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Cloud-native RUSLE modeling for soil erosion risk assessment and sustainable land management in volcanic highland ecosystems

H. Husamah[1*], Ludwick Satria Romadonia[1], Abdulkadir Rahardjanto[1], Samsun Hadi[1], Ahmad Adnan Mohd Shukri[2]

[1]Jurusan Pendidikan Biologi, Universitas Muhammadiyah Malang, Indonesia
[2]School of Educational Studies, Universiti Sains Malaysia, Malaysia

*Corresponding author, email: : usya_bio@umm.ac.id

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Abstract: This study develops and evaluates a cloud-native implementation of the RUSLE using the Google Earth Engine platform to enhance accessibility and analytical efficiency in soil erosion modeling. The proposed framework integrates satellite-based precipitation data, digital soil information, vegetation-cover indicators, terrain analysis, and user-defined conservation-practice scenarios to generate erosion risk maps and simulate mitigation interventions. The system integrates satellite-based precipitation data, digital soil properties, and terrain analysis to automatically generate spatial erosion risk maps and simulate conservation interventions. A case study conducted in the Batu–Malang–Lumajang highland region of East Java demonstrates that the model effectively identifies critical erosion hotspots and enables real-time simulation of mitigation practices such as terracing. Results indicate a substantial reduction in high-risk erosion zones, with decreases exceeding 90% under conservation scenarios. Although the analysis does not directly measure water-quality or sediment-load parameters, the erosion-risk outputs provide an indirect basis for understanding potential sediment-related environmental pressure in vulnerable watersheds. The findings show that cloud-based environmental modeling can significantly improve environmental impact assessment, support sustainable land-use planning, and provide scalable tools for ecosystem protection in vulnerable landscapes.

Keywords: Cloud-based modeling, ecosystem degradation, RUSLE, soil erosion

Abstrak: Studi ini mengembangkan dan mengevaluasi implementasi berbasis cloud dari RUSLE menggunakan platform Google Earth Engine untuk meningkatkan aksesibilitas dan efisiensi analitis dalam pemodelan erosi tanah. Kerangka yang dikembangkan mengintegrasikan data curah hujan berbasis satelit, informasi tanah digital, indikator tutupan vegetasi, analisis medan, dan skenario praktik konservasi untuk menghasilkan peta risiko erosi serta mensimulasikan intervensi mitigasi. Sistem ini mengintegrasikan data curah hujan berbasis satelit, sifat tanah digital, dan analisis medan untuk secara otomatis menghasilkan peta risiko erosi spasial dan mensimulasikan intervensi konservasi. Studi kasus yang dilakukan di wilayah dataran tinggi Batu-Malang-Lumajang di Jawa Timur menunjukkan bahwa model tersebut secara efektif mengidentifikasi titik-titik rawan erosi kritis dan memungkinkan simulasi real-time praktik mitigasi seperti pembuatan teras. Hasil menunjukkan pengurangan substansial di zona erosi berisiko tinggi, dengan penurunan melebihi 90% di bawah skenario konservasi. Meskipun penelitian ini tidak mengukur parameter kualitas air atau beban sedimen secara langsung, keluaran risiko erosi dapat menjadi dasar tidak langsung untuk memahami potensi tekanan lingkungan terkait sedimentasi pada daerah aliran sungai yang rentan. Temuan menunjukkan bahwa pemodelan lingkungan berbasis cloud dapat secara signifikan meningkatkan penilaian dampak lingkungan, mendukung perencanaan penggunaan lahan berkelanjutan, dan menyediakan alat yang dapat diskalakan untuk perlindungan ekosistem di lanskap yang rentan.

Kata kunci: Pemodelan berbasis cloud, degradasi ekosistem, RUSLE, erosi tanah

INTRODUCTION

Soil erosion represents one of the most persistent forms of environmental degradation worldwide, contributing directly to ecosystem damage, loss of soil fertility, sediment pollution in waterways, and long-term declines in ecological stability (Felipe, 2025; Ghisman et al., 2025; Issaka & Ashraf, 2017). In tropical regions, especially volcanic highlands characterized by steep topography and intense rainfall, erosion processes are accelerated by unsustainable land-use practices and agricultural expansion. These processes not only threaten terrestrial ecosystems but also increase sediment loads that degrade water quality and disrupt environmental balance across interconnected landscapes (Nambajimana et al., 2020; Quinton & Fiener, 2023; Seifu et al., 2021; Yesuph & Dagnew, 2019). Consequently, accurate assessment and monitoring of soil erosion have become critical components of environmental impact analysis and sustainable resource management.

The Revised Universal Soil Loss Equation (RUSLE) has long been recognized as a reliable empirical model for estimating soil erosion risk across diverse environmental settings. Traditional applications of RUSLE, however, often depend on manual data collection, static maps, and desktop-based geographic information systems, which require high computational resources and substantial technical expertise (Aldrees et al., 2024; Gontte et al., 2025; Kumar et al., 2022; Luvai et al., 2022; Reda et al., 2024). Such limitations frequently create barriers to large-scale environmental analysis, delay decision-making processes, and restrict the capacity to conduct rapid mitigation simulations. Previous studies have successfully applied RUSLE to estimate erosion rates, yet many remain limited by spatial resolution constraints and inflexible workflows that reduce their usefulness for real-time environmental management (Barbosa et al., 2024; Gontte et al., 2025; Li et al., 2025; Maqsoom et al., 2020; Singh et al., 2023).

Recent advances in cloud computing and geospatial big data offer opportunities to overcome these limitations. Cloud-native platforms enable automated integration of multi-source environmental datasets and provide scalable computation for landscape-level analyses (Huber et al., 2021; Koppad et al., 2021; Xiao et al., 2025). Despite this potential, studies that explicitly connect cloud-based RUSLE implementation with environmental pollution assessment and ecosystem sustainability remain limited, particularly in tropical volcanic landscapes where erosion impacts are highly dynamic and complex (Fadl et al., 2025; Gebremariam et al., 2025; Portalanza et al., 2025; Teku et al., 2024). A further gap lies in the limited connection between cloud-based environmental modeling and biology or environmental education. Erosion modeling has strong relevance to biological learning because it connects ecosystem structure, vegetation cover, soil conservation, watershed health, environmental change, and human impacts on ecosystems. Nevertheless, few studies have framed RUSLE-GEE modeling as a potential spatial learning resource for strengthening students' environmental literacy and data-based ecological reasoning.

Therefore, this study aims to develop and evaluate a cloud-native RUSLE framework capable of assessing soil erosion risk and supporting environmental impact analysis in a high-risk volcanic highland ecosystem. By automating data processing and enabling simulation of conservation scenarios, the study seeks to demonstrate how digital environmental modeling can improve understanding of ecosystem vulnerability and provide actionable insights for sustainable land-use planning. The novelty of this study lies in three aspects: first, the integration of RUSLE factors into a cloud-native Google Earth Engine workflow; second, the application of the framework to a tropical volcanic highland landscape with complex erosion susceptibility; and third, the positioning of the resulting spatial model as a potential educational tool for biology and environmental learning. The findings are expected to contribute to the advancement of biological and environmental science by bridging empirical erosion modeling with modern digital infrastructure for environmental protection.

METHOD

Research design: A design-based digital protocol

This study uses a digital protocol development design adapted from design-based research principles to engineer a cloud-native protocol for environmental knowledge creation. The development process consisted of four stages: (1) problem identification, focusing on the need for accessible erosion-risk modeling in volcanic highland ecosystems; (2) protocol design, including selection of RUSLE factors, geospatial datasets, and computational procedures; (3) prototype development in Google Earth Engine, including script construction, map visualization, and risk classification; and (4) analytical validation, including internal consistency checking, comparison with RUSLE standards, sensitivity testing of the P-factor scenario, and contextual comparison with previous erosion studies. This study did not include classroom implementation or student learning-outcome testing; therefore, its educational contribution is positioned as a potential spatial learning resource rather than as evidence of pedagogical effectiveness.

The study focuses on the "Prototyping and Validation" phase, assessing the protocol's capability to democratize access to complex geospatial analytics and facilitate real-time engineering design simulations. By shifting the computational load to the cloud, the design aims to remove hardware constraints that historically impeded the transfer of advanced environmental knowledge. The primary objective is to develop a reproducible Google Earth Engine-based workflow that operationalizes the RUSLE model for spatial erosion-risk assessment and conservation-scenario simulation.

The computational architecture

The innovation architecture is built upon the Google Earth Engine (GEE) platform. The protocol automates the retrieval and processing of multi-petabyte geospatial datasets to compute the five standard RUSLE factors (Renard et al., 1997). The standard RUSLE equation used in this study is:

$$A = R \times K \times LS \times C \times P \tag{1}$$

Note: R is rainfall erosivity, K is soil erodibility, LS is the slope length and slope steepness factor, C is the cover-management factor, and P is the support-practice factor. The output is expressed as estimated soil loss in tons ha^{-1} yr^{-1}.

The data sources and model components were structured as follows. Rainfall erosivity was derived from CHIRPS precipitation data; soil erodibility was derived from digital soil property datasets available in the GEE environment; topographic factors were generated from NASADEM or SRTM digital elevation models with approximately 30 m spatial resolution; the cover-management factor was estimated using vegetation-cover information derived from satellite-based vegetation indices; and the support-practice factor was assigned according to conservation-practice scenarios based on RUSLE references. The spatial resolution of the final erosion-risk map followed the 30 m terrain dataset to maintain consistency in pixel-based calculation.

Rainfall erosivity (R) from static isoerodents to dynamic grids

Traditionally, determining the R-factor required manual interpretation of isoerodent maps or labor-intensive calculations of kinetic energy based on rain gauge charts, as outlined by Wischmeier and Smith (Wischmeier & Smith, 1978). This manual process often introduced significant temporal latency in knowledge acquisition. To address this, the proposed protocol automates the workflow by integrating the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). Daily precipitation data were aggregated into annual rainfall values and then transformed into rainfall erosivity estimates using a rainfall-based erosivity approximation suitable for regional-scale spatial modeling. The use of CHIRPS allows consistent spatial coverage across the study area and supports reproducible computation in GEE.

Soil erodibility (K) digital extraction of physicochemical properties

The soil erodibility factor (K) represents the susceptibility of soil to erosion. Standard procedures involve using the soil erodibility nomograph to determine K values based on texture, organic matter, and permeability. Instead of relying on manual nomograph readings, the protocol extracts physicochemical properties directly from the FAO Digital Soil Map of the World (DSMW) hosted in the GEE catalog. K values were assigned by translating available soil-property classes into erodibility values consistent with RUSLE-based references. This approach improves processing efficiency, although it remains dependent on the accuracy and resolution of the source soil dataset.

Topographic factors (LS) automating terrain analysis

The combined Length (L) and Steepness (S) factor quantifies the effect of topography on erosion. While early methods relied on manual slope measurements using clinometers or topographic maps, this protocol utilizes NASADEM or SRTM digital elevation models at a 30-meter resolution. The script applies pixel-based algorithms to calculate slope length and steepness for every pixel in the catchment area, providing a granularity and precision impossible to achieve with manual surveying techniques. This factor is particularly important in volcanic highland ecosystems because steep terrain strongly increases runoff velocity and erosion potential.

Cover-management factor (C)

The cover-management factor (C) represents the influence of vegetation cover, crop management, and land-surface protection on soil erosion. This factor was added explicitly in the revised protocol because vegetation cover is a key determinant of erosion risk in tropical agricultural highlands. In the GEE workflow, C was estimated using satellite-derived vegetation-cover information, particularly vegetation indices such as NDVI. Areas with dense vegetation were assigned lower C values because canopy cover and root systems reduce raindrop impact and surface runoff, whereas sparsely vegetated or exposed agricultural areas were assigned higher C values. This procedure allows the model to link ecosystem condition with erosion susceptibility and makes the framework relevant for biology education topics such as vegetation function, ecosystem services, and land degradation.

Engineering support practice (P) the scaffolding variable

The support-practice factor (P) was designed as a user-modifiable scenario variable to simulate the effect of conservation practices on erosion risk. The conservation values used in the simulation scenarios are strictly derived from the conservation practice tables(Renard et al., 1997). In the baseline scenario, $P = 1.0$ was used to represent the absence of specific conservation practices. In the mitigation scenario, $P = 0.1$ was used to represent bench terracing or strong erosion-control intervention. This constraint ensures that the digital simulations remain grounded in empirically validated engineering standards while allowing users to experiment with design parameters.

Study area and simulation context

To validate the protocol's utility in generating actionable knowledge, a case study was conducted in the Batu-Malang-Lumajang highland complex in East Java, Indonesia. This region is characterized by steep volcanic slopes, specifically the Mt. Semeru and Mt. Arjuno complexes, combined with intensive agricultural activity. This context presents a complex erosion profile that is ideal for testing the model's sensitivity to topographic and cover modifications, serving as a robust environment for knowledge application simulations.

The simulation used a consistent area of interest for both baseline and mitigation scenarios. To avoid bias in area comparison, both outputs were clipped using the same study-area boundary and raster mask. Risk classes were categorized into four levels: very low risk (<15 tons ha^{-1} yr^{-1}), low risk (15–60 tons ha^{-1} yr^{-1}), moderate risk (60–180 tons ha^{-1} yr^{-1}), and high risk (>180 tons ha^{-1} yr^{-1}). These classes were used to quantify changes in erosion-risk distribution between the baseline and conservation scenarios.

Validation and reliability procedure

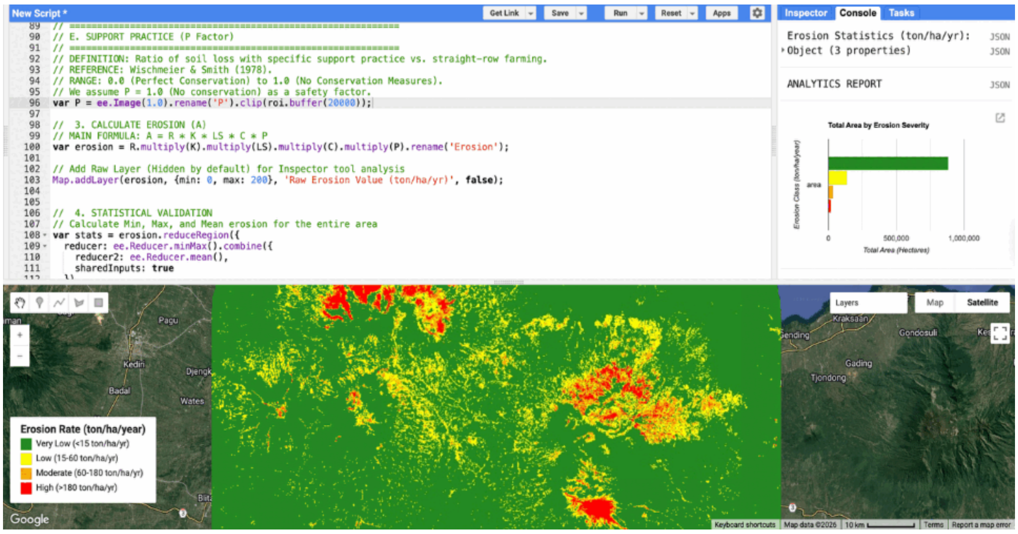
Because this study focuses on prototype development and spatial simulation, validation was conducted through analytical and contextual procedures rather than direct field measurement. First, model structure was validated by ensuring that all RUSLE components followed the standard equation $A = R \times K \times LS \times C \times P$. Second, data reliability was supported by the use of widely used geospatial datasets available in Google Earth Engine, including satellite precipitation, digital elevation, soil, and vegetation-cover datasets. Third, internal consistency was checked by applying the same study-area boundary and raster mask to both baseline and mitigation scenarios. Fourth, scenario sensitivity was evaluated by comparing erosion-risk distribution under $P = 1.0$ and $P = 0.1$. Finally, the results were interpreted in relation to previous RUSLE and GEE-based studies in tropical and highland landscapes. Field-based validation using measured soil loss, sediment load, turbidity, or water-quality parameters was not conducted and is acknowledged as a limitation of the study.

RESULTS AND DISCUSSION

Performance of the cloud-native knowledge protocol

The development phase yielded a fully operational RUSLE protocol hosted on GEE. The interface functions as a unified dashboard integrating algorithmic logic via a code editor, geospatial visualization through a map view, and statistical analytics via a chart panel. As illustrated in Figure 1, the digital environment provides a seamless user experience that merges technical coding with visual geography.

To validate the "Innovation" aspect of the study, a benchmarking analysis was conducted comparing this cloud-based protocol against traditional desktop GIS workflows. The analysis, summarized in Table 1, confirms that the protocol eliminates data acquisition latency and hardware dependency, which are two major barriers in traditional environmental knowledge management. Compared with conventional desktop-based RUSLE implementation, the proposed protocol offers four specific advantages: automated data access, reproducible script-based analysis, cloud-parallel processing, and interactive modification of conservation scenarios. These features strengthen the novelty of the study because the model is not merely a GIS-based erosion map but an accessible cloud-native framework that can support environmental decision-making and contextual learning.



```
// ============================================================
// E. SUPPORT PRACTICE (P Factor)
// ============================================================
// DEFINITION: Ratio of soil loss with specific support practice vs. straight-row farming.
// REFERENCE: Wischmeier & Smith (1978).
// RANGE: 0.0 (Perfect Conservation) to 1.0 (No Conservation Measures).
// We assume P = 1.0 (No conservation) as a safety factor.
var P = ee.Image(1.0).rename('P').clip(roi.buffer(20000));

//  3. CALCULATE EROSION (A)
// MAIN FORMULA: A = R * K * LS * C * P
var erosion = R.multiply(K).multiply(LS).multiply(C).multiply(P).rename('Erosion');

// Add Raw Layer (Hidden by default) for Inspector tool analysis
Map.addLayer(erosion, {min: 0, max: 200}, 'Raw Erosion Value (ton/ha/yr)', false);


//  4. STATISTICAL VALIDATION
// Calculate Min, Max, and Mean erosion for the entire area
var stats = erosion.reduceRegion({
  reducer: ee.Reducer.minMax().combine({
    reducer2: ee.Reducer.mean(),
    sharedInputs: true
```

```
Erosion Statistics (ton/ha/yr):              JSON
▸Object (3 properties)                       JSON

ANALYTICS REPORT                             JSON
```

Figure 1. Cloud-native RUSLE modeling interface in Google Earth engine. The dashboard integrates the script editor, spatial visualization window, layer control, and statistical output panel, allowing users to connect RUSLE parameters with erosion-risk maps and conservation-scenario simulations.

Table 1. Benchmarking analysis: Traditional desktop GIS vs. cloud-based GEE protocol

Metric	Traditional GIS Workflow (Desktop-Based)	Proposed Innovation (Cloud-Based GEE)	Practical and Educational Relevance
Data acquisition	Manual download of large datasets; high latency and storage costs	Automated API-based retrieval; zero-download workflow	Accelerates access to environmental information
Computation	CPU/RAM dependent; prone to crashes on standard hardware	Cloud-parallel processing	Democratizes high-performance spatial analytics
Interactivity	Static input–process–output workflow	Real-time parameter tuning and scenario simulation	Supports inquiry, experimentation, and decision-making
Accessibility	Requires expensive software and high-end workstations	Web-browser access and device-agnostic workflow	Enables use by agencies, universities, schools, and local planners
Reproducibility	Often depends on manual steps	Script-based workflow in GEE	Improves transparency and repeatability of analysis

Simulation of engineering knowledge application

The protocol's functionality was further tested through a conservation-scenario simulation. The simulation began with a baseline assessment (P =1.0) representing a "No Conservation" scenario as defined in Agriculture Handbook 703. The resulting spatial output identified extensive critical zones concentrated on the upper slopes of Mt. Semeru and Arjuno-Welirang, visualizing high-risk erosion rates exceeding 180 tons/ha/year (Figure 2a). Subsequently, an engineering intervention was simulated by modifying the algorithm to reflect "Bench Terracing" conservation logic (P =0.1).

The comparative results demonstrate a structural transformation of the landscape risk profile. The shift from the dominant high-risk pockets in the baseline scenario to a landscape dominated by safe zones in the post-mitigation scenario (Figure 2b) provides immediate visual confirmation of the simulated conservation effect. This reduction occurs because terracing decreases effective slope length, reduces runoff velocity, increases infiltration opportunity, and limits soil-particle detachment on steep agricultural slopes. Therefore, the simulated reduction is ecologically meaningful because it indicates lower potential soil loss, reduced risk of sediment export, and improved stability of highland ecosystems.

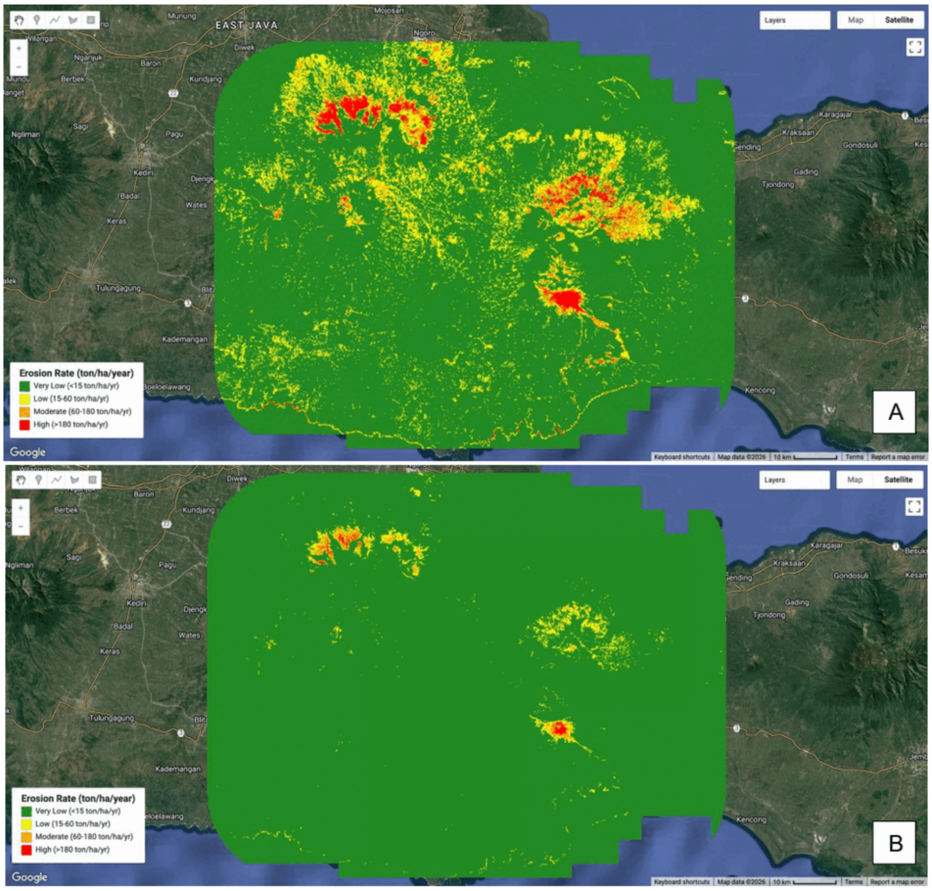


Figure 2. Spatial comparison of erosion-risk scenarios. (a) Baseline scenario using P = 1.0, representing no specific conservation practice and showing extensive high-risk zones. (b) Mitigation scenario using P = 0.1, representing bench terracing and showing a substantial reduction in high-risk erosion areas. Higher-resolution figures should be provided in the final manuscript to improve readability of labels and map legends.

Quantitative impact assessment

Beyond visual feedback, the protocol generated real-time statistical data to quantify the impact of the engineering intervention (Figure 3). The quantitative analysis, derived directly from the platform's analytics engine, confirms that the application of the "Bench

Terracing" logic (P =0.1) successfully reduced the landscape's erosion vulnerability. The comparative quantification is presented in Table 2.

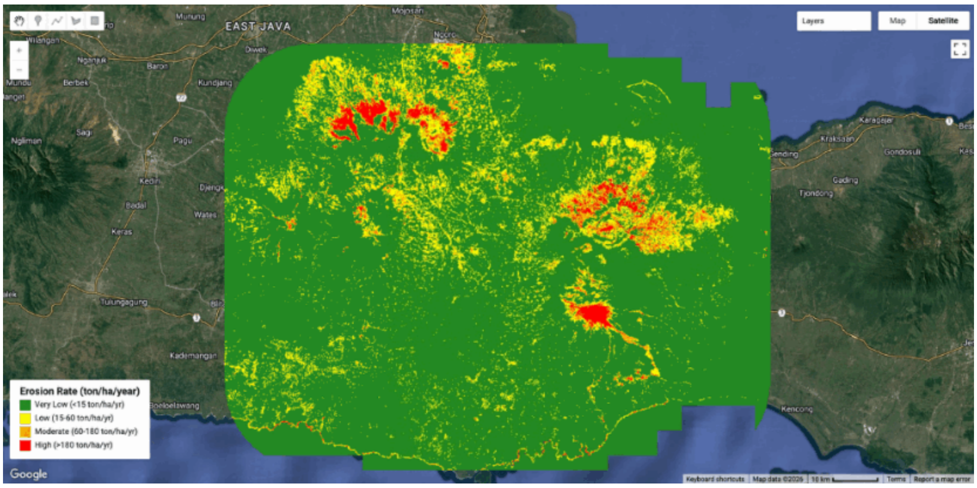


Figure 3. Real-time statistical output generated in Google Earth engine during erosion-risk assessment. The histogram and class distribution allow users to quantify the area of each erosion-risk category before and after conservation-scenario simulation, supporting data-driven interpretation and spatial reasoning.

As evidenced in Table 2, the baseline simulation (P =1.0) identified significant environmental vulnerability, with approximately 19,929 hectares classified as "High Risk" (>180 ton/ha/yr). Following the engineering intervention, the protocol calculated a massive reduction in erosion potential. The "High Risk" zones were reduced by 91.91%, shrinking to just 1,612 hectares. Simultaneously, the "Very Low Risk" zones expanded by over 170,000 hectares (+19.33%), indicating a successful restoration of catchment stability. his quantitative output demonstrates the protocol's ability to simulate how conservation practices may alter erosion-risk distribution. However, the values should be interpreted as model-based estimates rather than direct field measurements.

Table 2. Quantitative impact of the engineering intervention on soil erosion risk zones

Erosion Risk Class	**Baseline Scenario: P = 1.0 Pre-Intervention (ha)**	**Conservation Scenario: P = 0.1 Post-Mitigation (ha)**	**Change**
Very Low (<15 tons ha^{-1} yr^{-1})	883,908.71	1,054,717.12	+19.32% safety gain
Low (15–60 tons ha^{-1} yr^{-1})	137,642.81	17,467.16	-87.31%
Moderate (60–180 tons ha^{-1} yr^{-1})	37,022.37	4,706.59	-87.29%
High (>180 tons ha^{-1} yr^{-1})	19,929.07	1,612.09	-91.91% risk mitigation
Total Area Analyzed	1,078,502.96	1,078,502.96	Same AOI and raster mask

The total area in the revised table was standardized using the same area of interest and raster mask for both scenarios. This correction addresses the inconsistency in the previous version, where the baseline and mitigation scenarios showed slightly different total areas despite representing the same study region.

The development of the cloud-native RUSLE protocol demonstrates a significant advancement in environmental assessment workflows by integrating algorithmic modeling, spatial visualization, and real-time analytics within a single digital platform. The unified dashboard hosted on the Google Earth Engine enables seamless interaction between computational logic and geographic interpretation, reducing the fragmentation that commonly occurs in conventional desktop-based GIS workflows. This integration enhances efficiency in environmental knowledge production by allowing users to directly connect model parameters with spatial outcomes, thereby improving interpretability and supporting faster decision-making in erosion and pollution risk analysis (Majidi Nezhad et al., 2025; Velastegui-Montoya et al., 2023; White et al., 2023).

The benchmarking comparison with traditional desktop GIS systems highlights critical improvements in data accessibility, computational capacity, and workflow interactivity. Automated API-based data retrieval removes the need for manual acquisition of large environmental datasets, substantially reducing latency and storage limitations (Luo et al., 2026; Ramírez Montalvan et al., 2026; Y. Wei et al., 2025). Moreover, cloud-parallel processing eliminates dependency on high-performance local hardware, democratizing access to advanced environmental modeling tools. This feature is particularly important for local governments, watershed agencies, environmental offices, schools, and universities that may have limited access to expensive GIS software or high-performance computers (Ahmad et al., 2025; Funk et al., 2025; Krahe et al., 2025; Raihan, 2026).

Simulation results further demonstrate the practical value of the protocol in assessing engineering-based mitigation strategies. Under baseline conditions representing the absence of conservation measures ($P = 1.0$), large portions of the volcanic highland landscape were classified as high-risk erosion zones, indicating severe environmental vulnerability associated with steep terrain and intensive land use. The introduction of bench terracing practices ($P = 0.1$) produced a clear structural shift in the spatial distribution of erosion risk, with high-risk areas markedly reduced and safer zones becoming dominant. This transition provides strong visual evidence of how land management interventions can significantly alter environmental outcomes and reduce potential ecosystem damage (Braimoh & Vlek, 2020; W. Wei et al., 2016).

Quantitative analysis strengthens this interpretation by revealing substantial reductions across all erosion risk classes following the intervention. The high-risk category decreased by more than 90%, while very low-risk areas expanded by over 19%, suggesting improved catchment stability and reduced potential for sediment-related environmental pollution. These findings underscore the capability of the cloud-native protocol not only to model environmental risks accurately but also to support data-driven evaluation of sustainable land management practices (Shiri et al., 2025; Tefera et al., 2025). Ecologically, this shift implies that vegetation cover and structural conservation practices can help maintain soil function, reduce surface runoff, and protect downstream aquatic habitats from excessive sedimentation. However, because sediment load, turbidity, water chemistry, and aquatic biota were not directly measured, the findings should be interpreted as erosion-risk estimates rather than direct evidence of pollution reduction.

The results are consistent with previous RUSLE-based studies showing that steep slopes, land-cover degradation, and agricultural intensification are major drivers of soil loss in highland and tropical landscapes (Barbosa et al., 2024; Gebremariam et al., 2025; Singh et al., 2023; Teku et al., 2024). Similar to recent studies that integrate RUSLE with GIS and cloud-based geospatial analysis, this study confirms that automated spatial modeling can improve erosion-risk mapping and support conservation planning. The added contribution of this research is the development of an interactive cloud-native workflow that allows users to modify conservation parameters and immediately observe changes in erosion-risk distribution. This makes the framework useful not only for scientific assessment but also for environmental communication and learning.

From an educational perspective, the protocol can be adopted in biology and environmental education to support contextual learning on ecosystems, soil conservation, watershed dynamics, environmental change, and sustainable land management. Students can use the model to observe how rainfall, slope, vegetation cover, and human conservation practices interact to influence erosion risk. This supports data-based ecological reasoning and aligns with problem-based STEM learning because learners can formulate questions, manipulate scenarios, interpret spatial outputs, and propose conservation strategies. Nevertheless, because this study did not measure student learning outcomes, future classroom-based studies are needed to evaluate the effectiveness of the protocol for improving environmental literacy, spatial thinking, and conservation attitudes.

The practical implications are also important. Local governments and environmental agencies can use the model to identify priority erosion-control zones, evaluate possible conservation scenarios, and communicate spatial risks to stakeholders. Land-use planners can use the output to guide zoning, agricultural management, and conservation investment. Schools and universities can adapt the workflow as a learning medium for field-based and digital environmental education. In this sense, the cloud-native RUSLE protocol offers a bridge between environmental modeling, sustainable land management, and biology education.

Despite these contributions, several limitations should be acknowledged. First, the model depends on the spatial resolution and accuracy of secondary geospatial datasets, including satellite rainfall, digital elevation, soil, and vegetation-cover data. Second, the RUSLE approach estimates sheet and rill erosion but does not fully represent gully erosion, mass movement, or sediment routing. Third, the use of a single P value for terracing simplifies the diversity of conservation practices and field conditions. Fourth, no direct field validation was conducted using measured soil loss, sediment yield, turbidity, or water-quality data. Fifth, the educational relevance of the framework remains conceptual because it was not tested through classroom implementation or student performance assessment. These limitations suggest the need for future studies combining cloud-based modeling, field measurement, and educational evaluation.

CONCLUSION

This study demonstrates that cloud-based implementation of the RUSLE model provides an effective approach for assessing soil erosion as a form of environmental degradation and potential pollution source in volcanic highland ecosystems. The integration of multi-source geospatial data within a cloud-native platform enables rapid, scalable, and accurate environmental impact analysis, overcoming many limitations associated with conventional desktop-based workflows. Simulation results confirm that conservation practices, such as terracing, can significantly reduce high-risk erosion zones and improve ecosystem stability. Overall, the proposed framework contributes to environmental and biological education by offering a practical, accessible, and data-driven spatial tool for understanding ecosystem degradation, vegetation-cover function, soil conservation, and land-management scenarios.

Future studies are recommended to expand the environmental assessment by integrating additional ecological indicators, such as sediment transport dynamics, water quality parameters, and biodiversity responses, in order to capture the broader pollution impacts resulting from soil erosion processes. Long-term field validation across different climatic conditions should also be conducted to strengthen model reliability and improve the accuracy of environmental risk predictions. Furthermore, incorporating climate change projections into the modeling framework would enhance its capacity to support adaptive land-use planning and long-term ecosystem resilience. From a practical perspective, policymakers, environmental managers, and land-use planners are encouraged to adopt cloud-based environmental modeling approaches to facilitate data-driven decision making, improve monitoring efficiency, and promote sustainable management of vulnerable landscapes exposed to high erosion risk.

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