and columns of pixels, then examining sizes of training samples. It has been a massive computing procedure and requires a high competent calculation with hundred attempts to figure out number of samples, epochs and batch sizes. Figure 11 shows our performance of the rainfall for R factor with 100 and 250 of epochs. Currently, we are still working on performing the LSTM for other factors.

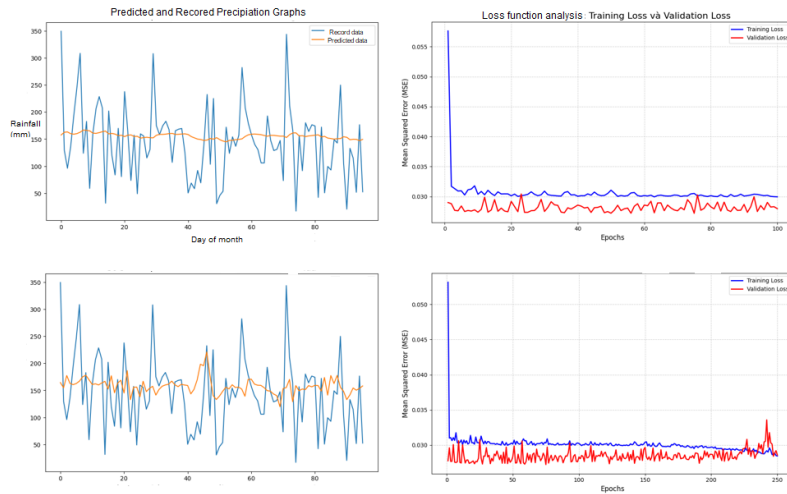


Fig 11. The LSTM performance for monthly rainfall prediction with epochs of 100 and 250 (top to bottom)

3.4 Discussion

This study tested three machine learning models — Random Forest (RF), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM, still in training) — for predicting soil erosion using remote sensing data on Google Earth Engine.

The RF model gave fast and reliable results and worked well with multiple environmental factors like rainfall, slope, vegetation, and soil texture. SVM also performed well but needed more tuning and didn't run as smoothly in GEE due to processing

limits. Further analysis for RF and SVM will be investigated to test on reliabilities of these two models.

The LSTM model, which is being trained externally, is expected to capture time-series changes in erosion patterns, such as seasonal shifts in rainfall and vegetation. While results are pending, it has strong potential for forecasting erosion trends rather than just mapping current risks.

One limitation we faced was the lack of detailed ground-truth data, especially for soil properties and land management practices. To address this, we simulated erosion labels based on slope and NDVI, which helped but also introduced uncertainty.

Even at this stage, the project shows that combining AI models with cloud-based tools like GEE can support scalable, low-cost erosion mapping. Once the LSTM model is finalized and more validation is done, this approach could be valuable for land managers, especially in data-scarce regions.

Future work will focus on finalizing the LSTM model, validating all model outputs using independent ground-truth data (where possible), and integrating user feedback into a web-based erosion app. This will strengthen the tool's practical utility for environmental managers, agricultural planners, and local authorities.

Acknowledgement

This research is sponsored by the research project T24 -2 “Research on an integration of a Recurrent Neural Network – LSTM (Long Short-Term Memory) and USLE model in forecasting soil erosion”, at Hanoi University of Mining and Geology.

We thank GEE team for the excellent platform and free data resources.

References

1. Lal, R., *Soil degradation by erosion*. Land degradation & development, 2001. **12**(6): p. 519-539.
2. Pimentel, D., & Kounang, N., *Ecology of soil erosion in ecosystems*. Ecosystems, 1998. **1**(5): p. 416-426.
3. Morgan, R.P.C., *Soil erosion and conservation (3rd ed)*. 2005: Blackwell Publishing.
4. Renard, K.G., Foster, G. R., Weesies, G. A., McCool, D. K., & Yoder, D. C., *Predicting soil erosion by water: A guide to conservation planning with the Revised Universal Soil Loss Equation (RUSLE)*. Vol. 703. 1997, USA: U.S. Department of Agriculture, Agriculture Handbook.
5. Nearing, M.A., Jetten, V., Baffaut, C., Cerdan, O., Couturier, A., Hernandez, M., ... & van Oost, K., *Modeling response of soil erosion and runoff to changes in precipitation and cover*. Catena, 2005. **61**(2-3): p. 131-154.
6. Nguyen, T.T., Pham, M. Q., & Chuong, H. V., *Soil erosion estimation using RUSLE, remote sensing, and GIS in a mountainous watershed of North Central Vietnam*. Environmental Earth Sciences, 2017. **76**(1): p. 66.
7. Vrieling, A., *Satellite remote sensing for water erosion assessment: A review*. Catena, 2006. **65**(1): p. 2-18.

8. Wulder, M.A., & Coops, N. C, *Satellites: Make Earth observations open access*. Nature, 2014. **513**(7516): p. 30-21.
9. Khosravi, K., Nhu, V. H., Chapi, K., Shirzadi, A., Dou, J., Panahi, M., ... & Lee, S., *A comparative assessment of decision trees algorithms for flash flood susceptibility modeling at Haraz watershed, northern Iran*. Science of the Total Environment, 2018(627): p. 744–755.
10. Pham, B.T., Bui, D. T., & Prakash, I., *Evaluation of machine learning methods for predicting soil erosion susceptibility*. Environmental Earth Sciences, 2019. **78**(206).
11. Dutta, D., Das, D. N., & Paul, S., *Machine learning models for predicting soil erosion using remote sensing data: A review*. Environmental Research, 2022(204).
12. Pham, B.T., Prakash, I., Bui, D. T., Dholakia, M. B., & Dinh, D. T., *A comparative study of support vector machines and random forests for landslide susceptibility modeling: A case study from Uttarakhand area (India)*. Remote Sensing of Environment, 2017(202): p. 18-27.
13. Kratzert, F., Klotz, D., Herrnegger, M., Sampson, A. K., Hochreiter, S., & Nearing, G. S., *Toward improved predictions in ungauged basins: Exploiting the power of machine learning*. Water Resources Research, 2019. **55**(12): p. 11344-11364.
14. Ghose, D., Samui, P., & Sitharam, T. G., *Time series prediction using LSTM networks for environmental systems*. Neural Computing and Applications, 2022. **34**(1): p. 651-662.
15. Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R, *Google Earth Engine: Planetary-scale geospatial analysis for everyone*. Remote Sensing of Environment, 2017. **202**: p. 18-27.
16. Hansen, M.C., & Loveland, T. R., *A review of large area monitoring of land cover change using Landsat data*. Remote Sensing of Environment, 2012. **122**: p. 66-74.
17. Zhou, P., Luukkanen, O., Tokola, T., & Nieminen, J., *Effect of vegetation cover on soil erosion in a mountainous watershed*. Catena, 2008. **75**(3): p. 319-325.
18. Arjhani, M., & Xu, X., *Estimation of soil erosion using RUSLE and remote sensing data: A case study in the Seymareh Dam Basin, Iran*. Remote Sensing, 2022. **14**(9): p. 2083.
19. Ouellette, W., *Soil Erosion Watch RUSLE (Version 1.0.0)*, in Github. 2021.
20. Basu, S., & Mehta, A., *Integrating machine learning and cloud-based geospatial platforms for environmental monitoring: Potentials and challenges*. Environmental Modelling & Software, 2021(144): p. 105136.
21. Wischmeier, W.H., & Smith, D. D., *Predicting rainfall erosion losses - A guide to conservation planning*. Vol. 537. 1978, USA: U.S. Department of Agriculture, Agriculture Handbook.
22. Angulo-Martínez, M., & Beguería, S., *Estimating rainfall erosivity from daily rainfall records: A comparison among methods using data from the Ebro Basin (NE Spain)*. Journal of Hydrology, 2009. **379**(1-2): p. 111-121.
23. Wischmeier, W.H., & Mannering, J. V., *Relation of soil properties to its erodibility*. Soil Science Society of America Journal, 1969. **33**(1): p. 131-137.
24. Liu, B.Y., Nearing, M. A., Shi, P. J., & Jia, Z. W., *Slope length effects on soil loss for steep slopes*. Soil Science Society of America Journal, 2000. **64**(5): p. 1759-1763.
25. McCool, D.K., Foster, G. R., Mutchler, C. K., & Meyer, L. D., *Revised slope length factor for the Universal Soil Loss Equation*. Transactions of the ASAE, 1989. **32**(5): p. 1571-1576.

26. Desmet, P.J.J., & Govers, G., *A GIS procedure for automatically calculating the USLE LS factor on topographically complex landscape units*. Journal of Soil and Water Conservation, 1996. **51**(5): p. 427-433.
27. Durigon, V.L., Carvalho, D. F., Antunes, M. A. H., Oliveira, P. T. S., & Fernandes, M. M., *NDVI time series for monitoring RUSLE cover management factor in a tropical watershed*. International Journal of Remote Sensing, 2014. **35**(2): p. 441-453.
28. Panagos, P., Meusburger, K., Alewell, C., & Montanarella, L., *Soil conservation in Europe: Wish or reality?* Land Degradation & Development, 2014. **25**(1): p. 1-14.
29. Breiman, L., *Random forests*. Machine Learning, 2001. **45**(1): p. 5-32.
30. Cortes, C., & Vapnik, V., *Support-vector networks*. Machine Learning, 1995. **20**(3): p. 273-297.
31. Hochreiter, S., & Schmidhuber, J., *Long short-term memory*. Neural Computation, 1997. **9**(8): p. 1735-1780.
32. Nguyen, H.T., Pham, V. N., Le, A. N., & Tran, D. K., *Application of RUSLE and GIS for soil erosion risk assessment in Quang Nam Province, Vietnam*. Geocarto International, 2020. **35**(8): p. 761-777.
33. Tung Gia Pham, J.D., Martin Kappas., *Integrated universal soil loss equation (USLE) and Geographical Information System (GIS) for soil erosion estimation in A Sap basin: Central Vietnam*. International Soil and Water Conservation Research, 2018. **6**(2): p. 99-110.