GIS-RUSLE-BASED SOIL EROSION RISK MAPPING, STATISTICAL VALIDATION AND BIOLOGICAL REHABILITATION OF GULLIED LANDS IN THE SANGZARSOY BASIN, UZBEKISTAN

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ABSTRACT

Introduction. *Reliable delineation of soil erosion risk zones is essential for prioritizing land-conservation measures, yet the Sangzarsoy basin (Jizzakh region, Uzbekistan) had lacked a statistically validated, spatially explicit risk map linked to a field-tested rehabilitation measure for its gullied piedmont land.*

Methods. *A localized RUSLE model ($A = R \times K \times LS \times C \times P$) was computed for a 255,376.0 ha modelled area using standardized R, K, LS, C and P raster layers. Model reliability was assessed via arithmetic-closure checks, Pearson correlation of the K-factor with particle-size fractions, a Welch's t-test with Cohen's d between two mechanical-analysis sample groups, a baseline-vs-localized sensitivity comparison (MAE, RMSE), and a 500-run Monte Carlo simulation. A 2024–2025 field trial at the Gallakon site compared direct seeding with a combined biological rehabilitation technology (contour strips, sod, cuttings, Agropyron-based vegetative material).*

Results. *The final map classified 51.9% of the basin (132,577.0 ha) as high or very-high erosion risk, with very-low risk covering 40.4% (103,153.7 ha). Localization shifted risk toward higher classes relative to the baseline scenario (MAE = 12,914.7 ha; RMSE = 15,263.0 ha). Internal consistency was confirmed by $r(K,SIL) = +0.791$, $r(K,CLA) = -0.800$, and a Welch's $t = 8.413$ ($p < 0.001$, $d = 1.88$); Monte Carlo simulation showed a stable high+very-high risk share of 23.85%*

± 1.95% (90% CI: 19.98–26.50%). At Gallakon, direct seeding failed on open substrate, whereas the combined technology improved cover stability.

Discussion/Conclusions. *The validated risk map and the Gallakon field results together provide a spatially targeted, statistically robust basis for prioritizing soil-conservation and biological rehabilitation measures across the Sangzarsoy basin, particularly on its high-risk pasture and piedmont zones.*

Keywords: *RUSLE, soil erosion risk mapping, GIS, Monte Carlo simulation, statistical validation, biological rehabilitation, Agropyron, Sangzarsoy basin, Uzbekistan.*

АННОТАЦИЯ

Введение. *Достоверное выделение зон эрозионного риска необходимо для приоритизации почвозащитных мероприятий, однако для бассейна Сангзарсай (Джизакская область, Узбекистан) ранее отсутствовала статистически проверенная карта риска, увязанная с апробированным на местности методом рекультивации оврагистых предгорных земель.*

Материалы и методы. *Локализованная модель RUSLE (A = R × K × LS × C × P) рассчитана для смоделированной площади 255 376,0 га на основе стандартизированных растровых слоёв R, K, LS, C и P. Надёжность модели оценена через проверку арифметической замкнутости, корреляцию K-фактора с гранулометрическими фракциями, критерий Уэлча и d Коэна между двумя группами образцов механического анализа, сравнение базового и локализованного сценариев (MAE, RMSE) и симуляцию Монте-Карло (500 прогонов). Полевой опыт 2024–2025 гг. на участке Галлакон сравнивал прямой посев семян с комплексной технологией биологической рекультивации (контурные полосы, дернина, черенки, вегетативный материал Agropyron).*

Результаты. *Итоговая карта отнесла 51,9% бассейна (132 577,0 га) к высокому и очень высокому риску эрозии, тогда как очень низкий риск охватил 40,4% (103 153,7 га). Локализация сместила риск в сторону более высоких классов относительно базового сценария (MAE = 12 914,7 га; RMSE = 15 263,0* *га). Внутренняя согласованность подтверждена коэффициентами $r(K,SIL) = +0,791$, $r(K,CLA) = -0,800$ и критерием Уэлча $t = 8,413$ ($p < 0,001$; $d = 1,88$); симуляция Монте-Карло показала устойчивую долю высокого и очень высокого риска 23,85% ± 1,95% (90% ДИ: 19,98–26,50%). На участке Гальакон прямой посев не дал результата на открытом субстрате, тогда как комплексная технология повысила устойчивость покрова.*

Обсуждение/Выводы. *Проверенная карта риска совместно с результатами полевого опыта в Галлаконе формируют пространственно адресную и статистически обоснованную базу для приоритизации почвозащитных и рекультивационных мероприятий в бассейне Сангзарсай, в первую очередь на пастбищных и предгорных землях высокого риска.*

Ключевые слова: *RUSLE, картирование эрозионного риска, ГИС, симуляция Монте-Карло, статистическая валидация, биологическая рекультивация, Agropyron, бассейн Сангзарсай, Узбекистан.*

АННОТАЦИЯ

Кириш. *Тупроқ муҳофазаси тадбирларини устуворлаш учун эрозия хавфи зоналарини ишончли ажратиш зарур, бироқ Сангзарсой ҳавзаси (Жиззах вилояти, Ўзбекистон) учун илгари статистик жиҳатдан текширилган ва дала шароитида синалган тиклаш усули билан боғланган хавф харитаси мавжуд эмас эди.*

Материаллар ва усуллар. *255 376,0 гектарлик моделлаштирилган майдон учун локализациялашган RUSLE модели ($A = R \times K \times LS \times C \times P$) стандартлаштирилган R, K, LS, C ва P растр қатламлари асосида ҳисобланди. Модель ишончлилиги арифметик ёпилиш назорати, K-омилнинг гранулометрик фракциялар билан корреляцияси, Уэлч мезони ва Коэн d кўрсаткичи, база вий ва локализациялашган сценарийлар қиёси (MAE, RMSE) ҳамда Монте-Карло симуляцияси (500 марта) орқали баҳоланди. 2024–2025 йиллардаги Ғаллакон дала тажрибасида тўғридан-тўғри уруғ сепиш комплекс*

биологик тиклаш технологияси (контур йўлаклар, чим-поя, кўчат-қаламча, Agropyron асосидаги вегетатив материал) билан солиштирилди.

Натижалар. *Якуний харита бўйича ҳавзанинг 51,9 фоизи (132 577,0 га) юқори ва жуда юқори эрозия хавфига, 40,4 фоизи (103 153,7 га) эса жуда паст хавфга киритилди. Локализация базавий сценарийга нисбатан хавфни юқорироқ синфлар томон силжитди (MAE = 12 914,7 га; RMSE = 15 263,0 га). Ҳисобнинг ички мослиги r(K,SIL) = +0,791, r(K,CLA) = −0,800 ва Уэлч мезони t = 8,413 (p < 0,001; d = 1,88) билан тасдиқланди; Монте-Карло симуляцияси юқори ва жуда юқори хавф улушининг барқарор 23,85% ± 1,95% (90% ишонч оралиғи 19,98–26,50%) эканини кўрсатди. Ғаллаконда очиқ субстратда тўғридан-тўғри уруғ сепиш натижа бермади, комплекс технология эса қоплам барқарорлигини оширди.*

Муҳокама/Хулоса. *Текширилган хавф харитаси ва Ғаллакондаги дала натижалари биргаликда Сангзарсой ҳавзасида, айниқса юқори хавфли яйлов ва тоғолди ерларида тупроқ муҳофазаси ва биологик тиклаш тадбирларини устуворлаштириш учун фазовий аниқ ва статистик асосланган база яратади.*

Калит сўзлар: *RUSLE, эрозия хавфи харитаси, ГАТ, Монте-Карло симуляцияси, статистик валидация, биологик тиклаш, Agropyron, Сангзарсой ҳавзаси, Ўзбекистон.*

INTRODUCTION

Spatially explicit soil erosion risk mapping using the Revised Universal Soil Loss Equation (RUSLE) integrated with GIS and remote sensing has become a standard approach across widely differing physiographic settings. Watershed-scale applications have been reported for the Nethravathi basin in India [5], the Shatt Al-Arab basin shared by Iraq and Iran [2], the Wadi Baysh catchment in Saudi Arabia [4], the Jhelum River watershed in Pakistan [19], the Swat River basin in the Eastern Hindukush [7], the Peshawar basin [16], the Balason River basin in the Darjeeling

Himalaya [15], the Silabati River basin in eastern India [12], and the Kosi River basin in Bihar [9].

Methodological refinements of the RUSLE workflow, including watershed prioritization and GIS-based erosion-risk reduction planning, are discussed by [3] and [11], while combined RUSLE and debris-flow susceptibility mapping is illustrated by [8]. Practical case studies applying RUSLE with remote sensing and geospatial techniques for watershed-level annual soil-loss estimation include [13], [17], [18], [6] and [21]. Erosion-hazard mapping using GIS techniques was also demonstrated for Belarusian landscapes by [10], and factor-based erosion modelling across the macroregion of European Russia was addressed by [20].

While this body of work confirms the robustness of RUSLE for delineating spatial erosion-risk patterns, comparatively few studies combine (i) a fully localized factor set validated by an independent statistical framework — Pearson correlation, Welch's t-test, Cohen's d and Monte Carlo uncertainty propagation — with (ii) a field-tested biological rehabilitation protocol for gullied piedmont land in an arid Central Asian setting. Erosion-risk assessments for floodplain and desert-margin conditions elsewhere, such as the Wadi Sudr watershed in Egypt [1], have likewise stopped short of linking model output to an implemented rehabilitation trial.

The aim of this study is to present the final localized erosion-risk map for the Sangzarsoy basin, to statistically validate the model output through internal-consistency and sensitivity analyses, and to evaluate a combined biological rehabilitation technology for gullied land at the Gallakon reference site.

MATERIALS AND METHODS

The final annual soil-loss layer ($A = R \times K \times LS \times C \times P$) was computed for the Sangzarsoy basin (259,719.3 ha vector area; 402–3437 m elevation range) using the RUSLE factor structure [14], by combining rainfall-erosivity (R), soil-erodibility (K), slope length-steepness (LS), cover-management (C) and support-practice (P) raster layers standardized to a common coordinate system and 30×30 m pixel grid in ArcGIS 10.8.1 and QGIS. After masking water bodies, edge pixels and no-data areas, the final modelled area was 255,376.0 ha.

Model reliability was assessed through: (i) arithmetic closure checks of area and percentage totals; (ii) internal consistency of the K-factor via Pearson correlation with sand, silt, clay and organic-carbon content across 28 SoilCode units; (iii) a Welch's t-test and Cohen's d comparing two independent groups of 40 mechanical-analysis samples each; (iv) sensitivity analysis comparing a generalized-coefficient baseline scenario against the final localized scenario (mean absolute error, MAE; root mean square error, RMSE); and (v) a 500-run Monte Carlo simulation applying literature-based uncertainty ranges to K (±10–20%), C (±10–20%) and LS (±15%), with R sampled from a triangular distribution bounded by the observed 2000–2024 rainfall extremes (211.3–626.7 mm).

A field rehabilitation trial was conducted in 2024–2025 at the Gallakon reference site, located in the Morguzar piedmont zone, where mudflow tracks, gully development, sparse cover and seasonal wind action co-occur. Two approaches were compared: (a) direct seeding of four grass species on open and washed substrate, and (b) a combined technology integrating contour strips/belts, sod, cuttings and mixed vegetative material based on Agropyron species and local perennial grasses.

RESULTS AND DISCUSSION

3.1. Final erosion risk classification

The localized RUSLE computation classified the 255,376.0 ha modelled area into five annual soil-loss classes (t ha^{-1} yr^{-1}). Very-low risk (0–1 t ha^{-1} yr^{-1}) covered 103,153.7 ha (40.4%), while the combined high (10–50) and very-high (>50) classes covered 132,577.0 ha, or 51.9% of the basin — indicating that erosion risk extends well beyond isolated gully sites into broad areas where relief, pasture/cropland use and cover condition coincide.

Table 1 — Final localized annual soil-loss risk classes

Soil loss, $t\ ha^{-1}\ yr^{-1}$	Risk class	Index	Area, ha	Share, %
0–1	Very low	1	103,153.7	40.4
1–5	Low	2	10,293.8	4.0
5–10	Moderate	3	9,351.5	3.7
10–50	High	4	38,128.7	14.9
>50	Very high	5	94,448.3	37.0

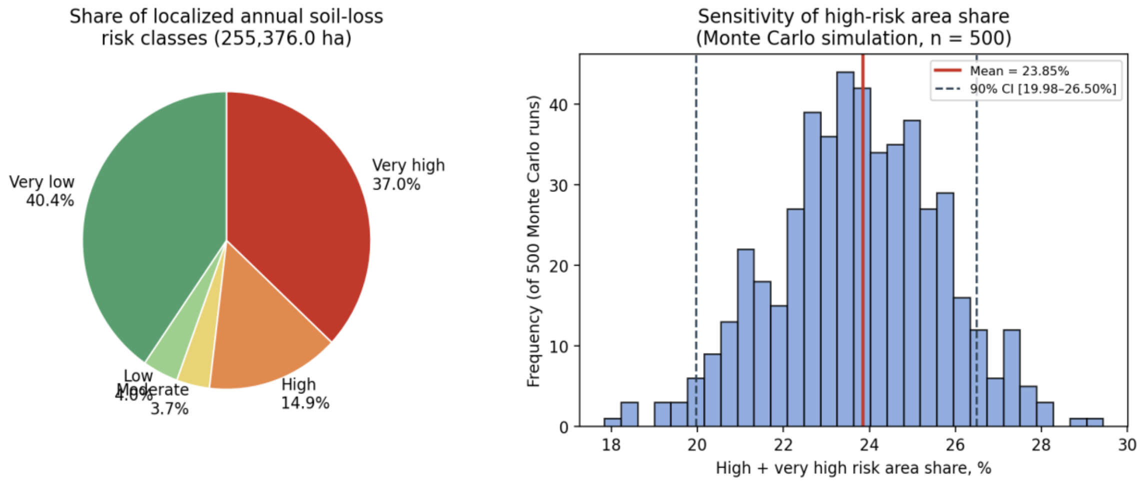

Figure 1 — (a) Share of final localized risk classes (255,376.0 ha); (b) Monte Carlo sensitivity distribution of the high+very-high risk area share (500 runs).

3.2. Comparison with the baseline scenario

Compared with a baseline scenario computed using generalized (non-localized) coefficients, the localized computation redistributed area toward higher-risk classes: the very-low class decreased by 24,133.5 ha, while the high and very-high classes increased by 16,460.1 ha and 15,594.0 ha, respectively. This shift reflects the combined effect of localized C–P values, a hydrologically corrected DEM, SoilCode-to-sample linkage, and a unified water/no-data mask.

Table 2 — Baseline versus localized RUSLE scenario: comparative risk-class areas

Risk class	Baseline area, ha	Baseline, %	Localized area, ha	Localized, %	Difference, ha
Very low	127,287.2	49.8	103,153.7	40.4	-24,133.5
Low	18,554.9	7.3	10,293.8	4.0	-8,261.1
Moderate	9,226.7	3.6	9,351.5	3.7	+124.8
High	21,668.6	8.5	38,128.7	14.9	+16,460.1
Very high	78,854.3	30.8	94,448.3	37.0	+15,594.0

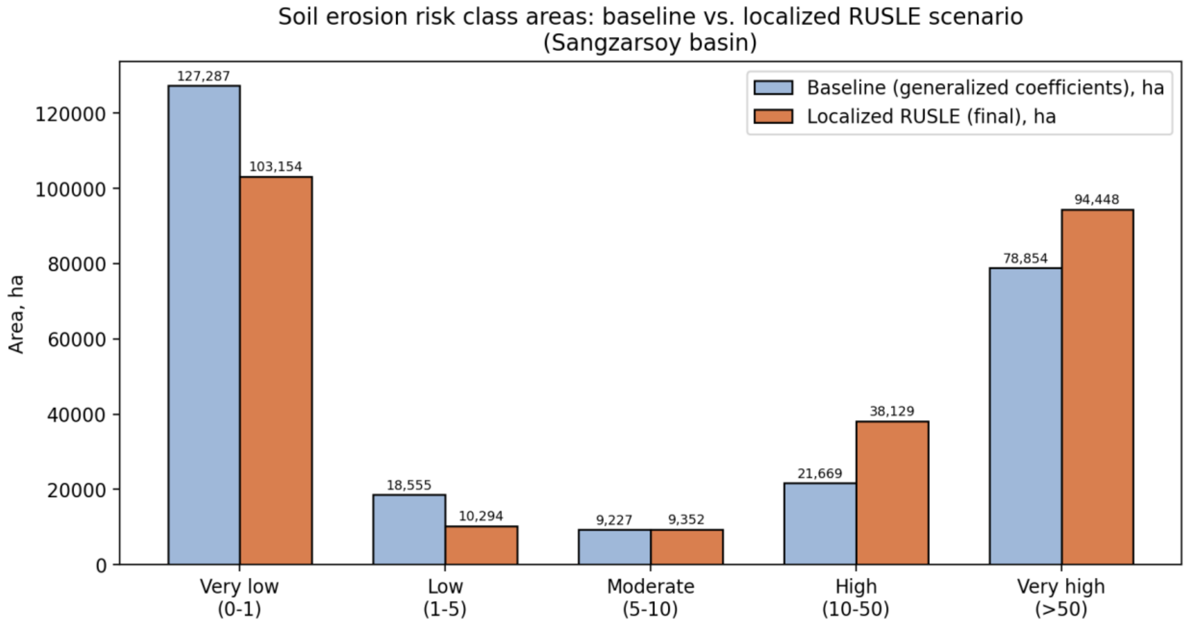

Figure 2 — Risk-class area comparison between the baseline (generalized-coefficient) and final localized RUSLE scenarios.

3.3. Statistical validation summary

Internal consistency and sensitivity checks are summarized in Table 3. Arithmetic closure was confirmed for both the R-factor control value (R = 457.7) and the area/percentage balance (255,376.0 ha; 100.0%). K-factor internal consistency was supported by Pearson correlations with silt ($r = +0.791$) and clay ($r = -0.800$) content. The Welch's t-test between two independent groups of mechanical-analysis samples ($n = 40$ each) yielded $t = 8.413$ ($df = 65.47$, $p < 0.001$), with a large effect size (Cohen's d = 1.88). Scenario sensitivity was expressed through MAE = 12,914.7 ha and RMSE = 15,263.0 ha.

Table 3 — Levels of model verification and validation status

Verification level	Statistic / evidence	Result	Interpretation
Arithmetic control	R = 1.03 × 444.4; class areas and shares	R = 457.7; ΣS = 255,376.0 ha; Σ% = 100.0	Formula and area balance fully closed
K-factor internal consistency	28 SoilCode units: K vs. SAN, SIL, CLA, OC	r(K,SIL)=+0.791; r(K,CLA)=−0.800; CV(K)=1.60%	Granulometric logic of the K model confirmed
Mechanical group difference	40+40 samples, physical clay content	t=8.413; df=65.47; p<0.001; d=1.88	Between-group difference statistically robust
Scenario sensitivity	Baseline vs. final, 5 risk classes	MAE=12,914.7 ha; RMSE=15,263.0 ha	Localization materially reshapes risk structure
Field spatial validation	Sheet wash, rills, gullies, sparse cover, deposition zones	High-risk classes matched field erosion signs	Spatial agreement supports regional decision-making

The 500-run Monte Carlo simulation, propagating literature-based uncertainty in K (±10–20%), C (±10–20%) and LS (±15%), together with a triangular rainfall distribution bounded by the observed 2000–2024 extremes, produced a stable high+very-high risk-area share of 23.85% ± 1.95% (90% CI: 19.98–26.50%). At the pixel level, 19.6% of the basin remained in the high-risk class in at least 95% of the 500 simulations, identifying this subset as the most robust priority zone independent of parameter choice.

3.4. Terrain–erosion associations

Aspect analysis indicated a higher mean erosion class on south-facing slopes (28.7% of basin area; mean class 2.69) than on north-facing slopes (41.1%; mean class 2.55), consistent with greater solar radiation, lower soil moisture and sparser cover on south-facing terrain. The topographic wetness index (TWI) correlated with erosion class at $r = 0.513$ ($p < 0.001$), while profile-curvature analysis showed concave surfaces (28.4% of the basin) reaching the highest mean erosion class (3.64), compared with convex surfaces (27.9%; mean class 2.43) — among the strongest geomorphometric associations identified in this study and a useful criterion for prioritizing gully-head stabilization.

3.5. Biological rehabilitation of gullied land at the Gallakon site

The 2024–2025 field trial showed that direct seeding on open and washed substrate did not establish a stable floristic layer in either season, primarily due to rapid moisture loss and seed displacement by surface flow. In contrast, plots where contour strips/belts, sod, cuttings and mixed vegetative material were combined showed improved plant survival, more stable cover and visibly reduced wash signs.

Table 4 — Biological rehabilitation trial stages and outcomes (2024–2025)

Stage	Action	Outcome / interpretation
Spring–autumn 2024	Direct seeding of 4 grass species on open, washed and gullied land	No dense, stable floristic layer formed; limitation of the method on open substrate identified
Spring 2025	Direct-seeding trial continued	Germination and seedling survival incomplete; moisture and substrate stability were limiting factors
Combined technology	Cuttings, vegetative material, sod and contour strips/belts applied	Technology tested under field conditions; 2024–2025 seasonal observations confirmed stable biological performance
Final field outcome	Establishment and green-mass formation observed on selected trial strips	Combined use of contour strips, sod, cuttings and vegetative material stabilized cover, formed a root barrier, and reduced wash signs

These findings indicate that the limited performance of direct seeding reflects a mismatch between technology and site conditions rather than an inherent ineffectiveness of biological methods. Because contour strips and sod cover primarily improve the P- and C-factors of the RUSLE framework, the Gallakon results provide a direct field link between the statistically validated risk map and an implementable, spatially targeted conservation measure.

CONCLUSIONS

1. The final localized RUSLE computation for the Sangzarsoy basin (255,376.0 ha modelled area) classified 51.9% of the basin (132,577.0 ha) as high or very-high erosion risk, with very-low risk covering 40.4% (103,153.7 ha).

2. Comparison with a generalized-coefficient baseline scenario showed a systematic redistribution toward higher-risk classes (MAE = 12,914.7 ha; RMSE = 15,263.0 ha), attributable to localized C–P values, a hydrologically corrected DEM, and SoilCode–sample linkage.

3. Internal model consistency was confirmed through K-factor correlations with silt ($r = +0.791$) and clay ($r = -0.800$) content and a statistically significant difference between mechanical-composition groups (Welch's $t = 8.413$, $p < 0.001$, Cohen's $d = 1.88$).

4. A 500-run Monte Carlo simulation confirmed the robustness of the high-risk area estimate (23.85% ± 1.95% of the basin; 90% CI: 19.98–26.50%), with 19.6% of the basin consistently classified as high-risk across at least 95% of simulations.

5. The 2024–2025 Gallakon field trial demonstrated that a combined biological rehabilitation technology — contour strips, sod, cuttings and Agropyron-based vegetative material — outperforms direct seeding alone on open, gullied piedmont substrate, offering a practical, spatially targeted measure for the basin's high-risk zones.

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