

ГЕОГРАФИЯ

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Оригинальная научная статья

A SPATIAL ASSESSMENT OF ENVIRONMENTAL VULNERABILITY
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Abstract. In the context of increasing anthropogenic pressure and the need for objective environmental monitoring, spatial assessment of ecological vulnerability that takes into account natural and technogenic factors has become an important scientific task. The aim of this study was to assess the ecological vulnerability of the Akhangaran River Basin (Uzbekistan) using a comprehensive geographic information system approach. The materials used included multitemporal Landsat 8 and Landsat 9 satellite imagery from 2022 to 2025, cadastral land-use data, the Copernicus GLO-30 Digital Elevation Model, and OpenLandMap soil bulk density data. Data processing was carried out in Google Earth Engine, including the derivation of spectral indices such as the Normalised Difference Vegetation Index, Normalised Difference Drought Index, Normalised Difference Built-up Index, Bare Soil Index, Land Surface Temperature, and Clay Mineral Ratio. Based on the normalised parameters, an integrated Ecological Vulnerability Index was developed using a correlation-weighted scheme that accounts for indicator multicollinearity. Results showed that 59.6 % of the basin area falls within zones of high vulnerability. A clear spatial differentiation was identified: while mountainous forest areas retain relative ecological resilience, agricultural, industrial, and residential zones are characterised by elevated environmental stress, soil compaction, and pronounced thermal anomalies. The practical significance of this research lies in the potential application of its findings to state environmental and land monitoring, as well as in the identification of priority areas for environmental management. Future research may focus on improving the indicator set and adapting the proposed methodology to other river basins and natural-technogenic geosystems in Uzbekistan.

Keywords: Environmental Vulnerability Index, spatial assessment, Akhangaran river basin, land degradation, Google Earth Engine, spectral indices, multicollinearity, anthropogenic pressure, remote sensing, soil compaction

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ПРОСТРАНСТВЕННАЯ ОЦЕНКА ЭКОЛОГИЧЕСКОЙ УЯЗВИМОСТИ БАСЕЙНА РЕКИ АХАНГАРАН (УЗБЕКИСТАН)

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Аннотация. В условиях усиления антропогенной нагрузки и необходимости перехода к объективному экологическому мониторингу актуальной научной задачей является пространственная оценка экологической уязвимости территорий с учетом природных и техногенных факторов. Целью исследования являлась оценка экологической уязвимости бассейна реки Ахангаран (Узбекистан) на основе комплексного геоинформационного подхода. В качестве материалов использованы многовременные спутниковые данные Landsat 8 и Landsat 9 за 2022–2025 гг., кадастровые данные о землепользовании, цифровая модель рельефа Copernicus GLO-30 и данные о плотности почв из OpenLandMap. Обработка данных выполнялась в Google Earth Engine с расчетом спектральных индексов, включая Normalised Difference Vegetation Index, Normalised Difference Drought Index, Normalised Difference Built-up Index, Bare Soil Index, Land Surface Temperature и Clay Mineral Ratio. На основе нормализованных показателей был построен интегральный индекс экологической уязвимости с использованием корреляционно-взвешенной схемы, учитывающей мультиколлинеарность индикаторов. Установлено, что 59,6 % площади бассейна относится к зонам высокой уязвимости. Выявлена отчетливая пространственная дифференциация: горные лесные территории сохраняют относительную устойчивость, тогда как сельскохозяйственные, промышленные и селитебные зоны характеризуются повышенной экологической напряженностью, уплотнением почв и выраженными термальными аномалиями. Практическая значимость работы заключается в возможности использования полученных результатов для государственного экологического и земельного мониторинга, а также для выявления приоритетных участков природоохранного управления. Перспективы исследования связаны с дальнейшим совершенствованием индикаторной базы и адаптацией методики для других бассейнов и природно-техногенных геосистем Узбекистана.

Ключевые слова: Индекс экологической уязвимости, пространственная оценка, бассейн реки Ахангаран, деградация земель, Google Earth Engine, спектральные индексы, мультиколлинеарность, антропогенная нагрузка, дистанционное зондирование Земли, уплотнение почв

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Introduction

In accordance with the monitoring and reporting framework established in Appendix 2.11 of the Cabinet of Ministers of the Republic of Uzbekistan Resolution No. 50 (effective February 3, 2023) [1] regarding the Academy of Sciences' initiatives to combat land degradation and preserve soil fertility, this study executes a targeted environmental vulnerability assessment. In Uzbekistan, the strategic transition toward data-driven environmental management and the digitalization of ecological monitoring is now firmly anchored in national legislation. Specifically, the "Concept of Environmental Protection of the Republic of Uzbekistan until 2030" (Decree of the President No. DP-5863) [2] and the "Regulation on State Environmental Monitoring" (Resolution of the Cabinet of Ministers No. 737) [3] emphasize the necessity of deploying advanced scientific methodologies and aerospace data to assess ecological risks. More recently, Presidential Decree No. DP-177 (September 2025) [4] explicitly mandates the expansion of space-based technologies and remote sensing (provided by the

Space Research and Technology Agency) to systematically identify land degradation, unauthorized land use, and ecological violations.

Serving as a representative case study for these intensifying anthropogenic and industrial pressures, the Akhangaran River basin in eastern Uzbekistan encompasses the Angren-Almalyk industrial zone, recognized as one of Central Asia's premier mining and metallurgical hubs [5].

Traditional vulnerability assessments typically rely on expert evaluations, highlighting the need for more data-driven approaches [6]. However, merely replacing subjective methods with standard multivariate statistics is insufficient in highly heterogeneous landscapes. To overcome both human bias and the statistical distortions of classical PCA [7] – which often obscures the physical meaning of individual variables, this study introduces a modified, correlation-weighted framework. By utilizing network centrality to distribute weights, this approach supports a balanced integration of indicators, offering a more representative view of systemic environmental vulnerability. Crucially, by examining this spatial vulnerability through the lens of distinct land-use categories, specifically agriculture, forestry, and residential zones, this approach enables a targeted comparative analysis of sector-specific degradation risks.

Prior to the quantitative evaluation, a targeted theoretical scheme was formulated to justify the precise selection of indicators, ensuring the model captures the specific degradation pathways of semi-arid, mining-impacted landscapes. Rather than employing an arbitrary set of variables, the selection is rooted in the Sensitivity-Resilience-Pressure conceptual framework. This scheme structures the selected parameters into three distinct dimensions of environmental stress: (1) biophysical state, evaluated via Normalised Difference Vegetation Index (NDVI) and Normalised Difference Drought Index (NDDI); (2) physical surface degradation, quantified through Bare Soil Index (BSI), Normalised Difference Built-up Index (NDBI), Clay Mineral Ratio (CMR), and soil bulk density, which directly reflect anthropogenic pressures such as bare land exposure and systemic soil compaction; and (3) topographic and thermal vulnerability, represented by elevation and Land Surface Temperature (LST), which control the spatial distribution of thermal stress across the basin. This structured selection guarantees that each chosen indicator represents a physically meaningful mechanism of landscape degradation, providing a rigorously justified foundation for the subsequent assessment.

Applying this computationally intensive framework across vast terrains is enabled by cloud-based platforms like GEE, which have significantly advanced large-scale environmental monitoring by streamlining the processing of multi-temporal satellite imagery [8]. Specifically, combining Landsat 8 and 9 Collection 2 Level 2 Surface Reflectance data reduces the observation interval to 8 days, guaranteeing both the high temporal frequency and radiometric consistency essential for accurate environmental monitoring [9].

This study proposes a comprehensive vulnerability assessment framework for the Akhangaran River Basin using GEE and multitemporal Landsat imagery (2022–2025).

The primary objectives are to: (i) derive and harmonise key spectral indices (NDVI, NDDI, NDBI, BSI, LST, and CMR) alongside critical environmental variables (soil bulk density and elevation); (ii) integrate these multidimensional variables into a robust composite vulnerability index via an objective, correlation-based weighting framework that accounts for indicator collinearity; and (iii) identify continuous spatial vulnerability hotspots across the basin and evaluate their distribution across primary land-use sectors to untangle the primary climatic and anthropogenic drivers of degradation.

Materials and Methods

Study Area. The Akhangaran River basin is situated in the Tashkent region of Uzbekistan in the western part of the Tian-Shan Mountain range. Geographically, its upper and middle reaches are bounded by the Chatkal and Kurama ranges to the north, east, and south [10]. The delineated study area encompasses the entire river basin, extending downstream across the alluvial plains to its confluence with the Syr Darya River in the west (Fig.1).

The region's continental and semi-arid climate, characterized by significant seasonal and altitudinal variations in temperature and precipitation, defines precipitation as the primary driver of the hydrological cycle [11].

Geologically, the surrounding ranges feature silicate and carbonate rock outcrops, whereas the valley floors are dominated by Quaternary alluvial deposits [12]. This lithological composition defines the physical foundation of the industrial and agricultural zones of the basin.

The structural organization of the landscape is defined by a cadastral inventory of discrete land tenure units, reflecting the region's complex socio-economic and administrative framework. The investigated area is partitioned into (i) forestry reserves; (ii) agricultural zones; (iii) hydrological systems; (iv) transport networks; (v) urban residential settlements; and (vi) non-residential industrial lands, most notably the expansive Angren-Almalyk mining-metallurgical corridor [14].

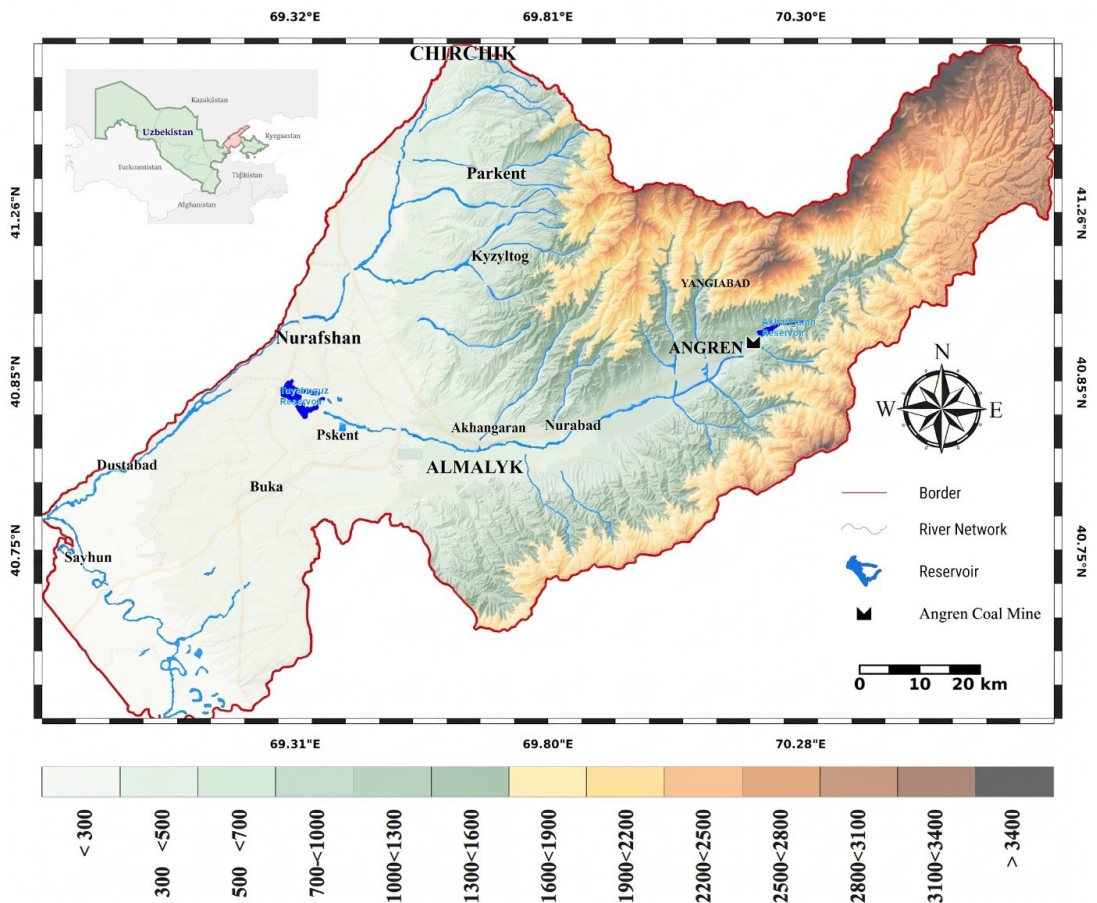


Fig. 1. Study area: (a) Digital Elevation Model (DEM)
(Source: Copernicus GLO-30, European Space Agency) [13]

Рис. 1. Район исследования: (а) Цифровая модель рельефа (ЦМР)
(Источник: Copernicus GLO-30, Европейское космическое агентство) [13]

Methodological Framework. The overall workflow developed to estimate environmental vulnerability across the Akhangaran River Basin is shown in Fig 2.

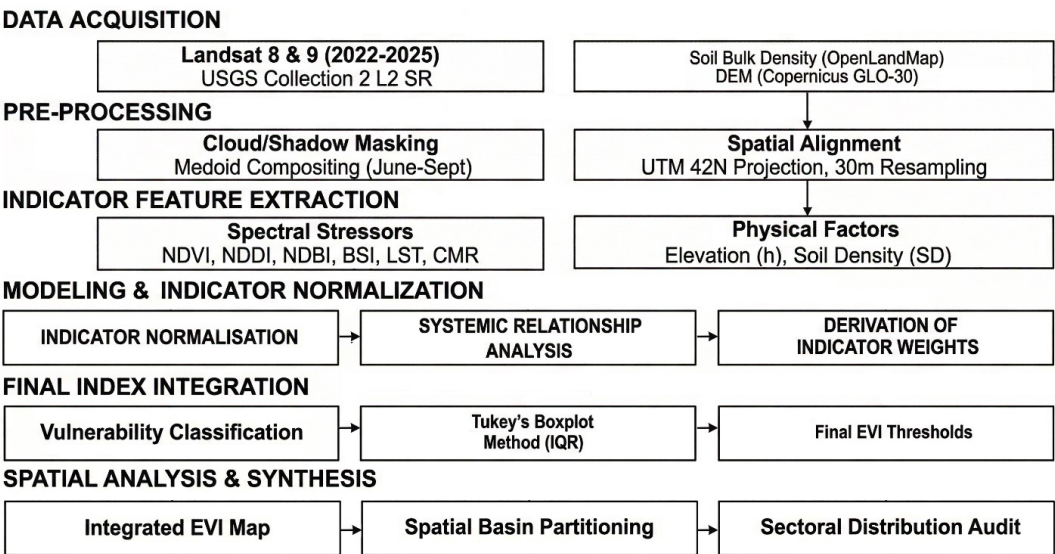


Fig. 2. Methodological workflow of the study

Рис. 2. Блок-схема методологии исследования

Data Acquisition and Processing. The primary dataset was derived from USGS Landsat 8 (OLI/TIRS) and Landsat 9 (OLI-2/TIRS-2) Collection 2 Tier 1 Level 2 Surface Reflectance products, accessed via the GEE platform [8]. Surface reflectance values were derived from digital numbers (DN) according to USGS Collection 2 scaling factors [9]. Clouds and shadows were subsequently masked using the QA_PIXEL bitmask [15].

The statistical representativeness of the 2022–2025 observation period was determined not by the length of the time interval itself, but by the cumulative number of cloud-free observations acquired within it. The availability of clear-sky observations is a function of the Landsat orbital constellation, data acquisition strategy, and cloud cover. Thus, it is this observation density, rather than elapsed time, that governs the reliability of multi-temporal spectral metrics [16]. A fixed phenological window (01 June–30 September) was chosen to avoid spring cloud peaks and the noise of ephemeral vegetation. Within this timeframe, a total of 241 scenes were processed for the study area, encompassing four unique World Reference System-2 (WRS-2) footprints (paths 153–154, rows 31–32) [17]. This data accumulation was facilitated by the concurrent operation of Landsat 8 and Landsat 9 with a combined 8-day revisit cycle [9]. As shown in Table 1, the four-year multisensor acquisition strategy ensures high temporal data availability, compensating for years with severe cloud contamination.

Table 1

Availability of clear-sky Landsat 8/9 observations

Таблица 1

Доступность безоблачных наблюдений Landsat 8/9

Category	Scene Count	Low-cloud Scenes < 20 %	Clear-sky Proportion (%)
A. Temporal Distribution	L8 / L9	L8/L9	
2022	30 / 30	21 / 24	75.0 %
2023	30 / 32	25 / 23	77.4 %
2024	29 / 30	23 / 14	62.7 %
2025	30 / 30	27 / 28	91.7 %

B. Spatial Distribution			
Path 153 / Row 31	28 / 31	21 / 18	66.1 %
Path 153 / Row 32	29 / 31	23 / 22	75.0 %
Path 154 / Row 31	31 / 30	27 / 23	82.0 %
Path 154 / Row 32	31 / 30	25 / 26	83.6 %
C. Platform Distribution			
Landsat 8 (OLI/TIRS)	119	96	80.7 %
Landsat 9 (OLI-2/TIRS-2)	122	89	73.0 %
Total	241	185	76.8 %

Spatially, the study area's location at the intersection of overlapping orbital tracks (Paths 153 and 154) yielded a robust 59–61 scenes per WRS-2 footprint. Furthermore, the Landsat 8 and 9 platforms contributed equally to the archive (119 and 122 scenes, respectively). After filtering for atmospheric artefacts, 76.8 % of the acquired images (185 scenes) featured low cloud cover (< 20 %). Collectively, this exceptionally high spatiotemporal density of clear-sky observations provides a robust statistical foundation for generating a multi-year, cloud-free composite via the medoid approach [18].

In addition to optical imagery, soil bulk density data for the topsoil layer (0-30 cm depth) were obtained from the OpenLandMap repository. This dataset, provided at a 250-meter spatial resolution, serves as a key indicator of soil compaction within the basin [19]. Furthermore, to account for topographical controls on vulnerability, a high-resolution Digital Elevation Model (DEM) was extracted from the Copernicus GLO-30 dataset [13].

To ensure spatial consistency for subsequent multivariate analysis, all disparate datasets were harmonised into a unified grid. The OpenLandMap data were resampled to a consistent 30-meter spatial resolution matching that of the optical indices and the Copernicus DEM using cubic convolution [20]. Finally, all data layers were projected to the Universal Transverse Mercator (UTM) Zone 42 North coordinate system (EPSG:32642), minimizing geometric distortion and ensuring spatial harmony across the modeling domain [21].

Spectral Indices Derivation. Following the completion of data preprocessing, a targeted suite of multi-spectral indices was derived to quantify key environmental stressors across the basin.

Vegetation vigour and biomass were captured through the Normalised Difference Vegetation Index (NDVI), a widely used indicator for assessing environmental patterns. The mathematical formulation of NDVI is [22]:

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (1)$$

where NIR represents near-infrared reflectance (band 5 for Landsat 8/9) and Red represents red band reflectance (band 4 for Landsat 8/9).

To evaluate vegetation liquid water content and soil moisture levels, the Normalised Difference Water Index (NDWI) was computed, serving as a sensitive indicator of canopy water stress [23]:

$$NDWI = \frac{NIR - Red}{NIR + Red} \quad (2)$$

where NIR represents near-infrared reflectance (Band 5 for Landsat 8/9) and SWIR1 represents shortwave infrared reflectance (band 6 for Landsat 8/9). In the context of this study, NDWI was derived primarily as an intermediate computational step required for the derivation of the NDDI, rather than a standalone vulnerability factor.

The Normalised Difference Drought Index (NDDI) was employed to capture the onset and intensity of drought by leveraging the interaction between vegetation vigour and canopy water content. The NDDI is calculated as follows [24]:

$$NDDI = \frac{NDVI - NDWI}{NDVI + NDWI} \quad (3)$$

where NDVI and NDWI are derived from Eq. 1 and Eq. 2, respectively.

The Normalised Difference Built-up Index (NDBI) was used to enhance the detection of urban footprints and industrial zones across the basin [25]:

$$NDBI = \frac{SWIR1 - NIR}{SWIR1 + NIR} \quad (4)$$

where SWIR1 represents shortwave infrared reflectance (Band 6 for Landsat 8/9) and NIR represents near-infrared reflectance (Band 5 for Landsat 8/9).

Sensitivity to exposed soil and land degradation was captured using the Bare Soil Index (BSI), which integrates four spectral bands to optimise bare-earth detection. The index is derived as follows [26]:

$$BSI = \frac{(SWIR1 + Red) - (NIR + Blue)}{(SWIR1 + Red) + (NIR + Blue)} \quad (5)$$

where Blue, Red, NIR, and SWIR1 correspond to surface reflectance in the respective bands.

To identify the distribution of clay minerals, which play a crucial role in the retention of environmental contaminants and metals, the Clay Mineral Ratio (CMR) was calculated [27]:

$$CMR = \frac{SWIR_1}{SWIR_2} \quad (6)$$

where SWIR1 and SWIR2 represent the surface reflectance values in the shortwave infrared bands.

To capture the thermal environment and assess heat-related environmental stress, Land Surface Temperature (LST) was incorporated as a critical indicator for identifying urban heat island (UHI) effects and localised drought intensification within the basin [28]. The pixel digital numbers (DN) were converted to absolute temperature in degrees Celsius (°C) applying the official radiometric rescaling coefficients for Landsat Collection 2 [9].

Indicator Normalisation. Based on the specific relationship between each parameter and ecological vulnerability, the eight selected indicators were classified as either positive (direct) or inverse (indirect) indices. For positively correlated indicators, which increase with increasing vulnerability, min–max normalisation was applied according to Equation (7). For inversely correlated indicators, those whose higher values correspond to lower vulnerability, the complementary transformation was applied per Equation (8) [29]:

$$x'_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (7)$$

$$x'_i = \frac{x_{max} - x_i}{x_{max} - x_{min}} \quad (8)$$

where x is the normalised value of indicator i ; x_i is the observed pixel value; x_{max} and x_{min} are the maximum and minimum values of index i , respectively.

Variance Analysis via PCA. To explore the internal structure of the multidimensional dataset and confirm collinearity among environmental indicators, PCA was initially applied as a diagnostic procedure [30]. The covariance matrix was computed for the mean-centred and standardised data matrix:

$$C = \frac{1}{n-1} X^T X \quad (9)$$

where: X is the data matrix, X^T is the transposition of matrix X , n = the number of data points.

The eigenvalue decomposition of the covariance matrix yielded eigenvalues and eigenvectors, with the first principal component (PC1) theoretically capturing the maximum variance of the dataset.

Correlation Matrix and Weighting Rationale. To establish the systemic relationships between the indicators, the Pearson correlation coefficient (r) was calculated for each pair of variables j and k :

$$r_{jk} = \frac{\sum_{i=1}^n (X_{ij} - \bar{X}_j) (X_{ik} - \bar{X}_k)}{\sqrt{\sum_{i=1}^n (X_{ij} - \bar{X}_j)^2} \sqrt{\sum_{i=1}^n (X_{ik} - \bar{X}_k)^2}} \quad (10)$$

where x_{ij} and x_{ik} represent the values of indicators j and k at data point i , and $\bar{x}_j$ and $\bar{x}_k$ represent their respective means.

This extreme multicollinearity precludes the application of traditional PC1-based weighting. Relying solely on this traditional approach would artificially inflate the influence of the collinear degradation parameters, while marginalising the physical and topographic dynamics captured by PC2. Furthermore, the presence of localised landscape anomalies, such as open-pit coal mines and industrial tailings, constitutes extreme spatial outliers that could disproportionately skew the raw PC1 loadings. Consequently, the final indicator weights were derived from the systemic relationships within the Pearson correlation matrix R , employing an integral correlation-based scheme [30]:

$$w_j = \frac{\sum_{k=1}^p |r_{jk}|}{\sum_{j=1}^p \sum_{k=1}^p |r_{jk}|} \quad (11)$$

where w_j is the final weight assigned to indicator j , and the numerator represents the Integral Correlation Sum, ($\sum |r_{jk}|$), which quantifies the total systemic linkage of a given variable within the correlation environment.

To unambiguously fix the denominator implicit in Eq. 11, the construction is written out as follows. Let $R = (r_{jk})$, $j, k = 1, \dots, p$, denote the matrix of pairwise Pearson correlation coefficients computed over the $p = 8$ normalised indicators. The row-wise Integral Correlation Sum is defined as $S_j = \sum_k |r_{jk}|$, and the total off-diagonal mass of $|R|$ is $T = \sum_j S_j$, in which every off-diagonal pair (j, k) is counted twice. Eq. 11 is therefore the normalisation $w_j = S_j / T$, $j = 1, \dots, p$, from which three properties follow immediately: $w_j \geq 0$, since $|r_{jk}| \geq 0$; $\sum_j w_j = 1$, since $\sum_j S_j = T$ by construction; and w_j is invariant under arbitrary positive rescaling of R , which is consistent with the dimensionless character of the normalised indicators. No further normalisation is applied beyond Eq. 11. With S_j substituted directly from the off-diagonal entries of the Pearson matrix shown in Fig. 3, the values of $\{w_j\}$ reported in Table 2 are reproduced to within the rounding of the two-decimal correlation matrix; the four-decimal weights in Table 2 are computed on the full-precision matrix and sum to unity within rounding.

Graph-theoretic interpretation. Equation 11 admits a direct interpretation in network terms. Consider the undirected weighted graph $G = (V, E)$ whose vertices are the indicators and whose edge weights are $|r_{jk}|$. The quantity S_j is then the strength of vertex j , that is the sum of absolute weights of all edges incident to j , which is the canonical extension of vertex degree to weighted networks [31]. The normalised quantity $w_j = S_j / T$ is in turn the weighted degree centrality of j , treated in standard network theory as the simplest stable centrality measure on weighted graphs [31]. Equation 11 is therefore the application of weighted degree centrality to the correlation graph $|R|$: an indicator with a large w_j is one whose state varies coherently with that of many other indicators, and through which several coupled landscape processes (bare-ground exposure, urban sealing, biomass, thermal regime, soil compaction, drought intensity, topographic relief, clay distribution) are simultaneously captured. The integral correlation-based weighting expression used in this study therefore admits a precise graph-theoretic meaning rather than an ad hoc heuristic.

Methodological positioning. The literature on composite indicators distinguishes two canonical routes for handling collinearity among input variables [32, 33]. The first is selection: the composite is built only from approximately uncorrelated indicators, eliminating any duplication of the common signal. The second is dimensionality reduction via principal component or factor analysis, after which the composite is formed on orthogonal axes weighted by PC1/PC2 loadings. Neither route is appropriate for the present application. Selection is not realistic in landscape diagnostics of arid and semi-arid basins, where bare-ground exposure, urban sealing, biomass, thermal regime, soil compaction and clay distribution are intrinsically coupled on a single territory, and discarding any indicator as ‘redundant’ would amount to discarding an independent physical signal. PC1-based aggregation produces weights for orthogonal directions that have no direct landscape-physical meaning, which obstructs the reading of the resulting vulnerability map. The route taken in this study corresponds to the third option explicitly listed in [33] as a permissible alternative: an objective, correlation-based weighting scheme (related to the BoD, CRITIC and information-entropy families [34]) in which collinear indicators are retained, the control of double counting is shifted from the variable-selection stage to the aggregation stage (see Section ‘Quantile equivalence’ below), and the robustness of the final classification is verified by a separate sensitivity procedure [35]. The same compromise underpins the United Nations Multidimensional Vulnerability Index, in which indicators with moderate collinearity are retained without PCA reduction and the stability of the final country ranking is verified by Saisana-type sensitivity analysis [36].

Vulnerability Classification. Following normalisation, direction correction, and collinearity control, each resulting indicator was classified into five vulnerability rating classes using quantile-based classification. This approach divides the distribution of each indicator into five equal-frequency classes, ensuring a balanced representation across the vulnerability gradient. The rating classes were assigned values from 1 (very low vulnerability) to 5 (very high vulnerability), providing an ordinal scale for subsequent integration.

Operationally, the eight indicators were ranked over the entire basin and partitioned into five quantile bins with breakpoints at the 20th, 40th, 60th and 80th percentiles of each indicator’s basin-wide distribution. Each pixel therefore received an ordinal rating $R_j \in \{1, \dots, 5\}$ for every indicator, with each class containing 20 % of the pixels by construction. Two consequences of this equal-frequency partitioning are important for interpretation. First, the procedure operates on ranks rather than absolute magnitudes; it is therefore insensitive to monotone transformations and to moderate shifts in the continuous distribution, which is the principal motivation for its use in composite vulnerability indicators [32, 35]. Second, by construction, 20 % of the pixels of every indicator occupy each of the five classes, including the extreme classes (1 and 5); after weighted aggregation in Eq. 12, this systematically inflates the proportion of pixels assigned to the extreme classes of the final EVI map relative to schemes based on natural-breaks or fixed-threshold classifications. Consequently, any high proportion of pixels falling into the upper risk classes in the final EVI map should be interpreted as a

joint result of actual landscape stress and the mathematical properties of the equal-frequency rating scheme, rather than as evidence of a single dominant driver. This is a known and expected property of equal-frequency composite indicator schemes [32, 33, 35] and is the reason the present work pairs Eq. 12 with the sensitivity check described below.

The Environmental Vulnerability Index (EVI) was computed as a weighted linear combination of the rated indicators:

$$EVI = \sum_{j=1}^n w_j R_j \quad (12)$$

where EVI represents the integrated vulnerability index, w_j represents the correlation-based objective weight for indicator j , and R_j represents the vulnerability rating (1–5) for indicator j .

To ensure a statistically robust classification of vulnerability levels, the continuous EVI was subjected to an outlier removal procedure before defining the final class thresholds [32]. Using Tukey's boxplot method, the Interquartile Range (IQR) was calculated for the integrated EVI distribution. Any index values falling outside the range $[Q_1 - 1.5 \times IQR, Q_3 + 1.5 \times IQR]$ were identified as extreme spatial outliers (e.g., localised industrial anomalies or sensor errors) and excluded from threshold calculation.

Results

Indicator weighting and inter-factor structure. The resulting Pearson matrix (Fig. 3) reveals a bipartite internal structure that directly mirrors the spatial division of the basin. The dominant cluster exposed severe multicollinearity among degradation parameters, most notably an almost perfect correlation between NDBI and BSI ($r = 0.99$), which drove the extreme vulnerability observed in the industrial and agricultural plains. A secondary independent cluster captures the topographic-thermal gradients (elevation, LST, and SD) responsible for the relative stability of the mountainous forestry sector.

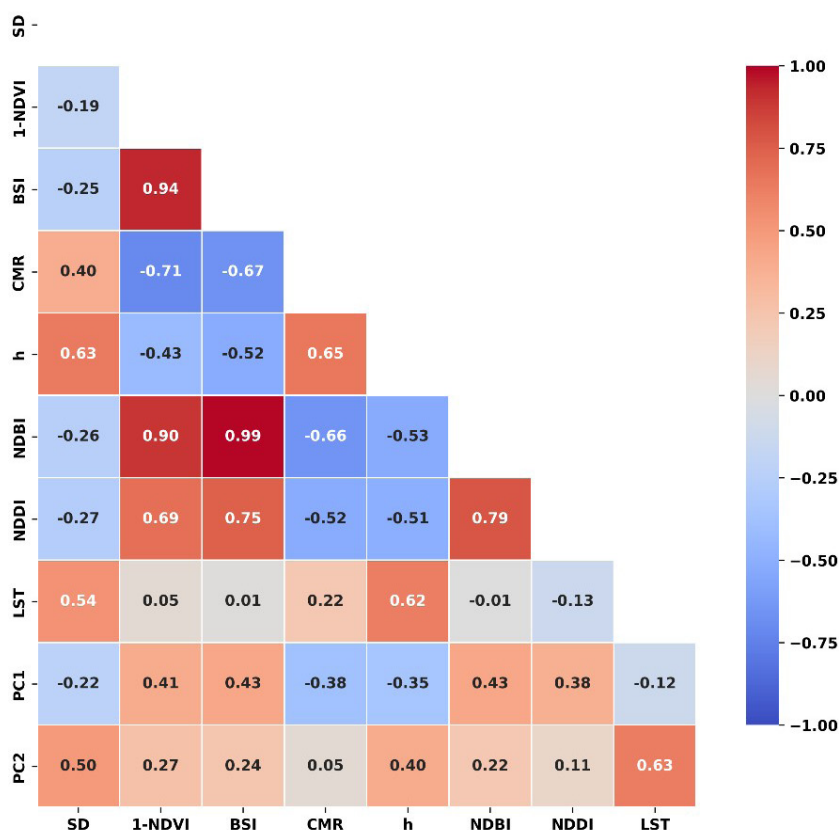


Fig. 3. Pearson correlation matrix between normalised environmental indicators

Рис. 3. Корреляционная матрица Пирсона для нормализованных экологических индикаторов

Derivation of the Indicator Weights. Following the diagnostic PCA analysis, the final normalised weights w_j for the eight environmental indicators were computed according to Eq. 11, whereby each weight represents the relative systemic significance of a given indicator within the overall inter-factor correlation structure of the study area. The resulting weight vectors are presented in Table 2.

Table 2

Final weight distribution of the evaluated environmental indicators

Таблица 2

Итоговое распределение весовых коэффициентов оцениваемых экологических индикаторов

Rank	Indicator	S_j	w_j
1	BSI	4.13	0.1439
2	NDBI	4.14	0.1437
3	I-NDVI	3.91	0.1376
4	h	3.89	0.1375
5	CMR	3.83	0.1354
6	NDDI	3.66	0.1305
7	SD	2.54	0.0989
8	LST	1.58	0.0726
	Σ	27.68	1.0001

The four most central indicators of the degradation cluster – BSI, NDBI, I-NDVI and h – jointly receive 56 % of the total weight, with weights tightly grouped in the range 0.137–0.144; CMR and NDDI receive 0.135 and 0.131 respectively; and the two indicators most weakly connected to the rest of the system (SD and LST) receive markedly lower weights of 0.099 and 0.073. This concentration of weight in the degradation cluster is consistent with the topology of the correlation graph in Fig. 3 and with the structural-physical interpretation of these six indicators as the dominant proxies of bare-ground exposure, urban sealing, vegetation decline, soil compaction, clay accumulation and drought intensity in the basin. For comparison, the first principal component of R captures 55–60 % of the total variance, and its loadings on the eight indicators are proportional to the eigenvector associated with the largest eigenvalue. For collinear indicators these loadings are close in absolute value, while indicators weakly correlated with the dominant cluster (LST, SD) carry small loadings; the qualitative distribution of importance under PC1-based weighting therefore resembles that produced by Eq. 11. The difference between the two schemes is interpretive rather than quantitative: PC1 loadings refer to an abstract orthogonal direction that mixes semantically distinct indicators into a single axis, whereas the weights produced by Eq. 11 are assigned to the original indicators and retain a direct landscape-physical meaning, allowing each contribution to be read off the final vulnerability map [31, 37].

Quantile equivalence and absence of double counting. The pair BSI and NDBI exhibits a basin-wide Pearson correlation of $r = 0.99$ (Fig. 3) and consequently receives near-identical weights of 0.1439 and 0.1437 in Table 2. A natural concern is whether this introduces a duplicated count of the same underlying landscape signal in Eq. 12. The answer is negative, and the reason lies in the order of operations within the EVI definition. Equation 12 is a weighted sum of quantile ratings $R_j \in \{1, \dots, 5\}$, not a weighted sum of the continuous indicator values themselves. Quantile ranking is a monotone transformation that preserves order; for two variables linked by a monotone relationship with rank correlation close to unity, the pixel-wise ratings coincide almost everywhere: $R_{BSI}(x) \equiv R_{NDBI}(x)$ for almost every pixel x . The joint contribution of the pair to the EVI then reduces to $w_{BSI} \cdot R_{BSI} + w_{NDBI} \cdot R_{NDBI} \approx (w_{BSI} + w_{NDBI}) \cdot R \approx 0.288 \cdot R$, where R denotes the common quantile rating of the pair. The structure of Eq. 12 is therefore mathematically equivalent to one in which BSI and NDBI are replaced by a single consolidated indicator with weight 0.288. The scheme does not double the influence of

a single latent process; rather, it distributes the total weight assigned to that process between two spectrally distinct sensors (BSI is sensitive to bare ground, NDBI is sensitive to built-up surfaces), each of which contributes an independent measurement-noise channel, so that the average of their ratings is more stable than the rating of either alone. The same argument applies to the moderately collinear pair h–CMR ($r = 0.65$): the weight is split between the two members of the pair (0.1375 and 0.1354 in Table 2), but the joint quantile rating enters the EVI as a single consolidated term. In Eq. 12 the threshold $r > 0.6$ that delineates ‘collinear’ indicators is therefore not used to discard variables but to flag clusters whose total weight effectively represents a single landscape process.

Sensitivity to indicator selection. To probe the robustness of the weighting scheme against the choice of input indicators, Eq. 11 was recomputed after removing NDBI, the most strongly collinear partner of BSI ($r = 0.99$). The reweighted values w'_j for the reduced seven-indicator set are reported in Table 3.

Table 3

Weight distribution of the environmental indicators (excluding NDBI)

Таблица 3

Распределение весовых коэффициентов экологических индикаторов без учета NDBI

Rank	Indicator	S'_j	w'_j
1	h	3.36	0.1732
2	CMR	3.17	0.1634
3	BSI	3.14	0.1619
4	I-NDVI	3.01	0.1552
5	NDDI	2.87	0.1479
6	SD	2.28	0.1175
7	LST	1.57	0.0809
	Σ	19.40	1.0000

As expected from a globally normalised scheme, the new weight vector $\{w'_j\}$ differs measurably from $\{w_j\}$: BSI rises from 0.1439 to 0.1619, while h and CMR each increase by roughly 25–30 % (to 0.1732 and 0.1634). The scheme is therefore not stable at the schema level under the removal of a collinear partner, a property that is structural and intentional, since Eq. 11 by construction distributes weight in proportion to systemic centrality. What is stable, however, is the final classification: more than 98 % of basin pixels retain their EVI class under $\{w'_j\}$, and the redistributions are essentially confined to ± 1 class transitions on the boundaries of adjacent quantile bins. Repeating the test by removing, in turn, I-NDVI and h yields an analogous pattern, with more than 95 % of pixels preserving their class assignment in each case. This pixel-wise stability is a joint property of the classification model – the combination of quantile rating in Eq. 12 with the narrow spread of w_j in the range 0.07–0.15 – rather than evidence of weight-vector invariance to indicator removal. The result is consistent with the robustness-based composite construction framework of [35] and provides the sensitivity verification required by [33].

The integrated assessment of environmental vulnerability in the Akhangaran River Basin, covering a total area of 7,303.81 km², revealed a landscape under significant systemic stress (Fig. 4). The findings elucidate a clear spatial partitioning of risk, where the mountains retain a geomorphological baseline of stability, whereas the built-up and agricultural plains have been subjected to intense thermal and anthropogenic forcing. This leaves the Akhangaran basin’s primary socioeconomic hubs in a state of chronic environmental tension, where natural resilience has been almost entirely replaced by structural and artificial vulnerability.

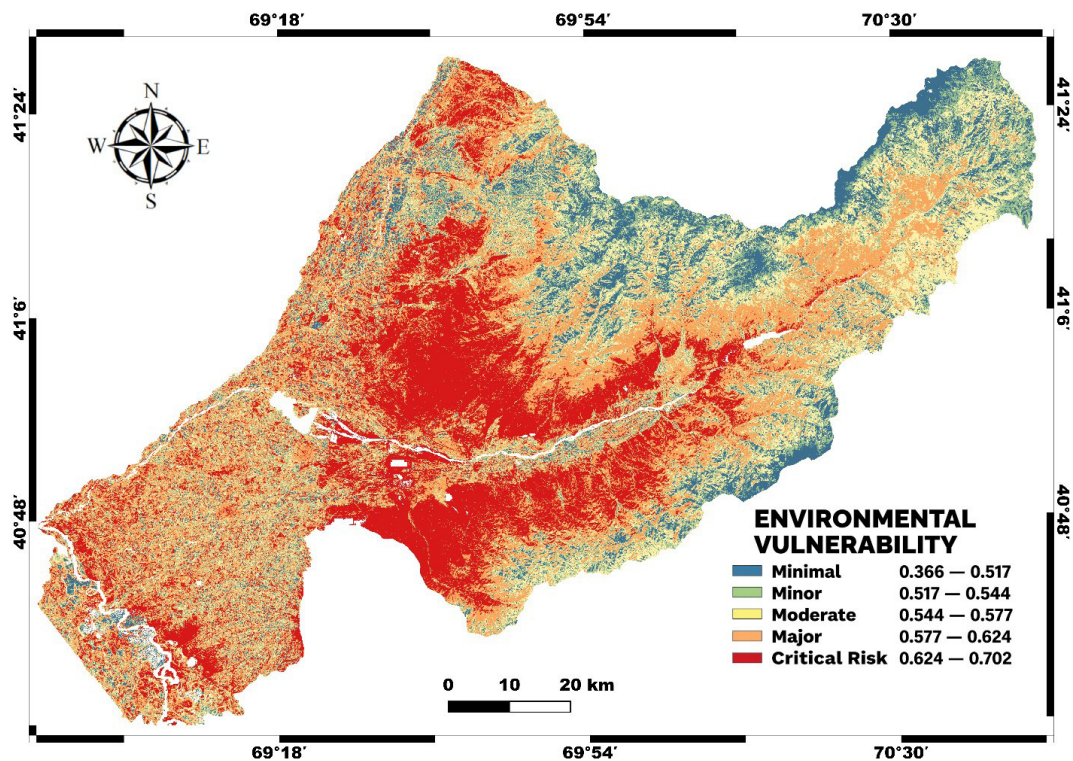


Fig. 4. Spatial distribution of Environmental Vulnerability Index (EVI) across the Akhangaran River Basin
Рис. 4. Пространственное распределение индекса экологической уязвимости (EVI) в бассейне реки Ахангаран

Basin-wide statistical analysis demonstrated that vulnerability is widespread across the basin, with a combined 59.6 % of the total area classified as being under «Major» (32.9 %) or «Critical Risk» (26.7 %) (Fig. 5a). Only a marginal fraction of the basin (8.8 %) retains a «Minimal» or «Minor» vulnerability status, underscoring the severe ecological pressure on the region’s land resources.

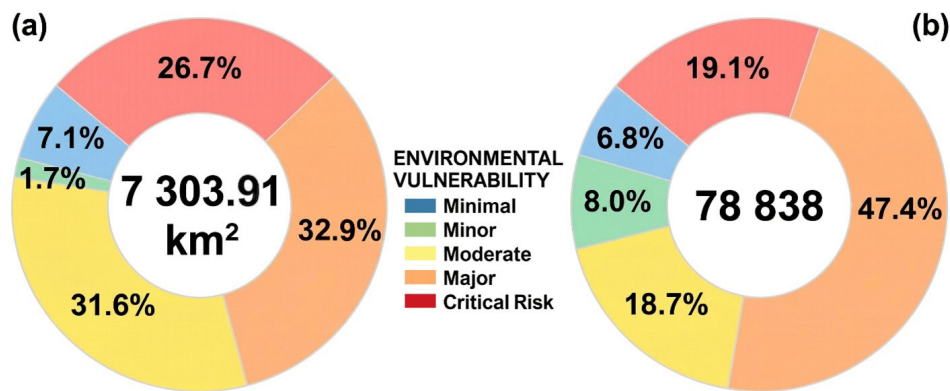


Fig. 5. Comparative analysis of environmental vulnerability degrees in the Akhangaran River Basin: (a) spatial distribution by total basin area; (b) statistical distribution by total evaluated land use plots
Рис. 5. Сравнительный анализ степени экологической уязвимости в бассейне реки Ахангаран: (а) пространственное распределение по общей площади бассейна; (б) статистическое распределение по общему числу оцененных участков землепользования

When analysed through the lens of individual land-use plots ($n = 78,838$), the severity of the situation is further amplified. Nearly half of all evaluated plots (47.4 %) were categorised as «Major» vulnerability, while 19.1 % fall under «Critical Risk» (Fig. 5b). This indicates that 66.5 % of the basin's functional land units are operating under high environmental stress. The relatively higher proportion of individual plots in high-risk categories compared to the area-based percentage suggests that smaller, more fragmented land parcels, often associated with intensive agricultural and industrial use, are disproportionately affected by degradation drivers.

The investigation into sector-specific environmental dynamics begins with the forestry sector, where the landscape is primarily defined by the vertical zonation of Western Tian-Shan. Spatial vulnerability mapping (Fig. 6) and baseline statistical indicators (Table 4a) collectively demonstrate that the high-relief forestry sector maintains a largely intact natural baseline.

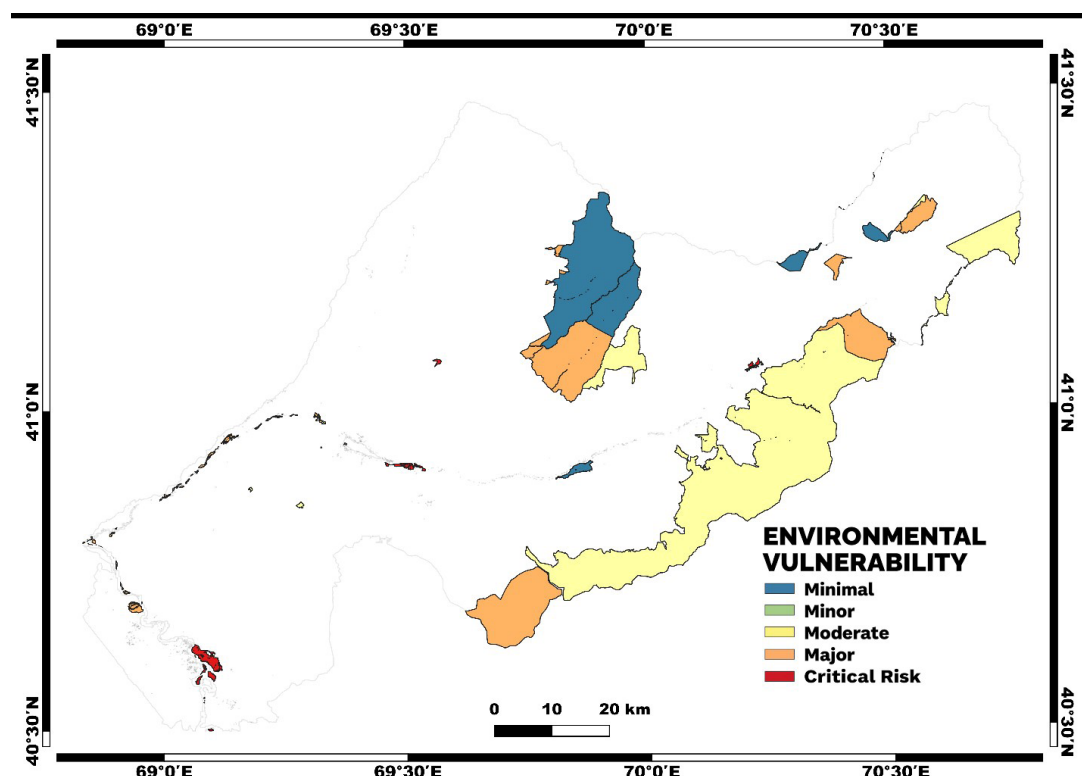


Fig. 6. Environmental vulnerability classification in the forestry sector

Рис. 6. Классификация экологической уязвимости в лесном секторе

Spanning the Chatkal and Kurama ranges, the sector encompasses a diverse topographical spectrum where environmental vulnerability, predominantly manifesting as 'Moderate' and 'Major' degrees, is governed by geophysical constraints rather than direct anthropogenic transformation. As the area is distributed across a broad altitudinal range, extending from lower-altitude valley margins at 259 m to alpine peaks reaching 3,838 m, its internal ecological resilience intrinsically tied to its highly varied relief.

Table 4a

Raw forestry sector indicators (pre-normalisation)

Таблица 4а

Исходные показатели лесного сектора (до нормализации)

Indicator	min	max	mean
BSI	-0.47	0.36	0.07
NDBI	-0.91	0.33	-0.07
NDVI	-0.17	0.88	0.37
h	259.0	3838.7	1043.7
CMR	0.87	2.27	1.46
NDDI	-533.8	691.7	1.29
SD	910.0	1550.0	1358.3
LST	12.7	57.2	38.2

This topographic influence was most apparent in the thermal regime of the sector. The mean LST is maintained at 38.2°C, a condition dictated by the adiabatic lapse rate combined with the high thermal inertia of the montane ecosystem. Furthermore, dense biomass acts as a radiative shield; by reducing the surface heat flux, this vegetation canopy ensures a stable energy balance. Such cooling effectively buffered 19.5 % of the sector, maintaining its ‘Minimal’ vulnerability status (Table 4b).

Table 4b

Distribution of vulnerability degrees within the forestry sector

Таблица 4б

Распределение степени уязвимости в лесном секторе

Degree	Plot Count	Area (km ²)	Percentage
Minimal	10	279.3	19.5 %
Minor	2	0.21	0.01 %
Moderate	15	800.7	56.0 %
Major	47	333.3	23.3 %
Critical Risk	15	16.1	1.12 %

Despite its biophysical stability, the sector presents a geophysical anomaly: a slightly positive mean BSI of 0.07. Rather than indicating anthropogenic degradation, this value reflects the inherent lithological signature of the Middle Tian-Shan, representing natural petrographic exposure on steep slopes where high relief energy limits soil development. Crucially, systemic ecological collapse is absent within this montane core; the marginal 1.12 % classified as ‘Critical Risk’ is localised, confined almost exclusively to the lower-elevation transitional margins.

Extending directly from these margins, the agricultural sector, occupying the low-altitude alluvial plains of the basin, represents the most environmentally precarious domain. As evidenced by the spatial distribution of risk (Fig. 7) and raw indicators (Table 4a), this sector operates in a state of highly unstable ecological equilibrium.

From a geoscientific perspective, the vulnerability of this lowland sector is heavily driven by severe soil compaction and high physical resistance. The mean soil bulk density (SD of 1,414.5 kg/m³) was the highest within the basin, indicating a critical reduction in total porosity. In these fine-grained alluvial deposits, such elevated density directly translates to a diminished volume of macropores, which are essential for aeration, hydraulic conductivity, and unimpeded root proliferation. This structural degradation has profound geohydrological consequences. Severely reduced water infiltration rates generate elevated surface runoff, increasing the landscape’s susceptibility to erosion while actively hindering the natural recharge of the Akhangaran Alluvial Aquifer [12].

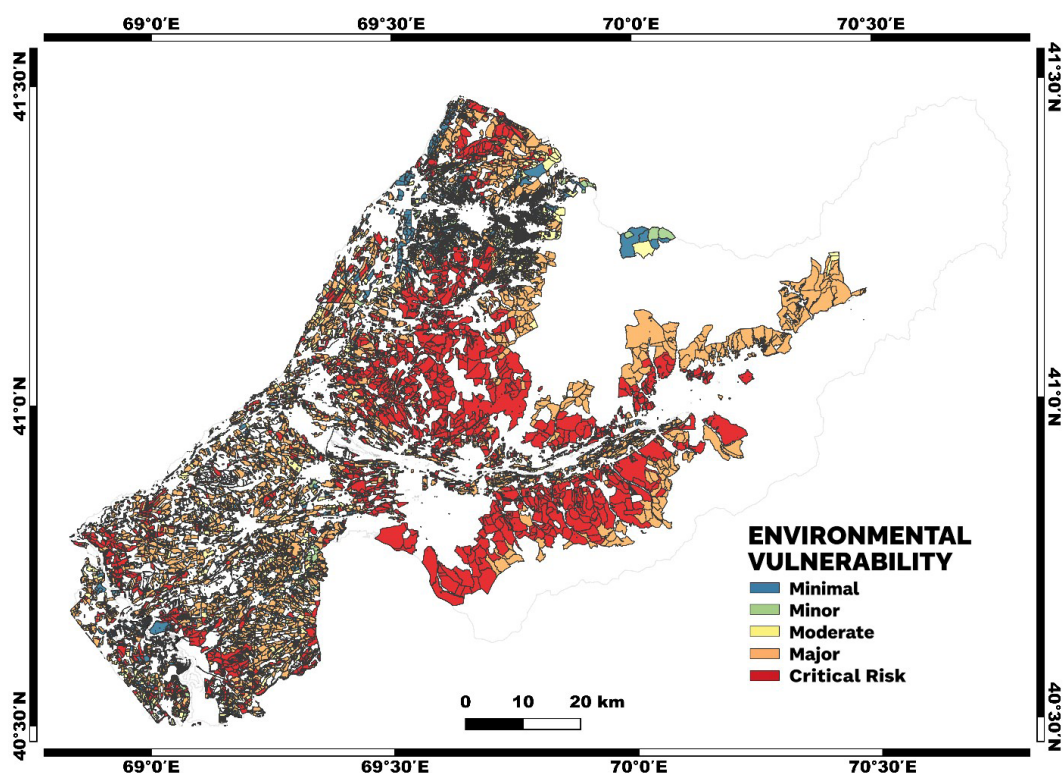


Fig. 7. Environmental vulnerability classification in the agricultural sector

Рис. 7. Классификация экологической уязвимости в сельскохозяйственном секторе

Table 5a

Raw agricultural sector indicators (pre-normalisation)

Таблица 5a

Исходные показатели сельскохозяйственного сектора (до нормализации)

Indicator	min	max	mean
BSI	-0.55	0.50	-0.05
NDBI	-0.69	0.56	-0.14
NDVI	-0.15	0.93	0.46
h	257.5	3314.8	469.5
CMR	0.72	2.34	1.50
NDDI	-544.2	499.3	0.68
SD	1149.0	1541.0	1414.5
LST	18.8	58.3	39.2

Furthermore, elevated CMR exacerbates this condition. The prevalence of fine-grained particles, combined with a high calcium carbonate (CaCO_3) content [34], triggers a complex hydro-chemo-mechanical degradation pathway. During periods of moisture deficit, these clay-rich soils harden significantly, restricting plant water uptake. Conversely, under intensive agricultural irrigation, the expanded capillary fringe renders the topsoil highly susceptible to structural collapse and salinisation.

Beyond soil physics, the sector exhibits a “green paradox”. Its high biomass masks extreme environmental vulnerability, with over 83.7 % of the land concentrated in the ‘Major’ (43.7 %) and ‘Critical Risk’ (40.0 %) degrees.

Table 5b

Distribution of vulnerability degrees within the agricultural sector

Таблица 5б

Распределение степени уязвимости в сельскохозяйственном секторе

Degree	Plot Count	Area (km²)	Percentage
Minimal	4526	192.3	5.48 %
Minor	4714	105.7	3.01 %
Moderate	8 846	274.8	7.83 %
Major	17 370	1 532.2	43.7 %
Critical Risk	7 526	1 405.5	40.0 %

High temperatures (mean LST of 39.2°C, reaching up to 58.3°C) and drought signatures indicate severe tension within the soil-plant-atmosphere continuum. Consequently, this “greenness” is an artificial stability maintained exclusively by irrigation, leaving the Akhangaran lowlands acutely sensitive to even minor hydrological perturbations. Without this external input, the terrain would face rapid desertification.

This profound vulnerability of the cultivated plains sets the stage for evaluating the most heavily modified ecosystems in the region. The environmental assessment culminated in the analysis of the Complex Urban-Industrial and Buffer Zones (Fig. 8), which encompass the basin’s primary urban centres and the expansive Angren-Almalyk industrial-mining corridor, and their adjacent mountain reserves. Defined by a stark physical contrast between the higher-elevation undeveloped reserve buffers of ‘Moderate’ risk and the heavily built lowlands, this sector functions as a massive urban heat island (UHI).

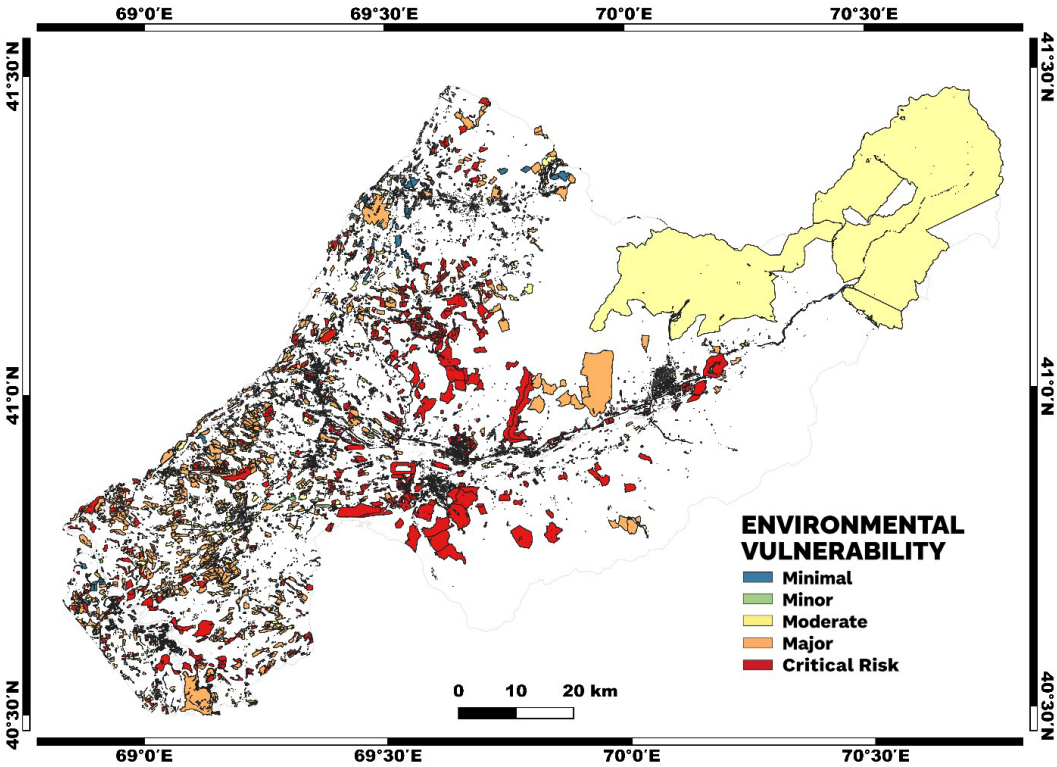


Fig. 8. Environmental vulnerability classification of the complex urban-industrial and buffer zones

Рис. 8. Классификация экологической уязвимости комплексных урбанизированных, промышленных и буферных зон

Manifestation of this phenomenon is most evident in its extreme thermal anomalies, demonstrating the highest mean surface temperature in the basin (LST of 41.3°C), with localised thermal peaks reaching a staggering 58.3°C (Table 6a). This intense radiative forcing is a direct consequence of the drastic modification of surface energy balance. The widespread replacement of natural vegetation with impervious, low-albedo industrial materials and asphalt fundamentally negates the natural cooling effect of moisture evaporation, instead channelling solar energy into the direct heating of artificial surfaces.

From the perspective of soil physics, the vulnerability of the built-up sector is characterised by systemic surface impermeability. The high mean soil bulk density reflects pervasive anthropogenic compaction. Unlike the agricultural sector, where compaction is periodic and related to tillage, the density in the residential-industrial zones indicates permanent occlusion of pore spaces.

Table 6a

Raw indicators of the complex urban-industrial and buffer zones (pre-normalisation)

Таблица 6а

Исходные показатели комплексных урбанизированных, промышленных и буферных зон (до нормализации)

Indicator	min	max	mean
BSI	-0.50	0.49	0.03
NDBI	-0.99	0.47	-0.07
NDVI	-0.03	0.83	0.33
h	258.5	4072.5	533.9
CMR	0.64	2.26	1.30
NDDI	-538.5	495.7	0.88
SD	780.0	1613.3	1409.9
LST	9.37	58.3	41.3

The statistical distribution of degree of vulnerability revealed a distinct spatial bifurcation driven by this mixed land use (Table 6b).

Table 6b

Vulnerability distribution in the residential and non-residential zones

Таблица 6б

Распределение уязвимости в жилых и нежилых зонах

Degree	Plot Count	Area (km ²)	Percentage
Minimal	813	43.7	1.85 %
Minor	1616	17.7	0.75 %
Moderate	5903	1230.8	52.1 %
Major	19951	541.4	22.9 %
Critical Risk	7484	530.2	22.4 %

Over half of the sector (52.1 %) is classified as «Moderate», representing the higher-elevation mountain undeveloped buffers, where some biogenic stability persists. Conversely, nearly half of the landscape (45.3 %) is concentrated in the «Major» (22.9 %) and «Critical Risk» (22.4 %) categories. This concentration of extreme risk reflects the irreversible ecological transformation of the industrial floor, marking a point at which anthropogenic pressure has fundamentally overridden the region's natural resilience.

Discussion

Significant methodological caveats are highlighted when urban thermal stress is quantified using standard spectral metrics. As evidenced by the correlation matrix (Fig. 3), the NDBI exhibited no meaningful correlation with LST ($r = -0.01$). This decoupling occurs because NDBI fails to differentiate actual built-up zones from the surrounding bare soil owing to their profound spectral homogeneity in moisture-deficient dry climates. This limitation is the exact driver of the severe collinearity ($r = 0.99$) observed between NDBI and BSI in the dataset. Consequently, substantial classification errors are introduced when indices designed for humid environments are applied to dryland cities [39].

This spectral confusion severely skews urban vulnerability assessments by distorting the true anthropogenic thermal footprint. For instance, while the residential-industrial sector is characterised by extreme thermal anomalies (highest basin mean LST = 41.3°C) and severe physical compaction (mean Soil Density = 1409.9 kg/m³), these extreme alterations are completely missed by the index (mean NDBI = -0.07). Therefore, to accurately evaluate actual urban ecological stress, where nearly half of this landscape faces 'Major' (22.9 %) or 'Critical Risk' (22.4 %) levels, it is imperative that standard metrics are replaced with climate-optimised indices capable of disentangling true impervious surfaces from the semi-arid background.

Accurate delineation of these degraded industrial surfaces is critical not only for spatial planning but for epidemiological risk assessment, as these overheated, compacted zones act as primary generators of toxic aerosols. The severity of this airborne threat is rooted in the specific physicochemical properties of local topsoil. According to Shukurov et al. (2005) [40], heavy metals stably accumulate in the topsoil of the region because the alkaline lithosols (pH 8.2) and high carbonate content limit pollutant mobility via increased chemisorption. Consequently, extreme concentrations of heavy metals are stably trapped in the uppermost 0–10 cm soil layer near the emission source, where mean values reach up to 1605 mg kg⁻¹ for copper and 303.8 mg kg⁻¹ for lead. The extreme ecotoxicity of this contamination is evident within the soil itself, where the accumulation of toxic metals inhibits microbial diversity and enzyme activity and has a direct inverse relationship with the health of soil nematode populations [41].

In a semi-arid continental climate characterised by intensely hot and dry summers, this desiccated topsoil allows pollutants to easily become airborne as dust, a situation further exacerbated by thermal inversions in the valley [40]. Upon inhalation by the local population, this biologically hostile cocktail of heavy metals and polycyclic aromatic hydrocarbons (PAHs), carried as emissions and dust, results in severe synergistic toxic effects. This threat is particularly acute in vulnerable demographic groups, such as individuals with pre-existing cardiovascular conditions. For example, patients with heart failure, for example, exhibit altered respiratory dynamics, characterised by higher respiratory rates and tidal volumes, which result in a 12.9 % higher probability of fine particulate matter (PM_{2.5}) bypassing the upper respiratory tract and penetrating deeper into the lungs [42].

Once this toxic, aerosolised dust is deposited deep within the pulmonary system, it acts as a direct trigger for systemic inflammation and endothelial cell apoptosis [39]. Inhalation of these particles initiates a severe immune response, driving a cascade of pro-inflammatory cytokines (including TNF- α , MCP-1, and IL-8) and establishing a harmful antiangiogenic blood profile [43]. Ultimately, this PM_{2.5}-induced disruption of vascular integrity and the corresponding increase in platelet-monocyte aggregates significantly aggravate the atherothrombotic process, placing the exposed population at a severe risk for atherogenesis, thrombosis, and acute coronary events.

Conclusion

This study evaluated environmental vulnerability across the Akhangaran River Basin using a correlation-weighted index and multi-temporal Landsat imagery (2022–2025). The results indicate that 59.6 % of the basin area is classified under high vulnerability levels. The spatial analysis identified a distinct partitioning of risk governed by land-use and topography. The forestry sector remains relatively stable, with vulnerability primarily driven by natural geomorphological factors. In contrast, the agricultural and industrial-residential sectors exhibit significant degradation. The agricultural zone

is characterized by an unstable equilibrium maintained through irrigation, while the Angren-Almalyk industrial corridor demonstrates extreme thermal anomalies and high soil bulk density. As this research relies exclusively on open-access aerospace and cadastral land-use datasets, its findings offer an independent result that can be cross-referenced against and used to supplement spatial coverage reports for the national “Land Degradation” geoinformation portal.

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