



Accelerating Students' Environmental Knowledge Creation through Digital Transformation: A Cloud-Native Geospatial Protocol for Soil Erosion Management

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Abstract

The application of cloud-native geospatial protocol in environmental science learning is novel and rare, warranting further in-depth study. This study aims to analyze cloud-native geospatial protocol for soil erosion management as part of the environmental science courses. This study employed a Design-Based Research (DBR) approach within the STEM learning framework. This study focused on prototyping the learning materials and validating their effectiveness through simulation the Revised Universal Soil Loss Equation (RUSLE) model hosted on Google Earth Engine. The Cloud-Native Geospatial Protocol serves as a valid and effective instructional material for environmental sciences learning. It successfully accelerates environmental knowledge creation by transforming abstract STEM concepts into visual and quantifiable experiences. This learning model simulates the annual reduction in soil erosion risk, providing a concrete context for mathematical and engineering reasoning in solving environmental problems.

Keywords: Cloud; digital; environmental sciences; RUSLE, STEM

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INTRODUCTION

The rapid development of digital technology has become a major force in education, transforming how students learn and how teachers design instruction. Technology facilitates access to a wide range of devices and applications that support learning, while also creating more interactive, effective, and engaging educational environments (Cheung et al., 2021; Haleem et al., 2022; Lim et al., 2025; Mena-Guacas et al., 2025; Mhlongo et al. Souza & Debs, 2024; 2023; Wang et al., 2024;; Zhang et al., 2025). In this context, digital learning environments expand access to broad, diverse, and in-depth learning resources beyond geographical boundaries, enabling students to explore scientific issues more actively and meaningfully (Banerjee et al., 2022; Mhlongo et al., 2023; Yu et al., 2024). One promising innovation is the use of a cloud-native geospatial simulation protocol in environmental science. Cloud-native systems are designed from the outset for cloud environments and offer key advantages such as scalability, resilience, and flexibility, making them well-suited for data-intensive educational applications (FreeWheel Biz-UI Team, 2025; Prangon & Wu, 2024; Raj et al., 2022).

The integration of cloud-native geospatial protocols into environmental science is particularly relevant for addressing complex environmental problems such as soil erosion, which requires spatial analysis, real-time data handling, and evidence-based decision

n-making. Soil erosion remains an urgent environmental issue because it degrades land productivity, threatens watershed functions, and increases ecological risk, yet these processes are often difficult for students to visualize and analyze using conventional instruction. Recent studies have highlighted the potential of geospatial technology, Geographic Information Systems, and cloud-based urban digital systems for environmental analysis and management (Alamri, 2024; Giuliani et al., 2024; Jeddoub et al., 2025; X. Li et al., 2024; Mkhitarian et al., 2025; Onungwa et al., 2021; Thakur et al., 2017; VoPham et al., 2024; Yang et al., 2017). However, their integration into classroom learning, especially through cloud-native geospatial protocols for soil erosion management, remains limited. This gap is important because such integration can strengthen STEM-oriented learning by connecting science concepts, spatial technology, data interpretation, and problem-solving within authentic environmental contexts (Aldhafeeri & Alotaibi, 2023; Bernhäuserová et al., 2022; Tramonti et al., 2024; Vance et al., 2019).

Based on this gap, the present study aims to analyze the implementation of a cloud-based geospatial protocol for soil erosion management in environmental science learning. Specifically, this study examines how the protocol supports the acceleration of students' environmental knowledge creation within a project-based learning environment. The study contributes by extending the application of cloud-native geospatial approaches from environmental analysis into STEM-based learning practice, while also offering a technology-supported model for engaging students with real-world environmental challenges.

METHODS

This study employed a Design-Based Research (DBR) approach. This approach is useful in designing a cloud-based simulation protocol that serves as a cognitive framework for implementing environmental science learning. This study focused on prototyping the learning materials and validating their effectiveness through simulation. The DBR approach in this study consisted of four iterative stages: (1) needs analysis, (2) prototype design and development, (3) classroom try-out/implementation, and (4) revision and refinement. In the needs analysis stage, the researchers identified instructional problems related to soil erosion learning, digital geospatial literacy, and STEM-oriented environmental science instruction through literature review, curriculum analysis, and preliminary field information from lecturers and students in Universitas Muhammadiyah Malang. The prototype design stage involved the development of the Cloud-Native RUSLE-GEE Protocol, STEM-based student worksheets, and inquiry-based learning procedures. The prototype was then reviewed through expert validation involving four experts in environmental science/geospatial education/learning media/STEM education. After expert review, the protocol was implemented in a limited try-out involving 29 students at the undergraduate level in Environmental Science at the Department of Biology Education, Universitas Muhammadiyah Malang. The try-out was conducted over six meetings, with each session lasting 150 minutes. The results of the try-out and expert suggestions were used as the basis for revising the protocol, both in terms of technical functionality and pedagogical clarity.

The research subjects were 29 students who were selected using purposive sampling based on the following criteria: (1) they were enrolled in environmental science learning, (2) they had basic experience in digital learning environments, and (3) they participated in the learning activities until completion. The study was conducted in [city, province, country], focusing on the learning context of soil erosion management using geospatial simulation.

Instructional Strategy STEM Integration

The Revised Universal Soil Loss Equation (RUSLE) model in environmental science learning within the STEM learning framework is mathematically formulated as $A=R \times K \times LS \times$

C x P. In reality, the integration is as detailed in Table 1. In this study, STEM integration was not positioned merely as a contextual label but as an instructional framework that connected scientific understanding of soil erosion processes, the use of cloud-based geospatial technology, engineering-oriented mitigation design, and mathematical reasoning for interpreting model outputs. Thus, students were guided to understand soil erosion as a real-world environmental problem that can be investigated, modeled, and mitigated through interdisciplinary thinking.

Table 1. Conceptual Mapping of the RUSLE-GEE Protocol

Discipline	Implementation in Instructional Strategy
Science	Physics: Conceptualizing rainfall erosivity (R) through kinetic energy transfer and shear stress mechanisms responsible for soil particle detachment. Biology: Examining the contribution of vegetation biomass (Cover factor, C) and soil organic matter (Soil erodibility factor, K) in enhancing aggregate stability and reducing susceptibility to erosion.
Technology	Employing the Google Earth Engine code editor to process large-scale satellite datasets (Sentinel-2, CHIRPS, NASADEM), promoting digital literacy and competency in cloud-based geospatial Big Data analytics (LS).
Engineering	Integrating the Engineering Design Process (EDP) where students assume the role of environmental engineers, systematically modifying the Support Practice factor (P) to design and evaluate soil conservation structures (e.g., terracing systems) aimed at disaster risk mitigation.
Mathematics	Applying computational thinking to interpret pixel-based raster matrix operations, perform spatial modeling calculations, and analyze statistical histograms for quantifying erosion intensity and environmental impact.

To operationalize this integration, science was represented through the interpretation of erosion drivers and ecosystem conditions; technology through the use of cloud-native geospatial tools; engineering through the design of conservation scenarios; and mathematics through the interpretation of model calculations, raster statistics, and sediment reduction estimates.

Learning Procedures

To support the inquiry process, the protocol is structured into five distinct pedagogical stages. This structure ensures that students engage in Higher-Order Thinking Skills (HOTS) rather than merely operating the software as a "black box." The learning implementation was carried out in a project-based inquiry setting, in which students worked individually/in groups of [number] to investigate erosion-prone areas, formulate explanations, test mitigation scenarios, and evaluate the environmental impact of intervention models. The classroom scenario was designed to ensure that students not only executed simulation commands, but also interpreted the scientific meaning of each output.

Table 2. The Inquiry-Based Learning Stages using RUSLE-GEE Protocol

No.	Inquiry Phase	Student Activity (Cognitive Process)	Feature Used in Protocol
1.	Orientation	Used in observing the basic conditions of river basins that depict high-risk zones (red pixels) and formulate questions that can be investigated by students regarding the main causes of erosion.	Map View (Layer with P =1.0)
2.	Conceptualization	Used to develop hypotheses about the dominant erosion determinants (rainfall erosion R, slope length factor LS, or land cover management factor C) through comparative visual-spatial analysis of thematic layers.	Layer Inspection Panel (R, LS, C)

No.	Inquiry Phase	Student Activity (Cognitive Process)	Feature Used in Protocol
3.	Engineering Design	Used in proposing mitigation strategies by modifying the supporting practice factor (P) as well as calculating the reduction coefficient for bench terracing (P = 0.1) based on conservation engineering standards.	Code Editor (Manipulation of variable P) in Google Earth Engine
4.	Experimentation	It runs simulation models to test proposed engineering interventions and observe spatial output changes in real time.	“Run” Command & Console Output
5.	Evaluation	Used to perform comparative statistical analysis (Before vs. After histogram) which is useful in validating erosion reduction and estimating sediment load reduction quantitatively.	Chart / Histogram Panel

The implementation procedure followed the DBR trial structure. In the first meeting, students were introduced to the environmental problem, spatial layers, and the RUSLE variables. In the second meeting, students formulated hypotheses and explored the thematic layers. In the third meeting, students modified the support practice factor (P) to simulate mitigation interventions. In the final stage, students interpreted the simulation output, compared baseline and mitigated conditions, and completed the worksheet-based reflection and analysis tasks.

Geospatial Data Details

The Cloud-Native RUSLE Protocol was implemented using Google Earth Engine (GEE) as the cloud-based geospatial platform. The geospatial datasets used in this study included Sentinel-2 imagery for land cover observation, CHIRPS data for rainfall-related analysis, NASADEM for topographic representation and slope-length estimation, and FAO Digital Soil Map data for soil-related properties. Each dataset was selected because it represents one or more RUSLE parameters and can be processed consistently in a cloud environment.

The RUSLE factors were derived as follows: rainfall erosivity (R) was estimated from rainfall-related geospatial data; soil erodibility (K) was derived from physicochemical soil information obtained from the FAO Digital Soil Map; slope length and steepness (LS) were generated from topographic data derived from NASADEM; cover-management factor (C) was estimated from land cover or vegetation-related information; and support practice factor (P) was manipulated to represent conservation scenarios, especially the bench terracing intervention (P = 0.1). The spatial unit of analysis followed the raster resolution of the input datasets processed in GEE.

The study area covered Mount Semeru, which was selected because it represents an area with soil erosion risk and is relevant to environmental science learning. The selection of the area also considered data availability, representativeness of erosion-prone landforms, and suitability for spatial simulation-based instruction.

Instruments and data analysis techniques

This study implemented the Cloud-Native RUSLE Protocol hosted on Google Earth Engine. Instrument validity was based on the formulas presented in Agriculture Handbook 703 (Renard et al., 1997) and Handbook 537 (Wischmeier & Smith, 1978). Physicochemical data, such as Soil Erodibility (K), were extracted from the FAO Digital Soil Map to ensure data accuracy. Data analysis techniques included quantitative spatial analysis and descriptive statistics. Spatial analysis interpreted the shift in erosion risk zones (from red pixels to green pixels), while descriptive statistics measured the reduction in affected land area (in hectares) and sediment yield (in tons) to gauge the effectiveness of engineering interventions. To validate usability in learning,

a STEM-based Student Worksheet was developed. The instrument consisted of three cognitive levels that corresponded to a simulation-based workflow. The structure of the worksheet instrument is detailed in Table 3.

Table 3. Structure of the STEM-based student worksheet instrument

STEM Component	Cognitive Task	Example Question Item
Science & Technology	Diagnostic Analysis: multi-layer satellite data to explain environmental phenomena.	Spatial Interpreting environmental drivers responsible for the observed erosion pattern. <i>“Identify the high-erosion (red) zones on the map. Examine their correspondence with the slope-length factor (LS) and rainfall erosivity (R) layers. Explain the dominant physical drivers responsible for the observed erosion pattern.”</i>
Engineering	Solution-Oriented Thinking: Modifying model parameters to develop and test mitigation strategies.	Design Interpreting environmental drivers responsible for the observed erosion pattern. <i>Propose an appropriate soil conservation strategy for steep slopes. Adjust the support practice factor (P) from 1.0 to 0.1 (bench terracing scenario) in the simulation code and evaluate the resulting spatial changes.”</i>
Mathematics	Quantitative Reasoning & Impact Estimation: Performing numerical analysis to determine intervention effectiveness.	Design Interpreting environmental drivers responsible for the observed erosion pattern. <i>“Using the histogram output, compute the total sediment reduction. If baseline soil loss is approximately 21 million tons per year and the mitigated scenario is approximately 9.5 million tons per year, estimate the total sediment prevented from entering the watershed system.”</i>

In addition to the simulation protocol, the educational instrument used in this study was a STEM-based student worksheet designed to assess students’ analytical, design, and quantitative reasoning skills during the learning process. The worksheet consisted of open-ended tasks and guided response items aligned with the three major STEM components represented in the protocol. Each item required students to interpret spatial evidence, propose a mitigation strategy, or calculate the environmental impact of a simulated intervention.

Content validity was examined through expert judgment involving [number] validators, consisting of experts in [subject matter, instructional design, geospatial learning, and/or STEM education]. The experts assessed the worksheet and protocol in terms of content relevance, conceptual accuracy, clarity of instructions, suitability for student level, and alignment with STEM-oriented inquiry learning. The validity criteria may be classified as follows: [e.g., 81–100% = very valid; 61–80% = valid; 41–60% = moderately valid; 21–40% = less valid; 0–20% = invalid, adjust to your actual rubric]. If reliability testing was conducted, it can be stated that the internal consistency of the worksheet was examined using [Cronbach’s alpha/inter-rater agreement/other method] with a coefficient of [value].

Student performance on the worksheet was scored using an analytic rubric. Each response was evaluated based on accuracy, completeness of reasoning, appropriateness of the proposed solution, and correctness of quantitative interpretation. Scores were then categorized into [e.g., high, moderate, and low / very good, good, fair, poor] based on predetermined score intervals.

The geospatial data analysis procedure involved four steps: (1) preparation of geospatial datasets in Google Earth Engine, (2) generation of RUSLE factor layers (R, K, LS, C, and P), (3) simulation of baseline and intervention scenarios, and (4) comparison of outputs using map visualization and histogram/statistical summaries. The educational data analysis involved descriptive analysis of students’ worksheet performance and interpretation of how students engaged in STEM-based environmental knowledge creation through the protocol. If pretest-posttest or other learning outcome measures were used, this section can be expanded by adding the corresponding statistical test.

RESULTS & DISCUSSION

Result

Technical Results of the Cloud-Native RUSLE-GEE Simulation

The development phase resulted in an integrated web-based interface, as shown in Figure 1. This interface supports environmental science learning by visualizing abstract equations into concrete spatial maps. This cloud-based tool allows students to access "Big Data" directly from a standard web browser, providing flexible access to high-performance computing systems in the classroom for environmental science learning activities. At the prototype stage, the primary result of this study was the successful development of a functional cloud-native geospatial learning interface that integrated script-based processing, spatial visualization, and statistical output within a single environment.

The existing protocol is able to facilitate the Engineering Design Process. In a simulation case study located in a highland complex in East Java (specifically in the Batu-Lumajang area), students were tasked with assessing a baseline scenario (where $P=1.0$ representing a "No Conservation" area) and designing a mitigation strategy (where $P=0.1$ representing "Roofed Terraces"). The visual results, as presented in Figure 2, show different transformations. The "Red Zone" or High Risk area concentrated on the steep slopes of Mount Semeru, representing an area with high kinetic energy impacts, was successfully mitigated into a "Green Zone" through simulation engineering interventions. These findings indicate that the protocol was technically capable of simulating environmental intervention scenarios and displaying interpretable spatial changes relevant to soil erosion management.

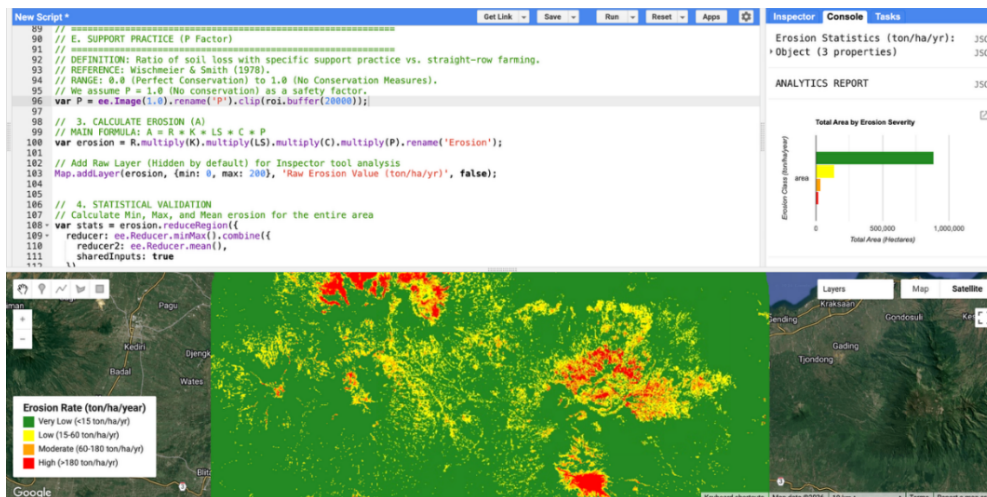


Figure 1. The Cloud-Based Digital Learning Interface. The dashboard integrates the script editor (left), geospatial visualization (center), and statistical analytics (right).

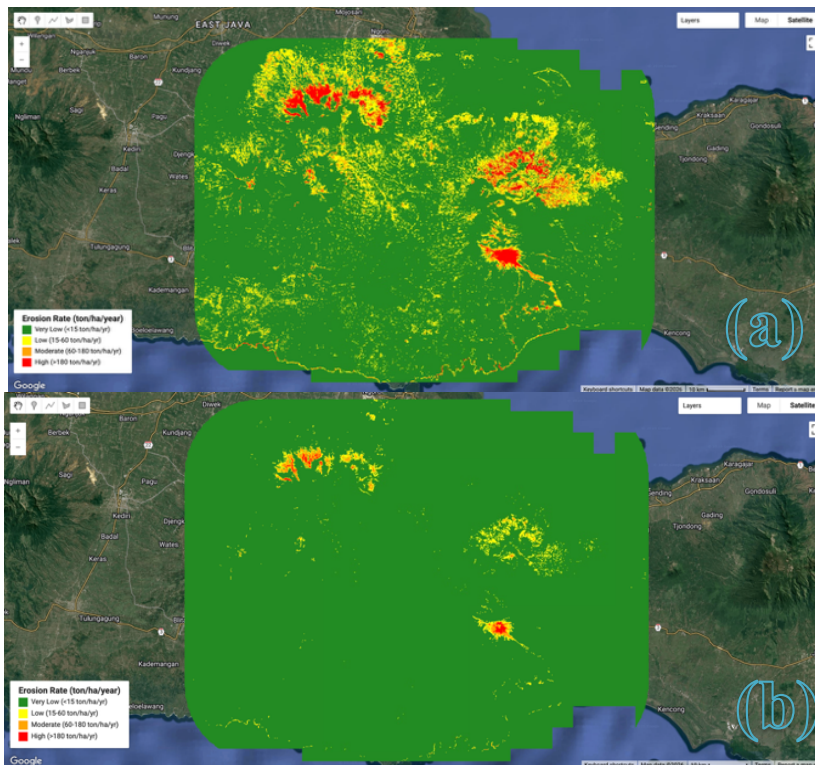


Figure 2. Visualization of the Engineering Design Process. (a) Baseline risk map ($P=1.0$) showing concentrated high-risk zones. (b) Post-mitigation design ($P=0.1$) showing the reduction of risk to safe levels.

In developing data literacy in environmental science learning, students are encouraged to shift from qualitative observation to quantitative analysis. To support quantitative interpretation, the protocol generated a real-time zonal histogram (Figure 3) that provided immediate numerical feedback on the distribution of erosion classes. From a technical perspective, this feature enabled the rapid conversion of spatial outputs into summary statistics that could be further used for instructional analysis.

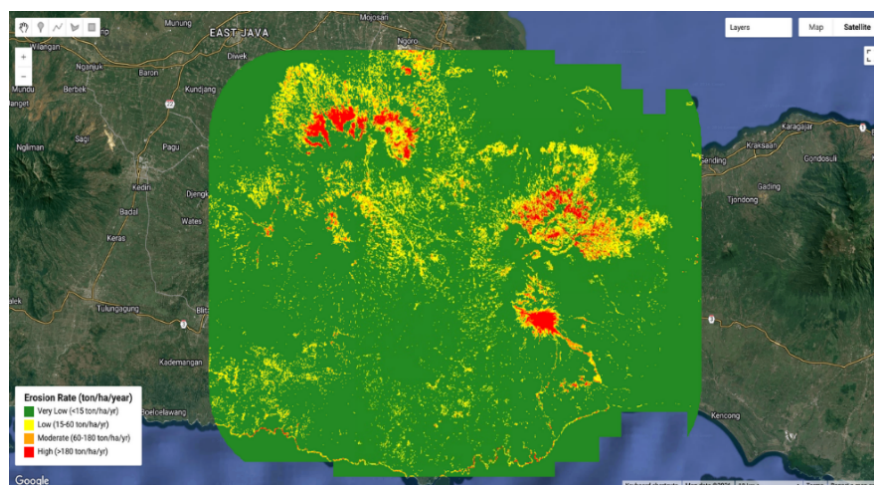


Figure 3. Real-time Analytics Report generated during the initial assessment phase ($P=1.0$).

The quantitative impact of the student-designed interventions on land cover is summarized in Table 4. Table 4 data shows that the engineering design (P=0.1) reduced the High-Risk area by 91.91%. This result demonstrates that the simulated conservation scenario substantially shifted the spatial composition of erosion risk classes, with the largest reduction observed in the high-risk zone.

Table 4. Quantitative Analysis of Student Simulation Results (Area)

Erosion Risk Class	Baseline (P=1.0) Area (Ha)	Post-Intervention (P=0.1) Area (Ha)	Change (Δ)
Very Low	883,908.71	1,054,798.13	+19.33%
Low	137,642.81	17,467.16	-87.31%
Moderate	37,022.37	4,706.59	-87.29%
High	19,929.07	1,612.09	-91.91%

The simulation also enabled estimation of total sediment yield under baseline and mitigation scenarios, allowing the environmental impact of the intervention to be quantified more precisely (Table 5).

Table 5. Estimated Reduction in Total Sediment Yield (Mathematical Reasoning)

Erosion Class	Mean Rate (t ha ⁻¹ yr ⁻¹)	Baseline Total Loss (t yr ⁻¹)	Mitigated Total Loss (t yr ⁻¹)
Very Low	7.5	6,629,310	7,910,985
Low	37.5	5,161,575	655,012
Moderate	120	4,442,640	564,720
High	250	4,982,250	403,000
TOTAL	-	21,215,775	9,533,717

Note: Mean rate is an approximate value derived for student calculation exercises.

As shown in Table 4, students can derive that their intervention prevented approximately 11.7 million tons of soil loss annually. Technically, this output confirms that the protocol was able to translate design-based intervention scenarios into measurable environmental outcomes, thereby linking spatial modeling with quantitative estimation.

The cognitive process undertaken by students during the simulation is visualized in Figure 4. This framework illustrates how students move from data acquisition to critical decision-making. At this stage, however, Figure 4 should be interpreted as a conceptual representation of the intended learning pathway supported by the protocol, rather than as conclusive evidence of full pedagogical effectiveness.

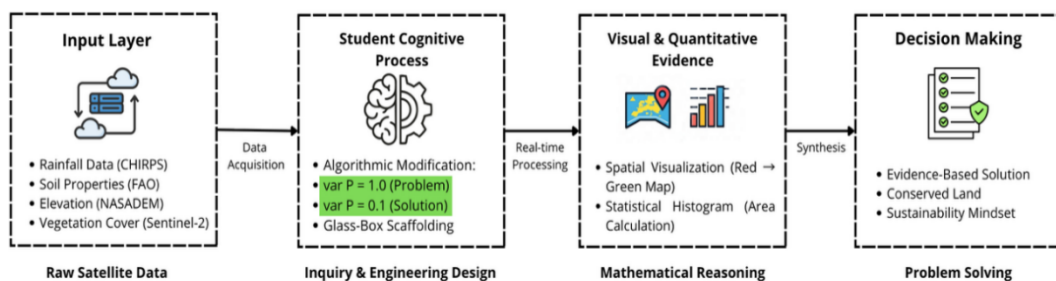


Figure 4. The Computational Thinking Framework in RUSLE-GEE.

Pedagogical Results at the Prototype Stage

In addition to the technical simulation outputs, this study also identified preliminary pedagogical results at the prototype stage. These results did not yet constitute a full effectiveness test, but rather demonstrated the pedagogical potential of the developed protocol for supporting inquiry-based and STEM-oriented environmental science learning.

The developed interface and workflow showed that the protocol could guide students through a structured sequence of learning activities, beginning with spatial observation, followed by interpretation of erosion drivers, intervention design, simulation testing, and quantitative evaluation. In this sense, the pedagogical result of this phase lies in the successful alignment between the technical features of the RUSLE-GEE system and the targeted cognitive processes in environmental learning.

The STEM-based worksheet and simulation sequence indicated that the protocol was suitable for engaging students in three interrelated forms of reasoning: (1) scientific reasoning to explain the causes of erosion, (2) engineering reasoning to propose and test mitigation measures, and (3) mathematical reasoning to estimate environmental impact based on simulation output. However, because this study primarily focused on prototype development and technical validation, claims regarding improvement in student learning outcomes should be interpreted cautiously.

Accordingly, the pedagogical findings reported here are limited to prototype usability and instructional feasibility, rather than full-scale evidence of effectiveness. A more comprehensive evaluation of pedagogical outcomes, such as worksheet scores, student responses, and gains in environmental reasoning, should be addressed in subsequent implementation studies.

Discussion

The findings indicate that the integration of the cloud-native GEE-RUSLE protocol can function as a meaningful STEM learning scaffold in environmental science. Through the interpretation of the C, LS, and R factors, students were not only exposed to biological and physical explanations of soil erosion, but were also encouraged to connect those explanations with spatial evidence and simulation outputs. This pattern is consistent with the principles of inquiry learning, in which students construct understanding by observing patterns, formulating explanations, testing intervention scenarios, and evaluating the consequences of their decisions. It also reflects computational thinking, particularly decomposition, parameter manipulation, and interpretation of model outputs, as well as geospatial thinking, because students were required to read spatial patterns, compare thematic layers, and reason across location-based environmental data. In this context, the reduction of high-risk zones by 91.91% and the estimated prevention of approximately 11.7 million tons of soil loss were not merely technical outputs, but served as authentic quantitative evidence that supported mathematical reasoning and environmental decision-making (Dominguez et al., 2024; Kandemir & Eryilmaz, 2025; Lai & Lin, 2025; H.-C. Li, 2025; Naseer et al., 2024; Siller et al., 2025; Weinhandl et al., 2025).

At the same time, these findings should be interpreted within the scope of the present study. The study primarily focused on prototype development and simulation-based implementation, so the pedagogical evidence remains limited to instructional feasibility rather than full effectiveness testing. As a result, the present findings cannot yet conclusively claim improvement in students' environmental awareness, critical thinking, or long-term achievement without broader classroom trials and direct learning outcome data. Nevertheless, the study has important implications for education. First, it shows that cloud-native geospatial tools can make abstract environmental models more visible, interactive, and relevant to real-world problems. Second, it suggests that environmental science instruction can be designed to integrate inquiry

learning, computational thinking, and geospatial reasoning in a more authentic way than text-based instruction alone. Third, it provides a practical model for educators who seek to connect STEM learning with current environmental challenges through data-rich and decision-oriented activities (Bufasi et al., 2022; Christensen, 2023; Drozdowski et al., 2024; Erdoğan et al., 2016; Hochschild et al., 2003; Kanaki et al., 2022; Kurniawan et al., 2025; Safaah & Karyaningsih, 2020; Saidin et al., 2021; Samodra et al., 2025; Tarolli & Straffelini, 2020). Future studies should therefore examine student worksheet performance, response data, and learning gains across larger and more diverse educational settings.

CONCLUSION

The present study demonstrated that the Cloud-Native Geospatial Protocol can function as a feasible instructional material for environmental science learning, particularly for supporting STEM-oriented and inquiry-based activities related to soil erosion management. In line with the research objective, the protocol enabled students to engage with cloud-based geospatial simulation by transforming abstract RUSLE variables into visual and quantifiable representations. The technical simulation results showed that the designed intervention scenario ($P = 0.1$) reduced the high-risk erosion area by 91.91%, while the estimated total soil loss decreased from 21,215,775 t yr^{-1} to 9,533,717 t yr^{-1} , indicating a potential annual reduction of approximately 11.7 million tons. These findings suggest that the protocol provides a concrete context for scientific interpretation, mathematical reasoning, and engineering-based environmental decision-making.

However, the findings should be interpreted within the scope of this study, which primarily focused on prototype development and limited instructional implementation rather than full-scale effectiveness testing. Therefore, the main contribution of this study lies in providing a cloud-native geospatial learning model that is technically functional and pedagogically promising for environmental science education. Future research should evaluate its effectiveness more comprehensively by examining student learning outcomes, worksheet performance, and responses across larger and more diverse educational settings

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