From Illegal Mining to Bush Burning: Understanding Public Perceptions of Environmental Threats in Ghana's Pra and Densu River Basins

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Highlights

- Primary survey of environmental risk perceptions in Pra and Densu basins, Ghana
- Identifies high-risk threats using mean perception scores and targeted analysis
- Ordered logit models reveal item-specific socio-demographic determinants
- Mixed-effects models address cross-classified clustering by basin and region
- Findings inform basin-tailored environmental management and policy design

Abstract

Understanding how local communities perceive environmental threats is critical for designing effective basin-scale management interventions. This study examines risk perceptions associated with multiple environmental pressors in the Pra and Densu river basins of Ghana. Using primary survey data from 1054 respondents, I first computed mean scores for perceived riskiness, difficulty of management, and availability of alternatives for 11 identified threats. Threats with mean risk scores above 4.0 were modelled individually using ordered logistic regression to assess the influence of socio-demographic characteristics, basin and regional location, and ecosystem service concerns on perceived risk. All explanatory variables were binary except for age and household size. Mixed-effects models were further employed to account for cross-classified clustering by basin and region. Results indicate that perceptions of high-risk threats vary significantly across socio-demographic groups and basins, with notable differences in the perceived manageability and availability of alternatives. Basin-specific governance and environmental contexts appear to shape these perceptions, suggesting the need for tailored policy approaches. The findings contribute to the environmental risk perception literature by offering context-specific, item-level determinants of perceived risk in a developing country setting with overlapping hydrological and administrative governance structures.

Key words: Environmental risk perception, Ordered logistic regression, Mixed-effects modelling, River basin management, River Basin, Ghana, and Environmental pressors

JEL Codes: Q53, Q54, Q56, Q57, and C25

1. Introduction

Freshwater ecosystems are among the most threatened globally, facing pressures from anthropogenic activities, climate variability, and governance challenges (Vörösmarty et al., 2010; Carpenter et al., 2011). River basins, in particular, represent complex socio-ecological systems in which ecological processes, human livelihoods, and institutional arrangements interact (Pahl-Wostl et al., 2013; Gain et al., 2016). In many developing countries, including Ghana, river basins support critical ecosystem services such as potable water supply, fisheries, recreation, biodiversity maintenance, and flood regulation (Amoako et al., 2018; Armah et al., 2020). However, pressures from land-use change, pollution, over-extraction, and unsustainable fishing or agricultural practices continue to degrade these systems (Osei-Wusu et al., 2019; Addo et al., 2021).

Community perceptions of environmental threats have emerged as an essential dimension of sustainable river basin management, influencing both compliance with regulations and participation in conservation activities (Bennett, 2016; Völker et al., 2016; De França Doria et al., 2020). Perception studies help to uncover the social salience of environmental problems, revealing which threats are considered most urgent, most difficult to address, or most easily substituted with alternatives (Milcu et al., 2013; Klöckner, 2015). This is particularly relevant in contexts where governance systems are multi-layered, and decision-making must balance local priorities with regional or national policies (Sivapalan et al., 2012; Akamani & Wilson, 2011).

Empirical work on environmental risk perception has examined drivers such as socio-demographic characteristics (e.g., age, gender, education), livelihood dependence, and trust in institutions (Sjöberg, 2000; Kellens et al., 2013; Wachinger et al., 2013). Methodologically, ordered logit and probit models are common tools for analyzing ordinal perception data (Botzen et al., 2013; Brouwer et al., 2017), while multilevel and hierarchical models address data structures in which individuals are clustered within higher-level units such as communities, districts, or basins (Gelman & Hill, 2007; Snijders & Bosker, 2012; Xu et al., 2018). More recently, cross-classified models have been applied to settings where geographical or administrative boundaries overlap, allowing simultaneous estimation of random effects for multiple, non-nested groupings (Browne et al., 2001; Goldstein, 2011; Leckie, 2013).

Studies in Africa have begun to explore these approaches. For example, Okumah et al. (2019) investigated Ghanaian farmers' perceptions of water pollution and found strong associations with education and access to information. Aidoo et al. (2021) applied ordered logit models to assess the perceived impacts of climate variability on agriculture in the Volta Basin, revealing significant heterogeneity across districts. Similarly, Nketiah et al. (2022) examined fishing communities' perceptions of ecosystem change along the Gulf of Guinea, identifying gender and livelihood dependence as key predictors. These findings echo patterns seen in other developing regions, where perceptions of environmental threats often diverge from scientific assessments (Baird et al., 2016; Gifford & Nilsson, 2014), creating potential mismatches between policy priorities and local realities (Reed et al., 2014; Stringer et al., 2017).

Comparable work elsewhere has applied innovative modelling approaches to integrate perception and ecosystem service assessments into water management at the river basin scale (Domínguez-Tejo et al., 2019), explored adaptive responses to environmental hazards such as flooding (Thennakoon et al., 2020), and examined the role of uncertainty in shaping environmental preferences in water-scarce environments (Zheng et al., 2022). Other studies have developed spatially explicit frameworks to integrate water resource

management and land-use planning (Christophe et al., 2015), highlighting the importance of addressing governance challenges where hydrological and administrative boundaries overlap. These methodological and thematic advances underscore the value of rigorous statistical modeling for linking perceptions to governance-relevant environmental indicators.

The challenge is particularly acute in Ghana's Pra and Densu basins. The Pra Basin spans five administrative regions—Ashanti, Central, Eastern, Western, and Western North—while the Densu Basin crosses three—Central, Eastern, and Greater Accra. This creates a cross-jurisdictional governance environment in which perceptions of environmental threats may be shaped by both basin-level and region-level contexts. Understanding these perceptions in a statistically rigorous manner, while accounting for the cross-classified nature of the data, can yield insights that are both scientifically robust and directly applicable to integrated water resource management (IWRM) strategies (GWP, 2013; FAO, 2016).

Although prior research has examined community perceptions of environmental threats within river basins, notable gaps remain in how such perceptions are modeled and interpreted in multi-jurisdictional contexts. For instance, recent work in the Nigua River Basin, Dominican Republic, linked perceived environmental risks to socio-demographic characteristics, revealing important spatial heterogeneity in perceptions. While valuable, this and similar studies often treat administrative or hydrological units as singular, non-overlapping clusters, overlooking the governance complexities of basins spanning multiple regions. Other approaches, such as participatory mapping of flood risk and land-use concerns, have successfully captured spatial variation in environmental perceptions but rarely integrate such perceptions into formal econometric models for predictive analysis. Network-based analyses of risk evolution in urban river governance systems have advanced our understanding of systemic vulnerabilities but focus primarily on governance interactions rather than community-level perceptions and perceived management feasibility.

This study addresses these gaps by jointly modeling perceived riskiness, difficulty of management, and perceived availability of alternatives for multiple environmental threats across two major Ghanaian basins—each spanning several administrative regions—using ordered logit and cross-classified multilevel models. By explicitly accounting for overlapping hydrological and administrative boundaries, the analysis provides a more nuanced understanding of how socio-demographic factors and governance contexts interact to shape perceptions, thereby offering actionable insights for integrated river basin management.

Figure 1. Conceptual Framework Diagram

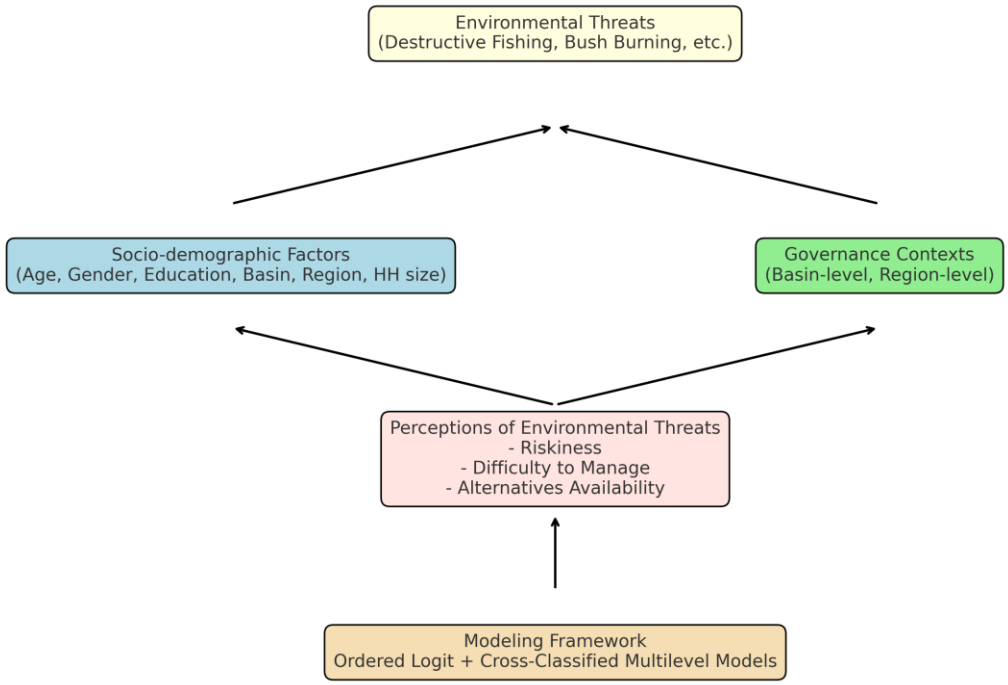


Figure 1 shows the conceptual framework linking environmental threats, socio-demographic factors, and governance contexts to perceptions of environmental threats—riskiness, difficulty to manage, and availability of alternatives—and subsequent statistical modeling. Environmental threats include destructive fishing, bush burning, and other basin-specific stressors. Socio-demographic factors (e.g., age, gender, education, household size, and basin-region affiliation) and governance contexts (basin-level and region-level) are hypothesized to influence perception dimensions directly. The analysis applies ordered logit and cross-classified multilevel models to capture both individual-level effects and higher-level influences from overlapping hydrological and administrative boundaries.

2. Methodology

2.1 Study area

The study was conducted in two major river basins of Ghana—the Pra Basin and the Densu Basin—both of which are critical for domestic water supply, agriculture, and biodiversity. The Pra Basin spans five administrative regions (Ashanti, Central, Eastern, Western, and Western North), while the Densu Basin covers three regions (Central, Eastern, and Greater Accra). These basins face similar environmental threats, including destructive fishing methods, sand mining, bush burning, and pollution from agricultural runoff, yet differ in socio-economic composition and

governance arrangements. The overlapping of hydrological and administrative boundaries makes these basins ideal for exploring the interaction between socio-demographic contexts and governance structures in shaping environmental threat perceptions.

2.2 Data sources

Data were collected using a structured questionnaire administered to households in communities along the Pra and Densu basins. The sampling frame was developed in collaboration with local water management authorities to ensure coverage of both upstream and downstream settlements. A multistage sampling technique was used: (1) purposive selection of basin regions, (2) random selection of communities within each region, and (3) random selection of households. Data collection took place over a two-month period with trained enumerators conducting face-to-face interviews. Respondents were asked to assess the riskiness, difficulty of management, and availability of alternatives for 11 environmental threats, as well as their level of concern for six ecosystem services.

2.3 Variable definitions

Dependent variables (ordinal):

- Riskiness (1–11 scale, where higher values indicate higher perceived risk)
- Difficulty to manage (1–11 scale)
- Availability of alternatives (1–11 scale, where higher indicates greater availability)

Independent variables:

Socio-demographic: Age (continuous), Gender (0 = female, 1 = male), Household size (continuous), Education (binary: secondary or higher vs. less), Occupation type (binary: agriculture vs. others). *Contextual*: Basin (Pra = 1, Densu = 0), Region (categorical), plus basin–region cross-classification. *Ecosystem concern variables*: Concern for recreation, fish, water quality, biodiversity, flood protection, and erosion (Likert-type scale). A detailed description and expected effect direction are provided in Table 1.

Table 1: Description and coding of variables used in the analysis

Variable	Description	Expected Direction
Riskiness	Perceived level of risk posed by each environmental threat (ordinal 1–11 scale).	+
Difficulty to manage	Perceived difficulty of managing each environmental threat (ordinal 1–11 scale).	+

Availability of alternatives	Perceived availability of alternatives to each environmental threat (ordinal 1–11 scale).	+
Age	Age of respondent in years (continuous).	?
Gender	Gender of respondent (0 = female, 1 = male).	?
Household size	Number of people in the household (continuous).	?
Education	Highest education attained (1 = secondary or higher, 0 = less).	+
Basin	Basin of residence (1 = Pra Basin, 0 = Densu Basin).	?
Region	Region of residence (categorical variable).	?

2.4 Analytical framework

Given the ordinal nature of the dependent variables, an Ordered Logit Model (OLM) was employed for initial estimation:

$$logit(P(Y_{ij} \leq k)) = \theta_k - X_{ij}\beta$$

Where Y_{ij} is the ordinal outcome for respondent i in cluster j, θ_k are cut points, and X_{ij} is the vector of predictors.

To account for the hierarchical and overlapping structure of the data—respondents nested within both regions and basins—a Cross-Classified Multilevel Model (CCMM) was applied:

$$Y_{ijk} = \beta_0 + X_{ij}\beta + u_{Basin_j} + v_{Region_k} + \varepsilon_{ijk}$$

Where u_{Basin_j} is the random effect for basin, v_{Region_k} is the random effect for region, and ε_{ijk} is the residual error. This approach accommodates the fact that Eastern region for example occurs in more than one basin.

2.5 Model estimation and diagnostics

All models were estimated in Stata 17 using the ologit and mixed commands, with covariance(identity) specified for random effects in the CCMM. Variance Inflation Factors (VIF) were computed to check for multicollinearity, and correlations between predictors were examined to ensure stability of estimates. Model performance was assessed using Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and likelihood ratio (LR) tests. Intraclass correlation coefficients (ICC) were computed to quantify the share of variance attributable to basin and region levels.

3. Results and Discussions

3.1 Descriptive Statistics

The survey covered 1,054 respondents, with near equal representation from the Densu Basin (50.85%) and the Pra Basin (49.15%). The regional distribution reflects the basins' hydrological reach: Greater Accra (50.85%), Ashanti (31.78%), Eastern (8.44%), Central (5.03%), Western (2.75%), and Western North (1.14%). Slightly more respondents were male (52.56%) than female (47.44%), and the majority (80.36%) had attained at least secondary education. The mean age was 47.31 years (SD = 13.15) and average household size was 4.44 members (SD = 2.21).

Access to assets and services varied: 63.85% held a bank account, 50.66% had access to radio, and 78.65% to television, whereas only 22.3% reported access to agricultural extension services. Two-thirds (67.36%) reported experiencing a flooding event in their community.

Average riskiness scores revealed substantial variation across the 11 environmental pressors. Illegal mining (mean = 4.7) emerged as the most serious perceived threat, followed by improper waste disposal (4.2), improper agro-chemical use near riverbanks (4.2), sand winning (4.2), and construction near riverbanks (4.2). Several threats scored just above the 4.0 threshold for "high risk," including cutting trees near riverbanks (4.0) and bush burning (4.0).

Perceived difficulty of management generally trailed riskiness scores and varied by basin. For instance, respondents in the Pra Basin rated the difficulty of managing illegal mining substantially higher (5.0) than those in the Densu Basin (1.4). Similarly, cutting trees near riverbanks was rated more difficult in Pra (4.1) than Densu (2.6). Notably, for some threats such as destructive fishing, difficulty scores were relatively low despite moderate-to-high risk scores, suggesting respondents perceive these threats as more manageable.

Availability of alternatives showed a different pattern: most threats received mean scores below 3.0, indicating limited perceived substitute practices. This was particularly acute for threats such as draw-down agriculture (2.3 pooled) and illegal mining (2.6 pooled). Lack of alternatives suggests a structural constraint in shifting away from harmful practices, which may hinder policy interventions unless viable options are developed.

Basin-level differences were consistent across dimensions: the Densu Basin tended to rate threats as riskier (e.g., destructive fishing: 4.4 vs. 3.9 in Pra), while the Pra Basin rated them as more difficult to manage (e.g., farming at riverbanks: 3.9 vs. 1.5 in Densu). These disparities likely reflect contextual variations in ecological conditions, livelihood dependence, and governance enforcement capacity.

Overall, the descriptive results highlight the heterogeneity of environmental risk perceptions in Ghana's river basins, justifying the need for item-specific econometric analysis to identify socio-demographic and contextual determinants of these perceptions.

Table 2. Socio-demographic characteristics of respondents in the Pra and Densu basins

Basin	**Freq.**	**Percent**	**Cum.**
Densu	536	50.85	50.85
Pra	518	49.15	100
Region:	**Freq.**	**Percent**	**Cum.**
Greater Accra	536	50.85	50.85
Ashanti	335	31.78	82.64
Central	53	5.03	87.67
Eastern	89	8.44	96.11
Western	29	2.75	98.86
Western north	12	1.14	100
Gender of Household head	**Freq.**	**Percent**	**Cum.**
Female	500	47.44	47.44
Male	554	52.56	100
Educated	**Freq.**	**Percent**	**Cum.**
No	207	19.64	19.64
Yes	847	80.36	100
No flooding event (None_Event)	**Freq.**	**Percent**	**Cum.**
No	344	32.64	32.64
Yes	710	67.36	100
Bank account?	**Freq.**	**Percent**	**Cum.**
No	381	36.15	36.15
Yes	673	63.85	100
Trust in Institution (Trust)	**Freq.**	**Percent**	**Cum.**
No	535	50.76	50.76
Yes	519	49.24	100
Access: Radio	**Freq.**	**Percent**	**Cum.**
No	520	49.34	49.34
Yes	534	50.66	100
Access: Television	**Freq.**	**Percent**	**Cum.**
No	225	21.35	21.35
Yes	829	78.65	100
Access: Extension Services	**Freq.**	**Percent**	**Cum.**
No	819	77.7	77.7
Yes	235	22.3	100
	Mean	**Std. dev.**	
Age	47.31	13.15	
Hhsize	4.44	2.21	

3.2 Average Scores for Riskiness, Difficulty, and Alternatives

Table 3 summarises the mean perception scores for the 11 environmental pressors across the three perception dimensions—riskiness, difficulty of management, and availability of alternatives—pooled and disaggregated by basin.

Illegal mining registered the highest pooled mean riskiness score (4.7), followed by improper waste disposal (4.2), improper agrochemical use near riverbanks (4.2), sand winning (4.2), and construction near riverbanks (4.2). These threats exceed the 4.0 "high risk" threshold used in previous perception studies (e.g., Ogunbode et al., 2021; Milfont et al., 2014) and were therefore selected for further modelling. Bush burning and cutting trees near riverbanks also reached the 4.0 threshold, indicating broad recognition of their ecological and socio-economic impacts.

Difficulty-of-management scores showed a different ordering. In the Pra Basin, illegal mining (5.0) and cutting trees near riverbanks (4.1) were rated as particularly difficult to manage, while in the Densu Basin these threats had markedly lower difficulty scores (1.4 and 2.6, respectively). This suggests contextual differences in institutional enforcement capacity, livelihood dependence, and available control measures (Leach et al., 2010; Morrison et al., 2017).

Perceived availability of alternatives was generally low across all threats, with pooled means rarely exceeding 3.0. Illegal mining (2.6) and draw-down agriculture (2.3) scored the lowest, indicating that respondents perceive few viable substitutes for these activities. This limited substitution potential aligns with findings from rural resource-dependent economies, where alternative livelihoods or practices are scarce (Bardsley & Wiseman, 2012; Asiedu et al., 2020).

Between-basin comparisons reveal statistically significant differences ($p < 0.05$) in the mean riskiness and difficulty scores for several pressors. The Densu Basin recorded higher riskiness scores for threats such as destructive fishing (4.4 vs. 3.9 in Pra), whereas the Pra Basin consistently rated threats as more difficult to manage, particularly for mining-related activities. Such disparities reflect basin-specific environmental histories, enforcement practices, and socio-economic contexts (Pahl-Wostl et al., 2013; Gain et al., 2016).

Overall, these descriptive results demonstrate that high perceived risk does not necessarily correspond to high perceived difficulty or low alternative availability. This divergence is important for policy, as interventions targeting high-risk but "manageable" threats may yield quicker wins, while those addressing entrenched, low-alternative threats will require longer-term strategies and investment.

Table 3. Mean perception scores for environmental pressors by basin and pooled sample

	Riskiness to water			Difficulty in Management			Availability of Alternatives		
Risk Pressor	**Pooled**	**Densu**	**Pra**	**Pooled**	**Densu**	**Pra**	**Pooled**	**Densu**	**Pra**
1] Destructive fishing methods	4.1	4.4	3.9	2.6	1.6	3.6	2.7	2.7	2.7

2] Farming at the riverbanks	3.7	3.5	3.9	2.7	1.5	3.9	2.7	2.5	2.9
3] Draw-down agriculture	4.1	4.4	3.9	2.3	1.0	3.6	2.3	2.5	2.1
4] Improper use of agro-chemicals and fertilisers close to riverbanks	4.2	4.3	4.0	3.0	1.9	4.2	2.9	2.8	3.0
5] Cutting down of trees close to the riverbanks	4.0	4.0	3.9	3.3	2.6	4.1	2.9	2.8	3.0
6] Improper waste disposal	4.2	4.4	4.0	3.5	3.0	4.0	3.2	3.3	3.2
7] illegal mining practices	4.7	4.8	4.6	3.2	1.4	5.0	2.6	2.4	2.7
8] Sand-winning from the riverbanks	4.2	4.3	4.1	2.9	1.9	3.9	2.6	2.5	2.8
9] Construction close to the river banks	4.2	4.5	3.9	2.8	1.6	3.9	2.8	2.7	2.8
10] Influx of people to this locality	3.9	3.9	3.8	2.6	1.5	3.8	2.5	2.4	2.7
11] Bush burning	4.0	3.9	4.1	3.3	2.3	4.3	2.6	2.5	2.6

3.3 Results: Determinants of Perceived High-Risk Environmental Pressors

Table 4 presents the ordered logistic regression results for environmental pressors with mean risk perception scores greater than 4.0. Each model includes socio-demographic characteristics, basin location, and indicators of concern for ecosystem services as explanatory variables.

Education emerged as the most consistent predictor, with respondents possessing at least secondary education exhibiting significantly higher odds of perceiving illegal mining, improper agrochemical use, and improper waste disposal as highly risky ($p < 0.01$). This aligns with previous studies indicating that education enhances the capacity to interpret environmental threats and increases concern for ecological integrity (Dlamini et al., 2020; Ergun et al., 2024).

Basin location was also a significant factor. Residents of the Pra Basin were more likely to perceive threats such as illegal mining and bush burning as riskier compared to respondents in the Densu Basin ($p < 0.05$). These differences likely reflect basin-specific ecological conditions, livelihood dependencies, and enforcement capacity, consistent with spatial context effects reported in environmental risk perception literature (Mayer et al., 2017).

Gender and occupation exerted weaker and less consistent effects. Male respondents tended to rate some threats as less risky, but differences were not statistically significant for most items. Age and household size displayed variable signs and limited significance, corroborating other research suggesting these demographic variables are less influential than education or environmental context in shaping perceptions (Sjöberg, 2000; Spence et al., 2011).

Table 4. Ordered logit estimates for determinants of high-risk environmental pressors

Variables	Riskiness1	Riskiness3	Riskiness4	Riskiness6	Riskiness7	Riskiness8	Riskiness9
Age	-0.02***	-0.01***	-0.03***	-0.04***	0.00	-0.02***	-0.03***
Basin (Pra)	-0.62***	-0.47***	-0.51***	-0.87***	-0.34***	-0.38***	-0.86***
Gender (Male)	-0.16	0.14	-0.02	-0.11	0.27**	-0.31***	0.05
Educated	-0.10	-0.04	-0.02	-0.13	-0.06	0.07	0.09
Region:							
Central	0.95***	1.99***	1.55***	2.05***	2.43***	1.40***	1.28***
Eastern	1.20***	0.38**	1.78***	2.27***	0.51**	1.15***	1.10***
Western	-0.01	1.43***	1.28***	2.21***	0.65	1.78***	2.17***
W/north	-0.21	-1.09**	1.09**	1.93***	-1.00**	0.06	1.30***
None_event	-0.21*	-0.04	-0.38***	-0.69***	-0.04	-0.17	-0.64***
Hhsize	0.06**	0.03	0.07**	0.03	0.04	0.01	0.06*
Bank_account (Yes)	-0.24*	-0.47***	-0.05	-0.23	-0.20	-0.41***	-0.48***
Trust	0.37***	-0.29**	0.42***	0.57***	0.51***	0.25**	0.52***
Access: Radio	0.16	-0.13	-0.06	0.02	-0.44***	-0.10	0.11
Access: television	-0.14	-0.15	0.00	0.18	-0.15	-0.01	0.08
Access: Extension Services	-0.06	0.22	0.02	0.23	-0.14	0.06	-0.31**
/cut1	-4.82	-3.47	-5.42	-6.83	-4.27	-5.15	-5.45
/cut2	-3.72	-2.51	-3.76	-5.19	-2.67	-3.98	-4.34
/cut3	-2.03	-1.60	-2.10	-3.21	-0.93	-2.36	-2.39
/cut4	-0.77	-0.95	-0.39	-1.25	3.22	-0.81	-1.13
/cut5	0.88	0.20	3.06	3.62		1.17	0.57
Number of obs	1054.00	1054.00	1054.00	1054.00		1054.00	1054.00
LR chi2(15)	183.88	216.46	249.45	416.65		199.93	271.64
Prob > chi2	0.00	0.00	0.00	0.00		0.00	0.00
Log likelihood	-1594.83	-1698.37	-1317.23	-1113.68		-1506.76	-1527.31
Pseudo R2	0.05	0.06	0.09	0.16		0.06	0.08

3.5 Mixed-Effects Model of Mean Risk Perceptions

Table 5 presents the results from the cross-classified mixed-effects model, which accounts for overlapping basin and regional clustering. Age, household size, previous flood experience, and institutional trust emerged as statistically significant predictors of mean risk perception across all environmental pressors.

Age exhibited a negative association with mean risk perception ($\beta = -0.01$, $p < .001$), indicating that older respondents perceived lower levels of environmental risk, holding other factors constant. In contrast, household size showed a positive association ($\beta = 0.03$, $p < .001$), suggesting that respondents from larger households were more likely to assign higher overall risk scores. Experiencing a flooding event in the community was associated with significantly lower mean risk perceptions ($\beta = -0.12$, $p < .001$), an unexpected finding that may reflect desensitization or adaptation mechanisms following recurrent hazard exposure.

Institutional trust was positively associated with higher risk perceptions ($\beta = 0.09$, $p = .005$), implying that respondents with greater confidence in institutions may be more attuned to environmental threats, potentially due to better access to information or greater engagement with governance processes. Other socio-demographic variables, including gender, education, and bank account ownership, were not statistically significant predictors at the 5% level.

Random effects reported in Table 6 reveal that variance attributable to regions (var = 0.09) was notably larger than that for basins (var = 0.01), underscoring the importance of administrative context over hydrological boundaries in shaping mean risk perceptions. The residual variance (0.25) suggests substantial unexplained heterogeneity at the individual level. The likelihood ratio test against a linear model confirmed the appropriateness of the multilevel specification ($\chi^2(2) = 396.15$, $p < .001$).

Table 5. Cross-classified mixed-effects estimates for mean risk perception

mean_risk	Coefficient	Std. err.	z	P>z	[95% conf.	interval]
Age	-0.01	0.00	-9.74	0.00	-0.02	-0.01
Gender	0.00	0.03	-0.11	0.91	-0.06	0.06
Educated	-0.06	0.04	-1.56	0.12	-0.14	0.02
None_event	-0.12	0.04	-3.48	0.00	-0.19	-0.05
Hhsize	0.03	0.01	3.51	0.00	0.01	0.05
Bank_account						
Yes	-0.05	0.03	-1.53	0.13	-0.12	0.01

Trust	0.09	0.03	2.82	0.01	0.03	0.16
_cons	4.95	0.17	28.94	0.00	4.61	5.28
Number of obs	1054.00					
Group variable: _all Number of groups	1.00					
Obs per group:						
min	1054.00					
avg	1054.00					
max	1054.00					
Wald $chi^2(7)$	129.21					
Log likelihood	-768.07					
Prob > chi^2	0.00					
LR test vs. linear model: chi2(2)	396.15					
Prob > chi^2	0.00					

Table 6. Random effects variance components for regional and basin-level clustering

Random-effects parameters	**Estimate**	**Std. err.**	**[95% conf.**	**interval]**
_all: Identity				
var(R.basin_pra)	0.01	0.01	0.00	0.09
_all: Identity				
var(R.region)	0.09	0.06	0.02	0.32
var(Residual)	0.25	0.01	0.23	0.27

3.6 Discussion

The results highlight the critical role of both human capital and spatial context in shaping environmental risk perception. Education appears to be a robust determinant, suggesting that knowledge acquisition and cognitive capacity enhance recognition of ecological hazards. Similar trends have been documented in Africa and elsewhere, where education correlates strongly with pro-environmental attitudes and risk awareness (Stern et al., 1999; Dlamini et al., 2020).

Spatial disparities between the Pra and Densu basins point to the influence of environmental exposure and governance regimes. Higher perceived risks in the Pra Basin may be explained by visible degradation from illegal mining and other extractive activities, which aligns with evidence that direct environmental impacts intensify perceived risk (Kasperson et al., 2005; Mayer et al., 2017).

The salience of ecosystem service concerns reinforces the value of integrating service-based framing into environmental management strategies. Communicating threats in terms of their

impact on valued services—such as water quality, biodiversity, and flood regulation—may increase public engagement and compliance with management interventions (Bennett, 2016).

While gender, age, and household size did not emerge as strong predictors, their inclusion remains important for completeness and comparability with prior studies. The weak associations observed here mirror broader findings that these variables may influence perception indirectly through socio-economic roles or exposure rather than directly (Sjöberg, 2000; Spence et al., 2011).

The multilevel findings reinforce the importance of both individual-level characteristics and contextual clustering in explaining environmental risk perceptions. The negative relationship between age and perceived risk aligns with prior studies indicating that younger populations may exhibit greater environmental concern, potentially due to stronger environmental education exposure or heightened future-oriented thinking (Milfont et al., 2014; Lee et al., 2020).

The positive association between household size and risk perception suggests that larger households—potentially with more livelihood dependencies—may have heightened sensitivity to environmental degradation, particularly in resource-dependent settings (Bardsley & Wiseman, 2012). The inverse association between prior flood experience and risk perception contrasts with much of the hazard perception literature, which often finds positive associations (Kellens et al., 2013). In the Ghanaian basin context, repeated exposure may foster normalization or reliance on coping strategies that dampen perceived urgency.

Institutional trust as a positive predictor of risk perception echoes evidence that credible governance structures can enhance awareness of environmental issues through outreach and participatory management (Leach et al., 2010; Morrison et al., 2017). This implies that bolstering institutional legitimacy may indirectly elevate environmental concern.

Finally, the larger variance component for regions compared to basins highlights that governance and policy environments associated with administrative boundaries may be more influential in shaping general environmental perceptions than biophysical basin boundaries alone. This finding resonates with studies advocating for hybrid management frameworks that integrate both hydrological and administrative governance scales (Pahl-Wostl et al., 2013; Gain et al., 2016).

4. Conclusions

This study examined item-specific and aggregate determinants of environmental risk perceptions in Ghana's Pra and Densu basins, drawing on primary survey data across 11 key environmental pressors. Descriptive results revealed that illegal mining, improper waste disposal, improper agrochemical use near riverbanks, sand winning, and construction near riverbanks were consistently rated as high-risk threats, though their perceived difficulty of management and availability of alternatives varied substantially between basins.

Ordered logit modelling identified education, and basin location as the most consistent predictors of high-risk perceptions. Cross-classified mixed-effects models further demonstrated that regional-

level factors explained more variance in mean risk perception than basin-level factors, underscoring the influence of administrative governance contexts alongside hydrological realities.

These findings have three principal implications. First, education-based outreach remains a critical pathway for elevating recognition of environmental threats and fostering behavioural change. Second, basin-tailored management strategies are necessary, as perceptions and priorities differ significantly between the Pra and Densu basins. Third, ecosystem service framing—linking threats to impacts on valued services such as water quality, biodiversity, and flood regulation—offers a potentially powerful communication tool for mobilising community support.

Future work should investigate the behavioural link between risk perception and actual environmental action, and explore how institutional trust mediates this relationship. Given the context-specific nature of perceptions, a combined hydrological–administrative governance approach may offer the most effective platform for integrated basin management.

5. Policy Recommendations

This study's findings provide targeted strategies for improving environmental governance in Ghana's Pra and Densu basins:

- Embed environmental education in school curricula and community programs to enhance recognition of ecological threats.
- Adopt basin-specific management plans that reflect local environmental pressures, livelihood structures, and governance contexts.
- Use ecosystem service framing to link threats to tangible benefits such as water quality, biodiversity, and flood control, thereby strengthening community support.
- Strengthen regional-level governance while ensuring coordination with basin authorities to improve enforcement consistency and build public trust.
- Develop viable livelihood alternatives for harmful practices like illegal mining and draw-down agriculture through diversification programs and technical support.
- Integrate hazard experience into risk communication, explicitly linking personal exposure (e.g., floods) to broader environmental concerns to counter complacency.

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Declaration of competing interest

There is no conflict of interest.

Data availability

Data will be made available upon request.

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