

Anthropogenic risk assessment of riverine habitat using an ecosystem-based risk approach for river management prioritization: A case study from the Biyonga River, Indonesia

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ABSTRACT

Riverine ecosystems are increasingly exposed to multiple anthropogenic pressures that interact across the river corridor, creating challenges for effective management prioritization. This study aimed to assess spatial patterns of relative cumulative anthropogenic risk at a screening level and identify priority areas for further management consideration along the Biyonga River, Indonesia. A spatial assessment framework was applied by integrating land use/land cover (LULC) analysis with the InVEST habitat risk assessment (HRA) model. Nine anthropogenic stressors representing hydromorphological alteration, land-use pressure, and water-quality stress were assessed. The analysis further examined the effect of buffer distances of 50, 100, 250, and 500 m on estimated relative cumulative risk and identified management priority hotspots based on the spatial distribution and intensity of stressors. Within the baseline 100-m buffer, the mean Exposure, Consequence, and cumulative Risk scores were 1.357, 1.344, and 2.689, respectively, with 52.75% of the assessed area classified as medium relative anthropogenic risk and 47.25% as low relative anthropogenic risk. Water-quality stressors, particularly organic pollution, sediment loading, chemical pollution, and aquatic oxygen stress, represented the dominant relative-risk dimension. Increasing buffer distance progressively increased the estimated cumulative Risk scores and the proportion of areas classified as medium relative anthropogenic risk, while the dominant stressor pattern remained consistent. Three management priority hotspots were identified along the Biyonga River, each characterized by different combinations of dominant anthropogenic stressors and relative risk levels. These findings provide a screening-level basis for identifying areas warranting further investigation and management consideration, rather than direct evidence of actual environmental degradation. Field verification, environmental monitoring, and ecological assessment are therefore needed to validate the identified priority areas and their potential ecological implications.

Keywords: riverine habitat, anthropogenic risk, habitat risk assessment, land use/land cover, water-quality stress, river management.

INTRODUCTION

Riverine ecosystems provide essential habitats for aquatic organisms and support important ecological processes and ecosystem functions along river corridors. However, their ecological integrity is increasingly affected by diverse anthropogenic disturbances that alter environmental conditions, habitat characteristics, sediment

dynamics, and ecological processes (Dermawan et al., 2026; Sundermann et al., 2013). Agricultural expansion, settlement development, and other forms of human-induced land transformation can modify riverine environments and generate spatially heterogeneous pressures along river corridors (Oeding et al., 2018). These pressures may occur simultaneously and interact, resulting in ecological responses that are more complex

than those caused by individual disturbances and highlighting the importance of considering multiple stressors in riverine ecological assessment (Calabrese et al., 2020; Erasmus et al., 2021).

Land use and land cover (LULC) represent an important pathway through which anthropogenic activities influence riverine habitats. Changes in watershed and riparian LULC can affect biological conditions and river ecological quality, particularly when natural vegetation is replaced by agricultural or developed areas (Gu and Li, 2024; Tanaka et al., 2016). Rapid land-use change can increase surface runoff, erosion, and pollutant transport, thereby contributing to spatial variation in river water quality (Burhan et al., 2026). Therefore, assessing anthropogenic influences on riverine environments requires consideration of land-use types and their spatial relationship with the river corridor.

Anthropogenic pressures on riverine habitats extend beyond land-cover transformation and include interacting hydromorphological, land-use, and water-quality stressors. Wastewater from urban areas and livestock activities can contribute substantially to organic pollution, while the accumulation of organic pollutants may stimulate microbial activity, reduce dissolved oxygen, and disturb aquatic ecosystems (Wen et al., 2017). River water quality can vary spatially and temporally in response to land-use patterns, hydrological conditions, and other anthropogenic activities (Horta Ribeiro Antunes et al., 2021). Because multiple stressors can jointly influence aquatic communities and ecosystem attributes, an integrated multiple-stressor approach is needed to characterize cumulative anthropogenic pressure and support freshwater ecosystem management (Lima et al., 2023).

The spatial scale used to represent anthropogenic pressures is another important consideration in riverine habitat assessment. Ecological responses to human pressures may vary across spatial scales because the influence of surrounding landscapes is not uniform throughout a river corridor (Bruno et al., 2014). Riparian buffer delineation can help identify the spatial extent within which landscape characteristics are associated with surface-water conditions, while land-use conditions farther upstream may also influence water quality at a sampling location (Brumberg et al., 2021; K. Li et al., 2018). Thus, different buffer distances may alter the spatial representation of LULC and associated

anthropogenic pressures, potentially influencing the estimated distribution of cumulative habitat risk and the areas identified as management priorities (Zhou et al., 2022).

Previous applications illustrate the methodological diversity of InVEST-HRA across coastal, marine, and riverine ecosystems. Caro et al. (2020) modified HRA by incorporating ecosystem-service abundance into habitat resilience assessment in a coastal-estuarine system, while Huang et al. (2020) integrated satellite remote sensing and ground investigations with spatially explicit HRA to assess risks associated with coastal land reclamation. Studwell et al. (2021) used HRA to evaluate cumulative disturbance from maritime activities and support seabird conservation planning, whereas Bastos et al. (2023) combined HRA with expert judgement to identify spatial patterns of water-pollution hazards in a coastal lagoon. Meilana et al. (2024) integrated cumulative risk assessment with Marxan to support marine spatial planning under multiple anthropogenic pressures. More closely related to the present study, Kantharajan et al. (2022) assessed nine anthropogenic stressors in the Pranhita River using field observations, remote sensing, secondary spatial data, and land-use information to support conservation and restoration planning. Collectively, these studies demonstrate the capability of InVEST-HRA to integrate multiple anthropogenic pressures and spatial datasets for ecosystem risk assessment and environmental planning. However, previous applications have primarily emphasized risk characterization, identification of sensitive areas, conservation, pollution management, or spatial planning, with less attention to translating cumulative-risk hotspots into differentiated, stressor-specific management priorities. In particular, the integration of hotspot identification with the intensity and spatial co-occurrence of individual stressors, surrounding LULC characteristics, and alternative spatial scales remains insufficiently explored for supporting differentiated management decisions.

Despite these advances, an important analytical challenge remains: translating cumulative riverine habitat-risk patterns into location-specific management priorities that reflect dominant anthropogenic pressures. Although cumulative-risk assessments can identify areas where relative risk is concentrated, they do not necessarily indicate which stressors require management attention at a particular location. Addressing this challenge

requires consideration of the stressors contributing to cumulative risk, their spatial co-occurrence, and the surrounding land-use context. It also requires examining whether the spatial scale used to represent anthropogenic influence alters risk patterns and, consequently, management priorities.

To address this gap, the present study develops an integrated workflow that combines stressor-specific interpretation, spatial-scale comparison, and LULC context to interpret relative cumulative anthropogenic risk in riverine habitats. Rather than relying on cumulative risk alone, the workflow links HRA outputs with stressor intensity, spatial co-occurrence, surrounding LULC characteristics, and alternative buffer distances. This approach enables relatively high-risk areas to be interpreted according to the intensity and spatial arrangement of anthropogenic stressors and their landscape context, providing a basis for differentiated, screening-level management prioritization. The contribution of this study lies not in introducing a new HRA model, but in connecting cumulative risk assessment with stressor-specific and spatial-contextual interpretation to support more targeted management interventions.

Accordingly, this study aims to assess relative cumulative anthropogenic risk to riverine habitat along the Biyonga River by integrating

river-corridor LULC information with the INVEST Habitat Risk Assessment framework. Specifically, the study aims to: (i) characterize the spatial distribution and intensity of multiple anthropogenic stressors; (ii) examine the effects of alternative buffer distances on relative cumulative risk patterns; and (iii) identify screening-level management-priority areas based on cumulative risk, stressor intensity, spatial co-occurrence, and surrounding LULC characteristics. The results are intended to support spatially differentiated management planning and guide the prioritization of areas for further field assessment, monitoring, and targeted intervention.

METHODS

Study area

This study was conducted along the Biyonga River, one of the principal rivers draining the Biyonga Sub-watershed within the Limboto Watershed system in Gorontalo Province, Indonesia (Figure 1). The river flows toward Lake Limboto and represents an important river corridor connecting upstream terrestrial areas with the lake system. The study reach extends approximately 18.8 km, covering the main channel from a

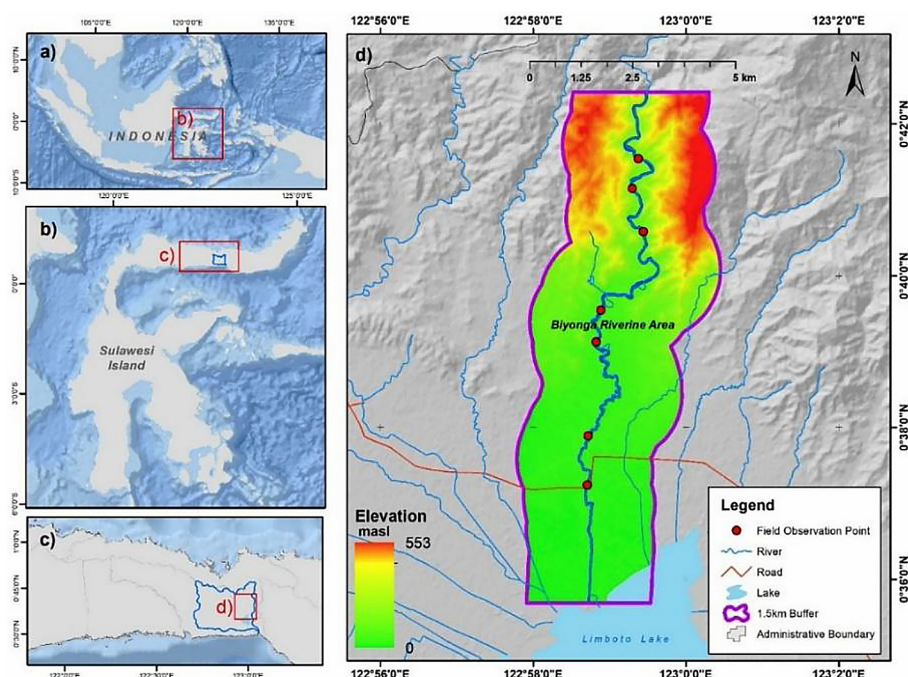


Figure 1. Location and topographic setting of the Biyonga River study area. Panels (a–c) show the regional geographic context from Indonesia to the study area, while panel (d) presents the Biyonga River, elevation, field observation points, river network, and the 1.5-km buffer boundary used to define the study area

relatively undisturbed upper section, where anthropogenic influence is limited, to its outlet toward Lake Limboto. The surrounding corridor comprises a heterogeneous mixture of agricultural land, built-up areas, forest, shrubland, water bodies, and flooded vegetation, reflecting spatially variable land-use conditions along the river.

A 1.5-km buffer from the river channel was delineated to characterize the surrounding LULC and examine changes in land-use composition with increasing distance from the river. The Biyonga River and its surrounding corridor have experienced environmental pressures associated with land-use change, riverbank modification, sediment loading, and other anthropogenic activities (Lihawa et al., 2022, 2025; Olli and Ichsan, 2020). The close relationship between the river channel and surrounding land uses provides an appropriate setting for assessing cumulative anthropogenic risk to riverine habitat. Accordingly, this study focuses on the spatial distribution of multiple anthropogenic stressors along the river corridor and their implications for spatially targeted river management.

LULC composition analysis

LULC composition was analyzed to characterize the landscape context of anthropogenic pressure along the Biyonga River. A 10-m resolution ESRI LULC 2025 dataset was clipped to a 1.5-km river corridor and reclassified into six classes: Waterbody, Forest, Flooded vegetation, Agriculture, Built-up, and Shrubland. The corridor was divided into left and right banks based on the upstream-to-downstream river orientation, and concentric buffer zones of 100, 250, 500, 1000, and 1500 m were generated on both banks to assess changes in LULC composition with increasing distance from the river, following a buffer-based approach for riverine LULC assessment (Kantharajan et al., 2022). LULC percentages were calculated and compared among buffer distances and between riverbanks to characterize the spatial distribution of land-use pressure and provide landscape context for interpreting anthropogenic stressors and cumulative riverine habitat risk.

Water quality assessment and validation

Water sampling followed the Indonesian National Standard (SNI) 6989.57:2008 for surface-water sampling and was conducted at seven

sampling points (T1–T7) along the Biyonga River on 15 January 2026. The points were selected using purposive sampling to represent variations in river conditions, surrounding land use, and anthropogenic pressures across the upstream, middle, and downstream sections. Sampling was conducted sequentially from upstream to downstream between 08:00 and 13:30 local time. Three samples were collected at each point, resulting in 21 laboratory samples for biochemical oxygen demand, chemical oxygen demand, and total suspended solids analyses, while dissolved oxygen was measured in situ using a DO meter. Field-level quality assurance and quality control were supported by replicate sampling and adherence to the standardized sampling procedures specified in SNI 6989.57:2008. Available laboratory records did not provide numerical detection limits or detailed laboratory QA/QC procedures; therefore, no additional laboratory QA/QC information was inferred.

Spatial interpolation and validation were performed using Ordinary Kriging (OK) to estimate the spatial distribution of dissolved oxygen (DO), biochemical oxygen demand (BOD), chemical oxygen demand (COD), and total suspended solids (TSS) across the Biyonga River study area. The interpolation was conducted in Python using PyKriging with an automatically fitted spherical variogram model and a global search neighborhood, in which all available sampling points were included in each estimation. Interpolated surfaces were generated at a 5 m spatial resolution within the study-area boundary. Model performance was evaluated using leave-one-out cross-validation (LOOCV), whereby each sampling point was sequentially excluded from the dataset and its value was predicted using the remaining observations. Prediction performance was assessed using mean error (ME), mean absolute error (MAE), root mean square error (RMSE), coefficient of determination (R^2), and normalized RMSE (NRMSE).

Habitat risk assessment model

The InVEST habitat risk assessment (HRA) model, developed by the Natural Capital Project, was applied to assess the cumulative anthropogenic risk to riverine habitat along the Biyonga River. The HRA model estimates habitat risk by integrating Exposure, which represents the degree to which habitat is subjected to individual

anthropogenic stressors based on their spatial and temporal overlap and intensity, and Consequence, which represents the potential response of habitat to stressor exposure based on habitat sensitivity and resilience (Arkema et al., 2014). In this study, the HRA framework was adapted to characterize the cumulative effects of multiple anthropogenic stressors representing hydromorphological alteration, land-use and anthropogenic pressure, and water-quality stress along the Biyonga River. The overall methodological framework consisted of stressor identification and spatial data generation, assessment of exposure and consequence criteria, habitat resilience characterization, cumulative risk estimation, and subsequent spatial interpretation for management prioritization.

Anthropogenic stressors – data generation

A total of nine anthropogenic stressors were identified for riverine habitat risk assessment in the Biyonga River based on field observations (January 2026 – February 2026), interpretation of high-resolution imagery, land-use/land-cover information, and water-quality measurements (Table 1). The stressors were grouped into three categories: hydromorphological alteration, land-use and anthropogenic pressure, and water-quality stress. Spatial input layers were generated from field observations and high-resolution imagery for physical and habitat-related stressors, while the ESRI Land Cover dataset was used to represent land-use pressure and field-measured water-quality parameters were spatially interpolated to characterize water-quality stress. Given the limited number of sampling locations, the resulting surfaces were interpreted as screening-level representations of relative spatial patterns rather than precise estimates of water-quality concentrations.

Hydro-morphological alteration

Riverbank modification was assessed based on field observations and visual interpretation of high-resolution imagery from Google Earth. Physical alterations along the riverbank were documented and spatially delineated to represent their extent along the Biyonga River. Modification of riverbank structure can alter channel morphology, bank stability, habitat structure, and local water-quality processes (Murniningsih, 2021). Given the moderate level of observed modification, the

resulting layer was assigned a medium-intensity impact score (2) in the HRA.

River fragmentation was assessed by identifying physical structures, such as dams, and channel discontinuities along the Biyonga River using field observations and high-resolution imagery from Google Earth. Wide channel segments with limited active water flow were also identified as potential discontinuities. Barriers can disrupt longitudinal connectivity, alter flow continuity, and restrict movement and dispersal of aquatic organisms (Wantania et al., 2025). These features were assigned the highest fragmentation intensity score (3) and used to generate the river fragmentation layer for the HRA.

Riparian modification was assessed using field observations and high-resolution imagery from Google Earth to identify anthropogenic changes within the riparian zone. Riparian degradation can reduce bank stabilization, sediment retention, water-quality regulation, and habitat support (Murniningsih, 2021). Within a 50-m buffer from the river, settlement areas were classified as high-intensity modification score (3), whereas agricultural or cropland areas were classified as medium-intensity modification score (2).

Sand mining was identified through field observations and high-resolution imagery interpretation from Google Earth. Areas showing evidence of sand extraction and channel-bed disturbance were delineated along the Biyonga River. Sand extraction can modify channel morphology, substrate conditions, channel depth, and aquatic habitat structure (Arsyad et al., 2020). Due to its limited spatial dominance, sand mining was assigned a low-intensity score (1) in the HRA.

Land-use & anthropogenic pressure

Land use pressure was represented using the ESRI Land Cover 2025 dataset and administrative status to characterize anthropogenic land-use conditions surrounding the Biyonga River. The surrounding areas were classified into urban, suburban, and rural zones and assigned high-, medium-, and low-intensity scores of 3, 2, and 1, respectively (Milledge et al., 2018; Shen et al., 2017). Built-up areas represent concentrated human activity and potential wastewater, solid-waste, and surface-runoff pressures adjacent to the river (Nita et al., 2026).

Water-quality stress

Sediment loading (TSS) was represented by total suspended solids (TSS) concentrations obtained from water samples collected during the rainy-season survey. The samples were analyzed in the laboratory using SNI 6989.3:2019, which specifies the gravimetric method for determining total suspended solids. The measured concentrations were subsequently interpolated using ordinary kriging to characterize suspended-sediment conditions along the river corridor. Elevated TSS concentrations can increase turbidity, reduce water clarity, modify substrate conditions, and adversely affect aquatic organisms (Bilotta and Brazier, 2008). The maximum allowable TSS concentration for Class II river water is 50 mg/L,

with concentrations exceeding this standard considered high-intensity sediment loading.

Organic pollution was represented by biochemical oxygen demand (BOD) concentrations measured from river-water samples collected during the rainy-season survey. The samples were analyzed in the laboratory using SNI 6989.72:2009, which specifies the method for determining biochemical oxygen demand. The resulting BOD concentrations were subsequently spatially interpolated using ordinary kriging to represent their distribution across the study area. Higher BOD concentrations indicate greater organic loading and oxygen consumption, which may reduce oxygen availability for aquatic organisms (Wen et al., 2017). The maximum allowable BOD concentration for Class II river water is 3 mg/L, with values

Table 1. Anthropogenic stressors included in the habitat risk assessment of the Biyonga River

No.	Stressor	Stressor group	Spatial representation	Source	Justification
Hydro-morphological alteration					
1	Riverbank modification	Channel morphological alteration	Polygon	Field survey (15/01/2026) and Google Earth imagery date (01/03/2025)	Modification of riverbank structure can alter channel morphology, bank stability, habitat structure, and local water-quality processes (Murniningsih, 2021).
2	River fragmentation	River connectivity disruption	Polygon	Field survey (15/01/2026) and Google Earth imagery date (01/03/2025)	Barriers can disrupt longitudinal connectivity, alter flow continuity, and restrict movement and dispersal of aquatic organisms (Wantania et al., 2025).
3	Riparian modification	Riparian degradation	Polygon	Field survey (15/01/2026) and Google Earth imagery date (01/03/2025)	Riparian degradation can reduce bank stabilization, sediment retention, water-quality regulation, and habitat support (Murniningsih, 2021).
4	Sand mining	Sediment extraction	Polygon	Field survey (15/01/2026) and Google Earth imagery date (01/03/2025)	Sand extraction can modify channel morphology, substrate conditions, channel depth, and aquatic habitat structure (Arsyad et al., 2020).
Land-use & Anthropogenic pressure					
5	Land use pressure	Land-use pressure	Polygon	ESRI LULC 2025 dataset (10-m resolution), supplemented by field observations (15/01/2026)	Built-up areas represent concentrated human activity and potential wastewater, solid-waste, and surface-runoff pressures adjacent to the river (Nita et al. 2026)
Water-quality stress					
6	Non-point source – sediment loading (TSS)	Suspended sediment pollution	Spatial raster	Primary water-quality measurements collected during 15/01/2026 field survey	High suspended sediment loads can threaten aquatic biodiversity and are associated with changes in riverine multi-trophic communities (Q. Li et al., 2025).
7	Non-point source – organic pollution (BOD)	Organic pollution	Spatial raster	Primary water-quality measurements collected during 15/01/2026 field survey	Elevated BOD concentrations indicate increased organic pollution and oxygen demand in river systems (Y. Li et al. 2026)
8	Non-point source – chemical pollution (COD)	Chemical pollution	Spatial raster	Primary water-quality measurements collected during 15/01/2026 field survey	Elevated COD concentrations reflect river organic pollution and show spatial variation associated with anthropogenic activities (Yan et al., 2025).
9	Non-point source: Aquatic oxygen stress (DO)	Dissolved oxygen stress	Spatial raster	Primary water-quality measurements collected during 15/01/2026 field survey	Low dissolved oxygen concentrations are associated with hypoxic conditions in river systems, particularly under high pollution loading (Zhang et al., 2025).

exceeding this standard considered high-intensity organic pollution.

Chemical pollution was represented by chemical oxygen demand (COD) concentrations obtained from water samples collected during the rainy-season survey. The samples were analyzed in the laboratory using SNI 6989.2:2009, which specifies the titrimetric method for determining chemical oxygen demand. The resulting COD concentrations were spatially interpolated using ordinary kriging to produce a spatial raster of COD distribution. Higher COD concentrations indicate a greater presence of oxidizable substances and may impose additional pressure on aquatic water-quality conditions (Z. Li et al., 2022). The maximum permissible COD concentration for Class II river water is 25 mg/L, with values exceeding this standard considered high-intensity chemical pollution.

Aquatic oxygen stress was represented by dissolved oxygen (DO) measurements obtained directly at the Biyonga River sampling locations during the rainy-season survey. DO was measured in the field using a DO meter, and the measurements were subsequently spatially interpolated using kriging to characterize the spatial distribution of oxygen conditions and identify areas potentially experiencing aquatic oxygen stress. Adequate oxygen availability is essential for aquatic organisms, whereas declining DO can increase physiological stress and reduce habitat suitability (Franklin, 2014). The minimum DO concentration specified for Class II river water is 4 mg/L, with values below this standard indicating high-intensity aquatic oxygen stress.

Risk assessment criteria rating and model execution

Each anthropogenic stressor was evaluated using predefined exposure and consequence criteria within the InVEST habitat risk assessment (HRA) framework (Arkema et al., 2014). Exposure was assessed using temporal overlap, management effectiveness, and stressor intensity, whereas Consequence was assessed using frequency of disturbance, change in affected area, and change in water quality. Habitat resilience was represented by recovery time. Each criterion was assigned an ordinal rating from 0 to 3 based on predefined rating instructions, together with a data-quality score and criterion weight. A rating of 0 indicated that the criterion was not scored,

whereas ratings of 1, 2, and 3 represented increasing levels of stressor influence or consequence. The ratings were informed by field observations, spatial datasets, and relevant literature, with spatially explicit intensity layers used where quantitative spatial information was available. These layers included TSS, BOD, COD, and DO for the corresponding water-quality stressors, while the remaining criteria were represented using standardized categorical ratings. The model was executed using a 100-m baseline stressor buffer, no distance decay, and multiplicative aggregation of exposure and consequence to derive relative cumulative anthropogenic risk. The resulting risk values were classified into low, medium, and high relative-risk categories for spatial interpretation.

Buffer sensitivity analysis

A buffer-distance sensitivity analysis was conducted to evaluate the influence of the assumed spatial extent of stressor influence on HRA outcomes (Hira et al., 2023). In addition to the 100-m baseline configuration, three alternative buffer distances of 50, 250, and 500 m were evaluated while maintaining the same stressor ratings, data-quality scores, weights, resilience parameters, aggregation method, and absence of distance decay. For each configuration, mean exposure, consequence, and cumulative risk were calculated and compared with the baseline results. The proportion of the assessment area within each risk class was also compared among buffer distances. Stressor-specific cumulative risk was examined to identify which anthropogenic pressures were most sensitive to changes in the spatial extent of stressor influence.

Management priority assessment

Management priority areas were identified from the continuous spatial distribution of cumulative habitat risk within the baseline 100-m buffer. The cumulative risk raster was reclassified into three relative-risk categories using the Natural Breaks (Jenks) classification method. Areas belonging to the highest relative-risk class were subsequently delineated as management-priority hotspots (Putri et al., 2025). This relative classification was used to identify locations with comparatively higher cumulative anthropogenic risk within the study area and was not interpreted as the standard HRA high-risk category. Within

each hotspot, the spatial distribution of individual stressors was examined to identify stressors with relatively high intensity and their spatial co-occurrence. The surrounding LULC characteristics were then evaluated to provide contextual information on the dominant anthropogenic pressures. Management priorities were assigned according to the dominant stressor combinations identified within each hotspot, including water-quality improvement, riverbank protection or rehabilitation, riparian restoration, and control of anthropogenic land-use pressure. Figure 2 presents the overall workflow of the study, illustrating the main data inputs, analytical procedures, and assessment stages undertaken to evaluate anthropogenic risk in the Biyonga River.

RESULTS

Land use/land cover composition

The LULC composition along the Biyonga River exhibited clear left–right bank asymmetry, particularly within the immediate 100-m river corridor (Figure 3). On the left bank, agriculture

(38.5%) and built-up areas (36.9%) were the dominant land-use classes, followed by forest (19.1%). In contrast, the right bank was dominated by built-up areas (52.0%), followed by agriculture (25.5%) and forest (15.1%). Accordingly, built-up land occupied 15.1 percentage points more of the right-bank corridor than the left-bank corridor, whereas agricultural land was 13.0 percentage points more extensive on the left bank.

With increasing distance from the river, built-up areas generally decreased while forest cover increased on both banks. On the left bank, built-up area declined from 36.9% at 100 m to 24.3% at 1500 m, while forest increased from 19.1% to 30.4%. On the right bank, the corresponding changes were more pronounced, with built-up area decreasing from 52.0% to 23.2% and forest increasing from 15.1% to 30.3%. Agricultural land showed a less consistent pattern, increasing initially on the left bank from 38.5% to 42.1% at 250 m before declining to 30.5% at 1500 m, while on the right bank it increased from 25.5% to 31.7%. Waterbody and shrubland generally increased with distance, whereas flooded vegetation remained a minor component throughout the corridor.

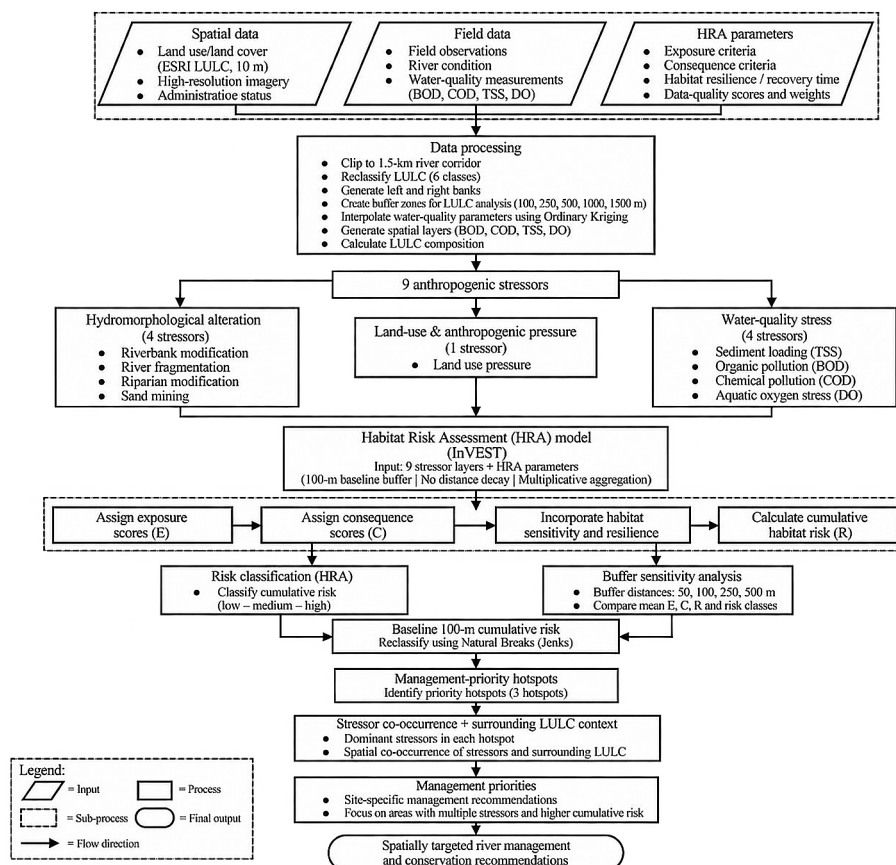


Figure 2. Methodological framework for assessing anthropogenic habitat risk in the Biyonga River

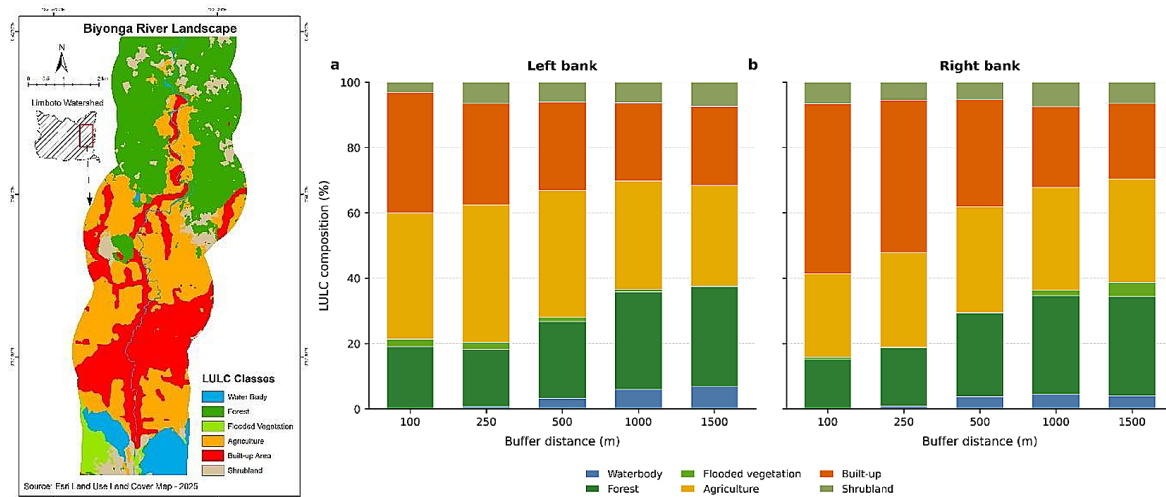


Figure 3. Land use/land cover composition along the Biyonga River corridor at different buffer distances. The map shows the spatial distribution of LULC classes within the study area, while the bar charts present the proportional composition of LULC classes along the left bank (a) and right bank (b) within 100, 250, 500, 1000, and 1500 m buffer distances

Overall, the strongest land-use contrast occurred within the immediate river corridor, where built-up land was concentrated on the right bank and agricultural land was more prevalent on the left bank. This asymmetry became less pronounced at broader buffer distances, as the proportions of forest and agricultural land became more similar between the two banks. These results show that the immediate river corridor has a relatively high concentration of anthropogenic land uses and therefore provides an important spatial context for interpreting the distribution of anthropogenic stressors and relative cumulative anthropogenic risk along the Biyonga River.

Water quality assessment

The water-quality assessment (Table 2) showed spatial variation among the seven sampling points along the Biyonga River. DO

concentrations ranged from 4.6 to 6.8 mg/L, whereas BOD, COD, and TSS concentrations ranged from 2.7 to 7.0 mg/L, 13 to 33 mg/L, and 30 to 85 mg/L, respectively. Sampling point T5 recorded the highest concentrations of BOD, COD, and TSS, as well as the lowest DO concentration. Compared with the Class II water-quality criteria, BOD concentrations exceeded 3 mg/L at sampling points T3–T7, while COD concentrations exceeded 25 mg/L at T4–T6 and TSS concentrations exceeded 50 mg/L at T4–T7. In contrast, DO concentrations remained above the minimum criterion of 4 mg/L at all sampling points. BOD, COD, and TSS concentrations increased from T1 to T5, reached their maximum values at T5, and subsequently declined toward T6–T7.

The LOOCV results indicated a generally acceptable predictive performance of the Ordinary Kriging models, with R^2 values ranging from 0.801 to 0.850 across the four water-quality

Table 2. Raw water-quality measurements at the seven sampling points along the Biyonga River, sampled on 15 January 2026

Sampling point	Latitude (°)	Longitude (°)	DO (mg/L)	BOD (mg/L)	COD (mg/L)	TSS (mg/L)
T1	0.69239	122.98955	6.8	2.7	13	30
T2	0.68582	122.98821	6.5	2.7	16	36
T3	0.68497	122.98888	6	3.5	19	46
T4	0.65208	122.98043	5	6.1	29	72
T5	0.65914	122.98141	4.6	7	33	85
T6	0.63147	122.97861	5.1	5.3	28	70
T7	0.62070	122.97668	5.5	4.5	25	58

Table 3. Leave-one-out cross-validation results for ordinary kriging interpolation of water-quality parameters

Parameter	n	ME	MAE	RMSE	NRMSE (%)	R ²
DO	7	-0.017	0.208	0.300	5.321	0.843
BOD	7	-0.004	0.458	0.602	13.245	0.850
COD	7	0.075	2.196	3.063	13.152	0.801
TSS	7	0.310	6.360	8.337	14.700	0.803

parameters (Table 3). The low ME values suggested limited systematic bias between observed and predicted concentrations. NRMSE values ranged from 5.32% for DO to 14.70% for TSS, indicating that prediction errors were relatively small compared with the corresponding mean observed values. However, the validation results should be interpreted with caution because the analysis was based on a limited number of sampling locations. Despite this limitation, the cross-validation results support the use of Ordinary Kriging to represent the spatial variability of water-quality parameters within the study area.

Riverine anthropogenic risk assessment

Exposure criteria

The exposure assessment showed variation among stressors in terms of temporal overlap, management effectiveness, and spatial intensity (Table 4). Land use pressure received the highest temporal-overlap rating (3), followed by the four water-quality-related stressors, sediment loading, organic pollution, chemical pollution, and aquatic oxygen stress, with a rating of 2. Riverbank modification, river fragmentation, riparian modification, and sand mining received the lowest temporal-overlap rating (1). These ratings were assigned according to the predefined ordinal categories of the adopted HRA Invest framework and represent relative differences in the expected temporal exposure of habitats to each stressor, rather than measured frequencies of environmental degradation.

Management effectiveness was rated 2 for riverbank modification, river fragmentation, and riparian modification, while the remaining stressors received a rating of 3, indicating lower expected effectiveness of existing management measures under the applied criteria. Where direct quantitative information on management effectiveness was unavailable, these ratings were treated as structured expert assessments based on the observed characteristics of the stressors and

the management context of the study area, rather than as direct measurements of management performance. Stressor intensity was represented spatially using the corresponding intensity layers, including TSS, BOD, COD, and DO for the water-quality-related stressors. Thus, the intensity component was derived from spatially explicit environmental datasets, whereas the categorical exposure criteria were assigned using the predefined HRA rating scheme and the available contextual evidence. These differences in temporal overlap, management effectiveness, and spatial intensity contributed to the variation in estimated relative Exposure among the assessed stressors.

Consequence criteria

The consequence assessment also varied among stressors based on frequency of disturbance, change in affected area, and change in water quality (Table 4). Frequency of disturbance received a rating of 2 for riverbank modification, river fragmentation, riparian modification, sand mining, and land use pressure, while the four water-quality-related stressors were not scored for this criterion because their temporal occurrence was not independently quantified in the available dataset. For these stressors, the potential consequence associated with water-quality conditions was represented through the change-in-water-quality criterion and the corresponding spatial intensity layers, avoiding the assignment of an additional frequency score unsupported by the available data. Change in affected area was generally rated 2, with land use pressure receiving a higher rating of 3. For change in water quality, ratings of 2 were assigned to riverbank modification, riparian modification, sand mining, sediment loading, organic pollution, chemical pollution, and aquatic oxygen stress, whereas river fragmentation received a rating of 1 and land use pressure a rating of 3. These categorical ratings follow the predefined HRA Invest rating scheme and, where direct quantitative measurements

Table 4. Rating of anthropogenic stressors based on exposure and consequence criteria for habitat risk assessment

No.	Stressor	Exposure criteria			Consequence criteria		
		Temporal overlap	Management effectiveness	Intensity	Frequency of disturbance	Change in affected area	Change in water quality
1	Organic pollution (BOD)	2	3	Spatial*	0	2	2
2	Chemical pollution (COD)	2	3	Spatial*	0	2	2
3	Land use pressure (Built-up)	3	3	Spatial*	2	2	2
4	River fragmentation	1	2	3	2	2	1
5	Riparian modification	1	2	2	2	2	2
6	Riverbank modification	1	2	2	2	2	2
7	Sand mining	1	3	1	2	2	2
8	Sediment loading (TSS)	2	3	Spatial*	0	2	2
9	Aquatic oxygen stress (DO)	2	3	Spatial*	0	2	2

Note: Rating score: 1 – low, 2 – medium, and 3 – high; 0 – not scored. *Intensity was represented using spatially explicit stressor layers rather than a single categorical rating. BOD – biochemical oxygen demand; COD – chemical oxygen demand; TSS – total suspended solids; DO – dissolved oxygen. The underlying criterion ratings, data-quality scores, weights, resilience parameters, and rating schemes are provided in Supplementary Tables S1–S3.

were unavailable, were assigned using the spatial characteristics of the stressors, available environmental information, and the ecological context of the Biyonga River.

Together with the habitat resilience parameters, these criteria determined the consequence component of the HRA and contributed to the resulting estimated relative cumulative anthropogenic risk. The resulting consequence values should therefore be interpreted as relative, screening-level estimates generated from the HRA scoring framework, rather than as direct

measurements of ecological consequence or evidence of actual environmental degradation.

Risk assessment

Under the baseline configuration using a 100-m stressor buffer, no distance decay, and multiplicative risk aggregation, the Biyonga River showed a mean exposure (E) of 1.357, consequence (C) of 1.344, and cumulative risk (R) of 2.689 (Figure 4). These values represent a relative, screening-level assessment of potential anthropogenic pressure and habitat risk within the

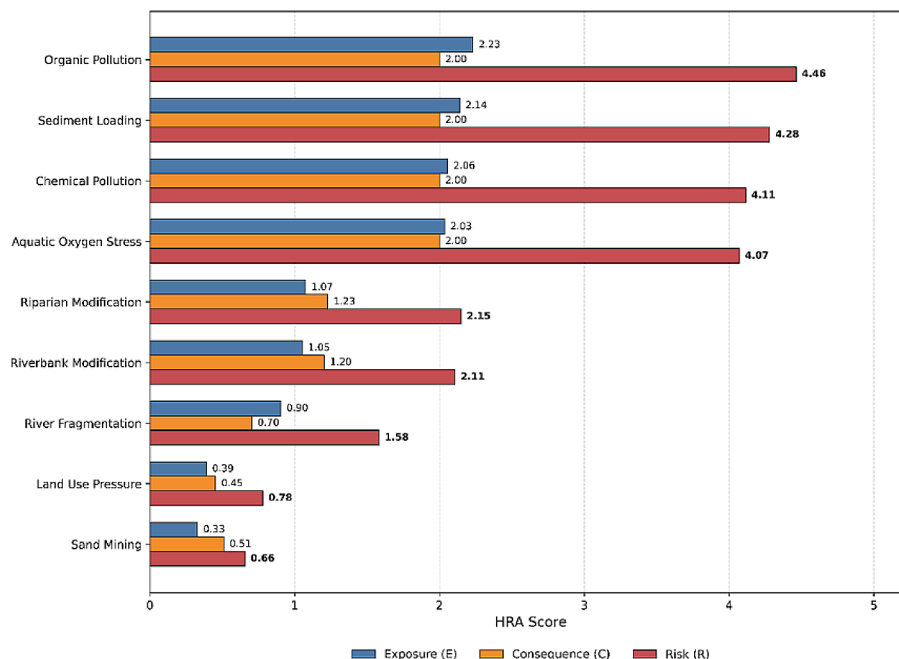


Figure 4. Exposure, consequence, and cumulative risk associated with individual anthropogenic stressors in the Biyonga River

assessed river corridor, rather than direct evidence of actual environmental degradation. Overall, 52.75% of the assessed area was classified as medium relative risk and 47.25% as low relative risk under the standard HRA classification, with no area meeting the high-risk classification threshold. The spatial distribution of individual stressors was heterogeneous along the river corridor, with different patterns of intensity and occurrence among hydromorphological, land-use, and water-quality stressors (Figure 5). Water-quality stressors showed the most extensive spatial distribution, whereas physical and land-use-related stressors were more spatially localized.

Marked differences were observed among stressors in their cumulative relative risk scores. Organic pollution had the highest relative cumulative risk score ($R = 4.463$; $E = 2.232$; $C = 2.000$), followed by sediment loading ($R = 4.279$; $E = 2.140$; $C = 2.000$), chemical pollution ($R = 4.115$; $E = 2.057$; $C = 2.000$), and aquatic oxygen stress ($R = 4.070$; $E = 2.035$; $C = 2.000$). These four water-quality stressors represented the comparatively highest relative-risk group within the screening assessment, with each showing the same spatial risk-class distribution of 75.11% medium risk and 24.89% low risk. Their differing cumulative risk scores primarily reflected

differences in exposure, while their consequence scores remained identical.

Comparatively intermediate relative risk scores were associated with riparian modification ($R = 2.149$; $E = 1.074$; $C = 1.228$) and riverbank modification ($R = 2.106$; $E = 1.053$; $C = 1.203$), followed by river fragmentation ($R = 1.582$; $E = 0.904$; $C = 0.703$). Riparian and riverbank modification were predominantly classified as medium relative risk, covering 61.39% and 60.16% of the assessed area, respectively, while river fragmentation covered 40.18% medium-risk area. The comparatively lowest relative risk scores were observed for land use pressure ($R = 0.779$; $E = 0.390$; $C = 0.453$) and sand mining ($R = 0.656$; $E = 0.328$; $C = 0.510$). Land use pressure comprised 77.34% no risk, 12.73% low risk, and 9.94% medium risk, whereas sand mining comprised 74.50% no risk and 25.50% low risk, with no medium- or high-risk area.

The stressor-specific results revealed a clear gradient in relative cumulative risk scores, with water-quality stressors > riparian and riverbank modification > river fragmentation > land-use pressure > sand mining. Under the baseline HRA configuration, water-quality-related stressors contributed the highest relative risk scores, while hydromorphological and land-use pressures

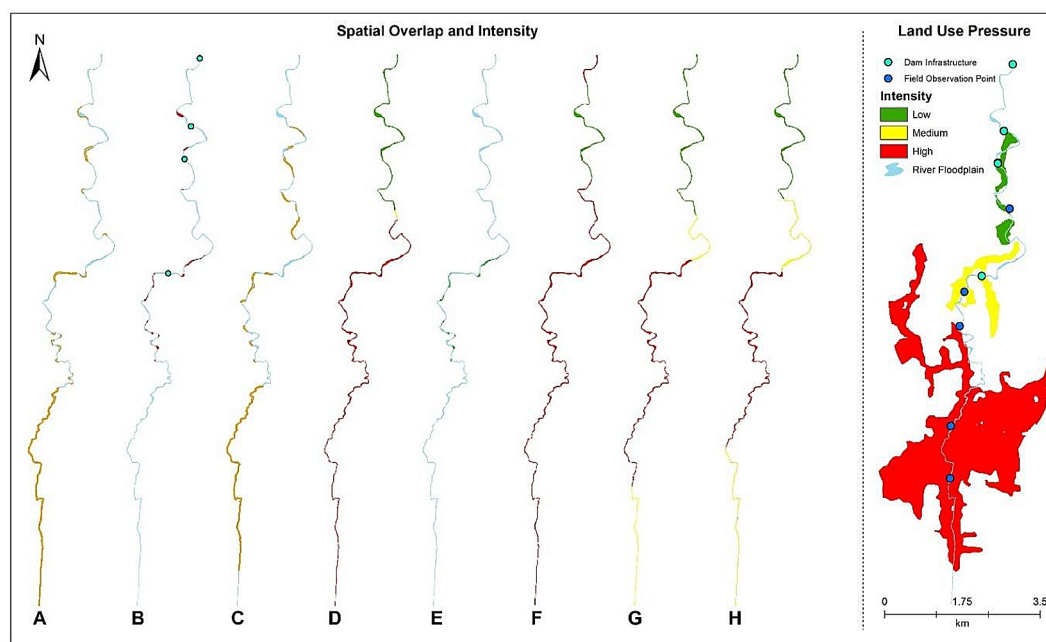


Figure 5. Spatial distribution of anthropogenic stressor intensity along the Biyonga River and the corresponding land-use pressure. Panels A–H represent the spatial distribution and intensity of: (A) riverbank modification, (B) river fragmentation, (C) riparian modification, (D) sediment loading, (E) sand mining, (F) organic pollution, (G) chemical pollution, and (H) aquatic oxygen stress, classified as low, medium, and high. The final panel shows the spatial distribution of land use pressure and associated observation points

contributed comparatively lower but spatially distinct levels of potential anthropogenic risk. These findings should be interpreted as a screening-level indication of relative stressor importance and spatial management concern, rather than as direct evidence of measured habitat degradation or environmental impairment.

Stressor-specific risk and dominant risk drivers

The exposure–consequence assessment revealed a clear separation among the evaluated stressors (Figure 6). Using the overall mean exposure ($E = 1.357$) and consequence ($C = 1.344$) as reference thresholds, the stressors occupied three of the four exposure–consequence domains. Organic pollution, sediment loading, chemical pollution, and aquatic oxygen stress were positioned in the high-exposure, high-consequence quadrant, forming the dominant relative-risk cluster. Riparian modification, riverbank modification, and river fragmentation were characterized by lower exposure and moderate to low consequence, whereas land use pressure and sand mining occupied the low-exposure, low-consequence quadrant. These domains represent relative positions within

the HRA screening framework and should not be interpreted as direct evidence of actual ecological degradation associated with individual stressors.

The water-quality stressors showed the highest exposure values, ranging from 2.035 to 2.232, while all had a consequence score of 2.0. The uniform consequence values resulted from the common ratings assigned to the consequence criteria for these stressors, including a rating of 2 for change in affected area and change in water quality, together with the same habitat-resilience parameters. Frequency of disturbance was not independently scored for these stressors because their potential consequences were represented through the change-in-water-quality criterion and corresponding intensity layers. Consequently, differences in estimated relative cumulative anthropogenic risk within this group were determined primarily by variation in exposure. Organic pollution showed the highest exposure and estimated relative cumulative anthropogenic risk, followed by sediment loading, chemical pollution, and aquatic oxygen stress. The identical consequence scores should therefore be interpreted as a result of the applied ordinal assessment structure rather than as evidence that the four water-quality stressors have equivalent ecological consequences.

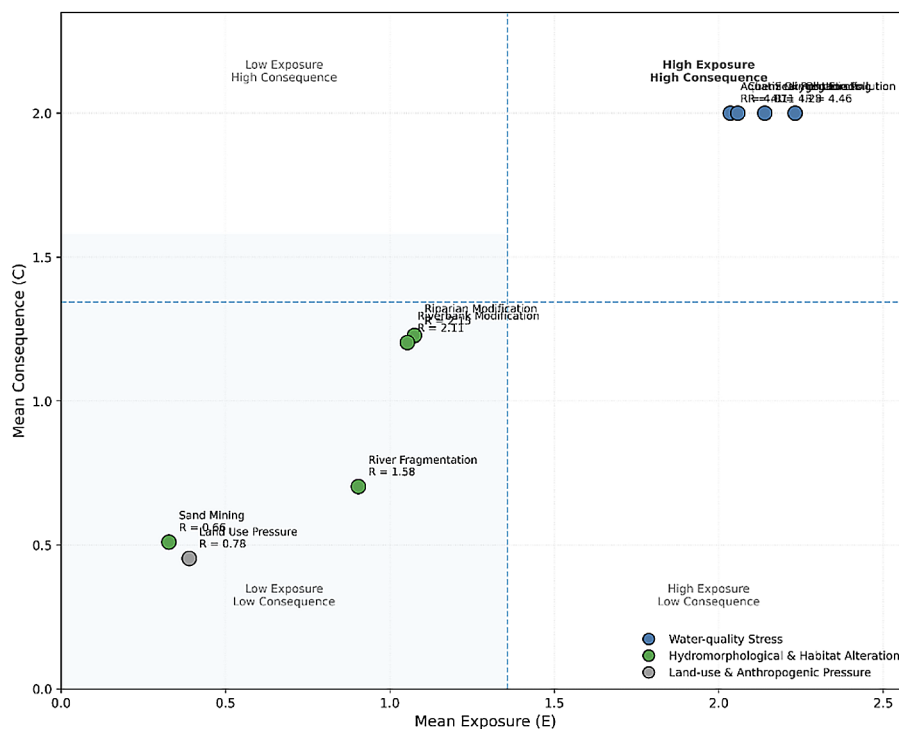


Figure 6. Exposure–consequence relationship and risk grouping of anthropogenic stressors in the Biyonga River. Stressors are positioned according to their mean exposure and consequence scores, with dashed lines representing the overall mean exposure (1.357) and consequence (1.344) thresholds

The exposure–consequence relationship indicates that water-quality stressors constituted the dominant relative-risk dimension in the HRA screening assessment, characterized by relatively high exposure and consequence scores. Hydro-morphological stressors formed an intermediate relative-risk group, while land use pressure and sand mining contributed comparatively lower estimated relative cumulative risk under the baseline configuration. This differentiation provides a basis for screening-level stressor-specific management prioritization, particularly by distinguishing areas warranting further investigation of water-quality pressures from those warranting investigation of physical riverbank or riparian conditions. The identified relative-risk patterns should be considered indicative rather than confirmatory and should be evaluated against field measurements and ecological observations before being interpreted as evidence of actual environmental degradation.

Sensitivity of habitat risk to buffer distance

The sensitivity analysis showed a consistent increase in estimated relative habitat risk with increasing buffer distance (Figure 7). Mean exposure (E) increased from 1.298 at 50 m to 1.581 at 500 m, while mean consequence (C) increased from 1.280 to 1.587. Accordingly, mean cumulative relative risk (R) increased from 2.575 to 3.120, representing an approximately 21.2%

increase between the narrowest and widest buffer distances. Relative to the 100-m baseline ($R = 2.689$), the estimated cumulative relative risk at 500 m was approximately 16.0% higher. This pattern indicates that the assumed spatial extent of stressor influence affects the magnitude of relative risk estimated by the HRA framework and should be interpreted as a sensitivity of the screening-level assessment rather than as evidence of increasing environmental degradation.

The increase in estimated cumulative relative risk was accompanied by a systematic shift in relative risk classification from low toward medium risk (Figure 8). Medium-risk areas increased from 48.34% at 50 m to 52.75% at 100 m, 60.85% at 250 m, and 72.43% at 500 m, while low-risk areas decreased correspondingly from 51.66% to 27.57%. No high-risk or no-risk areas were identified under any of the tested configurations. Thus, increasing buffer distance expanded the proportion of the river corridor classified as medium relative risk within the HRA screening framework, without changing the overall low-to-medium classification range. These classifications indicate relative differences in estimated anthropogenic risk among spatial units and do not represent direct measurements or confirmation of environmental degradation.

The sensitivity of individual stressors differed substantially among stressor types (Table 5). The four water-quality stressors, organic pollution, sediment loading, chemical pollution, and aquatic

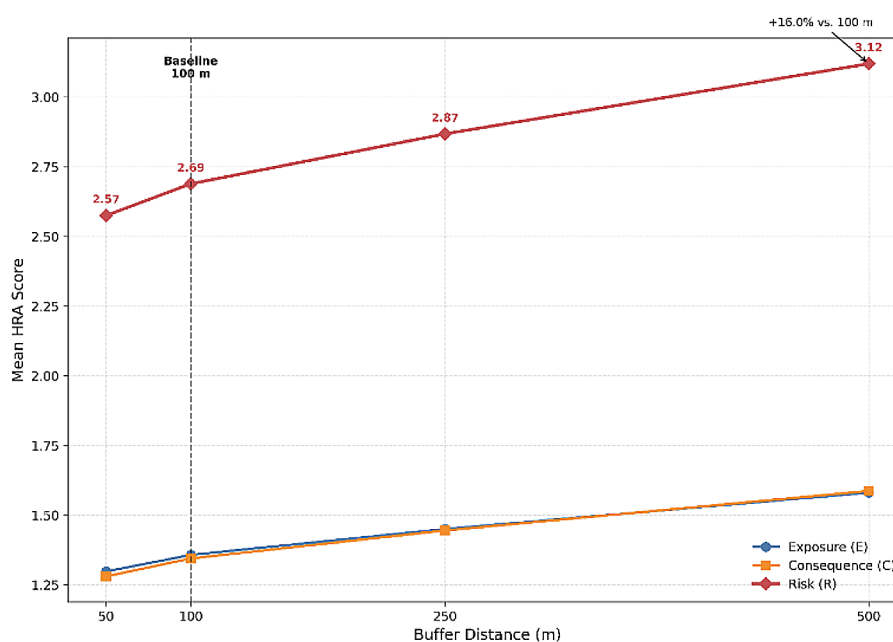


Figure 7. Sensitivity of habitat risk assessment results to buffer distance in the Biyonga River

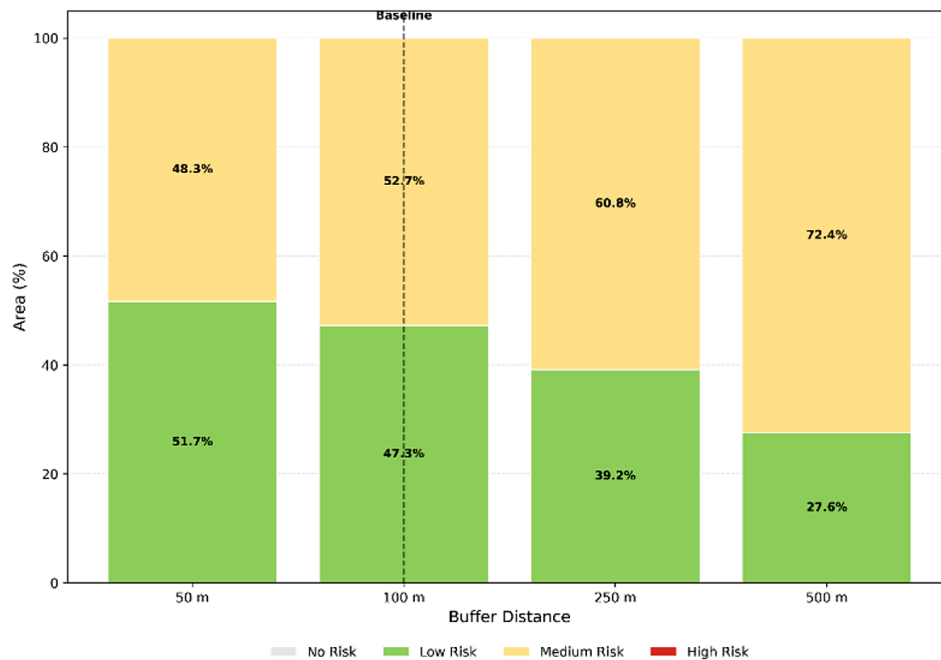


Figure 8. Sensitivity of habitat risk classification to buffer distance in the Biyonga River. The proportions of areas classified as low, medium, and high risk are shown for 50, 100, 250, and 500 m buffer distances. The 100 m buffer represents the baseline configuration

oxygen stress, remained unchanged across all buffer distances, with cumulative relative risk values of 4.463, 4.279, 4.115, and 4.070, respectively. In contrast, cumulative relative risk increased with buffer distance for the spatially distributed physical and land-use stressors. River fragmentation showed the largest relative increase, from 1.280 at 50 m to 2.607 at 500 m (approximately 104%), followed by riverbank modification (1.901–3.251), riparian modification (1.860–3.185), land use pressure (0.647–1.158), and sand mining (0.559–0.949). Despite these changes in estimated magnitude, the four water-quality stressors remained the dominant relative risk group across all buffer configurations. Overall, the 100-m baseline represents an intermediate estimated

relative risk level within the tested range, while the persistence of the dominant stressor pattern indicates that the relative risk structure identified by the screening assessment was relatively robust to buffer-distance variation.

Priority areas for river management

Although no area was classified as high risk under the standard HRA classification, the continuous cumulative risk surface revealed spatial differences in relative risk across the 100-m buffer corridor (Figure 9). To identify locations with comparatively elevated cumulative anthropogenic pressure, the continuous risk raster was reclassified into three relative-risk categories using the

Table 5. Stressor-specific risk under different buffer distances

Stressor	50 m (R)	100 m (R)	250 m (R)	500 m (R)
Organic pollution	4.463	4.463	4.463	4.463
Sediment loading	4.279	4.279	4.279	4.279
Chemical pollution	4.115	4.115	4.115	4.115
Aquatic oxygen stress	4.070	4.070	4.070	4.070
Riparian modification	1.860	2.149	2.650	3.185
Riverbank modification	1.901	2.106	2.602	3.251
River fragmentation	1.280	1.582	1.991	2.607
Land use pressure	0.647	0.779	0.845	1.158
Sand mining	0.559	0.656	0.796	0.949

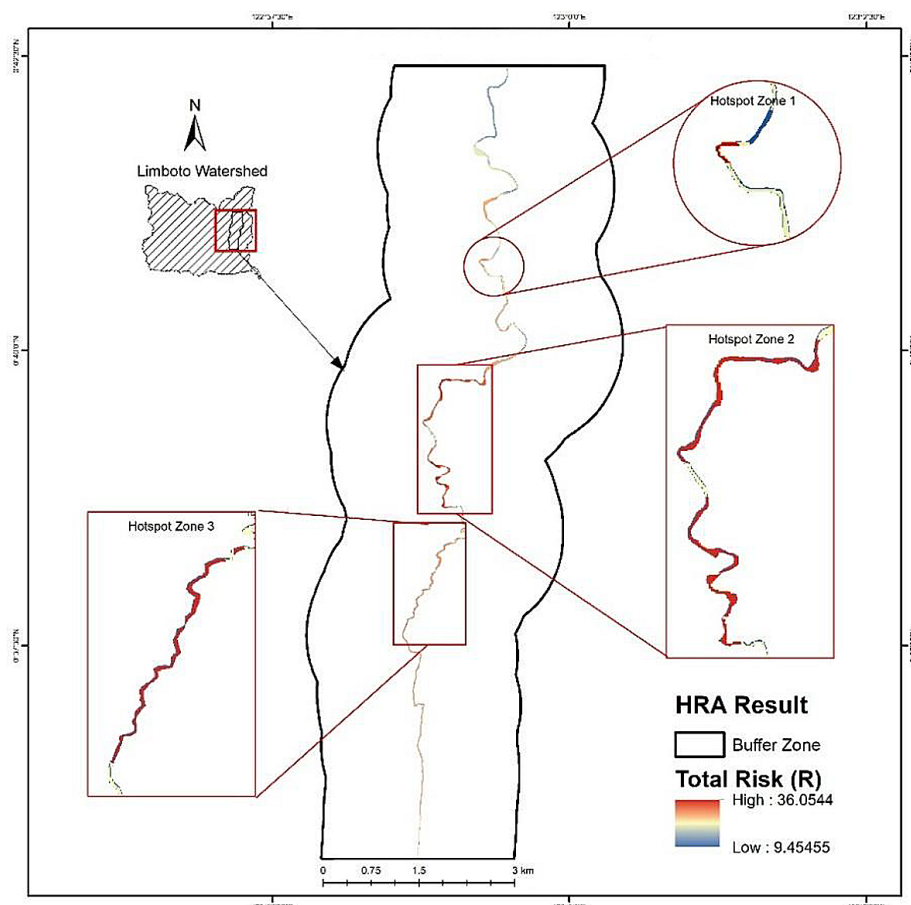


Figure 9. Spatial distribution of cumulative riverine habitat risk and management priority hotspots along the Biyonga River

Natural Breaks (Jenks) method. Areas belonging to the highest relative-risk category were subsequently delineated as management-priority hotspots. These hotspots represent locations with comparatively higher relative screening-level risk within the study area and should not be interpreted as confirmed areas of environmental degradation or standard high-risk areas. Rather, they indicate locations where anthropogenic pressures may warrant further investigation, monitoring, and management attention. The three hotspots differed in the combination and intensity of mapped anthropogenic stressors, indicating spatial variation in potential management priorities along the river corridor (Table 6).

Hotspot Zone 1 was characterized by relatively high mapped organic pollution intensity and medium riverbank modification intensity. This spatial pattern indicates a potential management concern related to water-quality stress and riverbank conditions, while further field-based assessment would be required to confirm the extent and ecological effects of these

pressures. Accordingly, management attention may focus on reducing potential organic pollution sources, maintaining riverbank conditions, and preventing further physical modification. Hotspot Zone 2 showed relatively high mapped water-quality-related stress intensity within a transition zone between moderately to densely settled areas and active agricultural land. The spatial co-occurrence of these mapped pressures suggests a potential area for integrated monitoring of water-quality conditions and anthropogenic land-use influences. Management attention may include maintaining the river corridor and controlling further expansion of anthropogenic land uses toward the river. Hotspot Zone 3 exhibited the most complex combination of mapped anthropogenic stressors, including dense settlement, relatively high water-quality-related stress intensity, riverbank modification, and riparian modification. This pattern identifies the zone as a potential priority for further investigation and integrated management planning. Potential management actions include

Table 6. Characteristics and potential management priorities of hotspots identified within the highest relative-risk class along the Biyonga River

Risk hotspot	Dominant mapped stressor characteristics	Potential management priority
Management-priority Hotspot 1	Relatively high mapped organic pollution intensity; medium riverbank modification intensity	Further investigation and monitoring of organic pollution, together with riverbank modification control
Management-priority Hotspot 2	Relatively high mapped water-quality-related stress intensity; moderately to densely settled areas and agricultural land	Further investigation and monitoring of water-quality conditions and anthropogenic land-use pressure
Management-priority Hotspot 3	Relatively high mapped water-quality-related stress intensity; riverbank modification; riparian modification; dense settlement	Integrated monitoring of water-quality conditions, riverbank modification control, and assessment of riparian conditions for potential rehabilitation

Note: The identified hotspots represent locations within the highest relative-risk class and should be interpreted as screening-level management priorities rather than confirmed areas of environmental degradation. The dominant stressor characteristics refer to mapped anthropogenic pressures identified within each hotspot.

monitoring water-quality conditions, preventing further riverbank modification, rehabilitating riparian areas where degradation is confirmed, and managing anthropogenic pressures associated with densely settled areas.

The three management-priority hotspots represented distinct combinations of relatively elevated mapped anthropogenic pressures: Organic pollution and riverbank modification in Zone 1, water-quality-related stress associated with settlement and agricultural land use in Zone 2, and combined water-quality, riverbank, and riparian pressures in Zone 3. These spatially differentiated patterns provide a screening-level basis for identifying locations for further investigation, monitoring, and stressor-specific management planning along the Biyonga River. The identified hotspots should therefore be interpreted as relative management priorities rather than confirmed areas of environmental degradation or ecological impairment.

DISCUSSIONS

Anthropogenic land-use context along the river corridor

The spatial distribution of land use along the Biyonga River indicates that the anthropogenic landscape context varies substantially along the river corridor. The contrasting composition between the two riverbanks, particularly within the 100-m corridor, indicates that different river sections are characterized by distinct combinations of built-up and agricultural land uses. Such spatial heterogeneity is important because different land-use types can be associated with changes

in river water quality and ecological condition through multiple pathways, including runoff alteration, pollutant delivery, physical habitat modification, and changes in riparian conditions (Kakore et al., 2022; Z. Li et al., 2022). However, the strength and direction of these relationships are spatially dependent, with different land-use types showing different associations with river conditions across riparian, reach, and broader catchment scales (Lee et al., 2023; Wu et al., 2021). The LULC pattern observed along the Biyonga River therefore provides an important landscape context for interpreting the spatial distribution of anthropogenic stressors represented by the HRA.

The contrasting distribution of built-up and agricultural areas also highlights the need to distinguish between land-use-specific pressure pathways rather than treating anthropogenic land use as a uniform source of risk. Built-up areas are frequently associated with elevated pressures on water quality at relatively fine spatial scales, whereas agricultural land may contribute to sediment and nutrient loading through land–river connections that vary with landscape and hydrological conditions (Ouyang et al., 2021; Wu et al., 2025). Conversely, riparian vegetation and forest cover may provide important buffering functions, although their effectiveness depends on spatial scale and landscape context (Heidkamp and Christian, 2022; Z. Li et al., 2022). Importantly, the presence of built-up or agricultural land in the Biyonga River corridor should not be interpreted as direct evidence of pollution or ecological degradation, but rather as an indicator of the anthropogenic landscape context in which multiple stressors may occur. Consequently, management

should combine protection of the immediate river corridor with appropriate land-use management in surrounding areas, particularly where intensive anthropogenic land use spatially coincides with elevated relative cumulative anthropogenic risk.

Contribution of water-quality-related stressors to relative cumulative risk

The relatively strong contribution of water-quality-related stressors to cumulative risk estimates in the Biyonga River can be interpreted in the context of the multiple pressures that characterize riverine ecosystems. Changes in water-quality conditions rarely result from a single pressure and may reflect the combined influence of nutrient and organic enrichment, sediment inputs, toxic substances, and other anthropogenic disturbances operating across river systems (Burhan et al., 2026; Shu et al., 2022). These pressures may interact in additive, synergistic, or antagonistic ways, meaning that their potential ecological implications cannot always be inferred from individual stressors alone (F. Li et al., 2023). Water-quality conditions can also represent an important pathway through which multiple upstream and surrounding pressures may be associated with ecological responses, with previous studies reporting relationships between water quality and aquatic biological indicators in river systems (Z. Li et al., 2024). The relatively high contribution of water-quality-related stressors in the Biyonga River therefore suggests that aquatic environmental conditions represent an important dimension of relative cumulative anthropogenic risk.

The potential ecological relevance of these stressors is supported by evidence that physicochemical pressures such as oxygen depletion and fine sediment accumulation can adversely affect biodiversity across multiple riverine organism groups (Kaijser et al., 2025). However, the relative importance of individual stressors and their interactions is context-dependent, and a stressor contributing strongly to risk in one river or biological response may not have the same importance elsewhere (Brauns et al., 2022). This reinforces the value of a cumulative assessment such as HRA, which provides a common spatial framework for considering multiple pressures rather than evaluating each stressor independently. For the Biyonga River, the relatively

high contribution of water-quality-related stressors suggests that management should place strong emphasis on maintaining and improving water-quality conditions while recognizing their potential connections with broader land-use and physical disturbances. Consequently, water-quality management should be complemented by measures addressing sediment delivery, riverbank and riparian conditions, and anthropogenic land-use pressures, particularly in areas where these pressures spatially co-occur.

Spatial-scale implications of buffer-distance variation

Buffer distance represents an important source of spatial uncertainty in riverine risk assessment because anthropogenic pressures and ecological responses operate across multiple spatial scales. Previous studies have shown that the relative importance of land-use drivers can vary with buffer width, with near-river scales often capturing the influence of built-up and agricultural areas, while broader spatial scales may better reflect landscape composition and forest cover (Guo et al., 2025; Song et al., 2021). This scale dependency indicates that the contribution of a stressor should not be interpreted independently of the spatial extent used to represent its potential influence on the river system. Moreover, different ecological indicators may respond to land use at different spatial scales, suggesting that a single buffer width may not adequately capture all stressor–response relationships (Comte et al., 2022; Forio et al., 2022). Therefore, the greater variation of localized riverbank and riparian stressors across buffer configuration observed in this study can be understood as a consequence of the spatially heterogeneous nature of river–land interactions rather than evidence that wider buffers necessarily provide more ecologically accurate risk estimates (Brumberg et al., 2021).

From a management perspective, these findings support a scale-aware approach to river management, in which the spatial extent of assessment is selected according to the characteristics of the stressor and the management objective. Fixed-width buffers are practical for spatial assessment, but their ecological relevance may vary among locations and stressor types, and variable or multi-scale approaches have consequently been proposed for riverscape conservation and riparian management (Graziano et al., 2022; Hira et al., 2023). A narrow assessment

zone may be more appropriate for interventions targeting immediate riverbank and riparian conditions, whereas broader spatial scales may be necessary when considering surrounding land-use pressures and cumulative landscape effects. Thus, the 100-m buffer used as the baseline in this study should be interpreted as an analytical configuration rather than a universal ecological or management boundary. The persistence of the dominant stressor pattern across alternative buffer configurations nevertheless supports the robustness of the principal risk pattern, while the scale-dependent variation in risk extent emphasizes the importance of considering spatial scale when delineating areas for river protection, restoration, and land-use management.

Spatial prioritization for differentiated river management

The identification of spatially distinct management hotspots highlights the value of moving beyond stressor-specific assessment toward an integrated spatial perspective of river management. Anthropogenic pressures can occur in different combinations across river networks, and their potential cumulative effects may vary among locations according to local environmental and land-use conditions (Comte et al., 2022). Spatially explicit multi-stressor assessment can therefore help identify areas where multiple pressures overlap and distinguish locations according to their relative management needs, rather than treating the river corridor as a uniformly impacted system. This approach is particularly relevant for river management because different combinations of stressors may require different forms of intervention, and spatial prioritization can provide a basis for directing management attention toward areas where it may be most warranted (Stein et al., 2022). In this context, the HRA framework provides a useful decision-support approach for translating the spatial distribution of relative cumulative anthropogenic pressures into geographically differentiated management priorities (Kantharajan et al., 2022).

The management value of spatial prioritization is further strengthened when risk information is linked to the type of intervention that may be appropriate at each location. Conservation and protection are generally more appropriate where ecological conditions remain relatively intact but face increasing pressure, whereas restoration or

active management may be more appropriate where evidence of ecological degradation and anthropogenic stress occur concurrently (Glassic et al., 2024; Riato et al., 2023). Similarly, systematic spatial prioritization can improve the allocation of restoration actions by identifying locations where management interventions may provide greater potential ecological benefits (Gilby et al., 2021). For the Biyonga River, areas with relatively high contributions from water-quality-related stressors may warrant measures aimed at reducing pollutant pressures, whereas locations characterized by riverbank or riparian modification may warrant protection or rehabilitation of the river corridor. Where several pressures occur together, management may be more effective when integrated rather than implemented through isolated stressor-specific actions. Thus, spatially differentiated prioritization can help align the type and location of potential intervention with the prevailing combination of anthropogenic pressures, providing a more targeted basis for river protection, restoration, and management.

Limitations and uncertainties

Several limitations and sources of uncertainty should be considered when interpreting the results of this study. First, the HRA framework relies partly on ordinal ratings to represent stressor characteristics and habitat responses, meaning that the resulting risk estimates depend on the assumptions and parameterization used in the assessment. In particular, criteria such as management effectiveness, temporal overlap, and changes in affected area and water quality may involve uncertainty when empirical information is limited. Although the ratings were assigned using predefined criteria and supported by field observations, spatial datasets, and relevant literature, a degree of subjectivity remains in their application. The use of data-quality scores and weights within the HRA framework improves the transparency of the assessment by distinguishing the confidence and relative importance of individual criteria; however, these parameters do not eliminate uncertainty associated with the underlying observations and assumptions. In addition, the identical Consequence values obtained for BOD, COD, TSS, and DO reflect the application of the same standardized criterion ratings and weights rather than empirically identical ecological effects. Therefore, variations in

parameter assignment may influence the resulting exposure, consequence, and risk scores.

Second, the spatial representation of anthropogenic stressors does not capture all processes operating within the river system. Water-quality stressors were represented using TSS, BOD, COD, and DO datasets, while physical and land-use-related stressors were represented through spatially explicit layers and observed or derived stressor footprints. These representations provide a spatially consistent basis for comparative risk assessment but may not fully describe temporal fluctuations, pollutant transport, or localized ecological responses. The sensitivity of risk estimates to buffer distance further indicates that spatial scale is an important source of uncertainty and should be considered when interpreting the extent of identified risk areas. Therefore, the 100-m buffer should be interpreted as a baseline analytical configuration rather than a definitive ecological threshold.

Third, the limited number of water-quality sampling locations represents an important source of uncertainty in the interpolated stressor surfaces. Although the sampling points covered the upstream, middle, and downstream segments of the river, the spatial density was insufficient for robust independent validation of the kriging outputs. Consequently, the interpolated water-quality layers and derived HRA results should be interpreted as relative screening-level patterns rather than definitive estimates of spatial water-quality conditions.

Finally, the HRA results represent relative cumulative anthropogenic risk and spatial patterns of stressor overlap rather than direct measurements of ecological degradation or causal relationships between individual stressors and habitat condition. The assessment therefore does not directly quantify habitat condition, biodiversity loss, or ecological responses to individual stressors. Accordingly, terms such as ecological risk should be interpreted as potential ecological implications of anthropogenic stressors rather than empirically demonstrated ecological effects. Future studies could reduce these uncertainties through denser and repeated water-quality monitoring, more detailed field-based assessment of riverbank and riparian conditions, improved documentation of management effectiveness, and ecological validation of predicted risk patterns.

CONCLUSIONS

This study developed an integrated spatial framework for assessing relative cumulative anthropogenic risk at a screening level and supporting differentiated management prioritization along the Biyonga River, Indonesia. The LULC assessment revealed a clear spatial asymmetry within the river corridor, particularly at the 100-m buffer, with agriculture dominating the left bank and built-up areas more prominent on the right bank. These contrasting land-use patterns indicate that anthropogenic pressures are spatially heterogeneous along the river corridor and provide important spatial context for interpreting the relative risk patterns identified by the HRA.

The InVEST Habitat Risk Assessment indicated predominantly low-to-medium relative cumulative anthropogenic risk, with mean Exposure, Consequence, and Risk values of 1.357, 1.344, and 2.689, respectively. Water-quality-related stressors contributed most strongly to the relative risk estimates, particularly Organic Pollution, Sediment Loading, Chemical Pollution, and Aquatic Oxygen Stress, whereas Riparian Modification and Riverbank Modification contributed intermediate levels of relative risk. Comparison across alternative buffer distances showed that increasing buffer distance generally increased cumulative risk and the proportion of areas classified as medium relative risk, while the overall pattern of dominant stressors remained consistent. These results represent relative, screening-level estimates based on the HRA framework and should not be interpreted as direct evidence of measured environmental degradation or ecological impairment.

Three management-priority hotspots were identified along the Biyonga River, each characterized by distinct spatial combinations of anthropogenic stressors. These findings suggest that river management priorities may be differentiated according to the dominant stressors and their spatial distribution rather than based solely on cumulative risk values. By integrating LULC context, multi-stressor risk assessment, buffer-distance comparison, and hotspot interpretation, the proposed framework provides a screening-level basis for identifying areas that warrant further investigation and potentially targeted river management interventions. The identified priority areas should therefore be regarded as areas of relative concern rather than confirmed sites of environmental degradation, and should subsequently be evaluated

through field verification, continued monitoring, and ecological assessment before specific management actions are implemented.

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