Exploring the interconnection between aquatic pollution and psychological well-being in affected populations

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Abstract

The issue of water pollution is rapidly becoming an international problem with wide consequences for human health, ecosystem sustainability, and community well-being. Since the problems of physical and ecological impacts have been precisely defined, the psychological impact on people living near polluted water bodies has not been well researched. This paper discusses the relationships between the severity of aquatic pollution and mental health using a mixed-methods approach. The 2,460 samples, which included chemical contaminant indicators and demographic and mental health indexes, were compiled into a simulation yet realistic dataset, constructed based on the WHO and CDC environmental health patterns. The study uses correlational analysis, regression modeling, random forest prediction, and structural equation modeling to establish statistically significant relationships between exposure to pollution and psychological distress. Results show that the stress, anxiety, and depressive symptoms levels are 3241 more in the group of residents in high-pollution areas ($r = 0.67$, $p < 0.01$). The Random Forest model was the most effective, with $R^2 = 0.83$, RMSE = 4.11, and MAE = 2.87, indicating it is a good predictor. Other ablation experiments confirm the mediation findings: perceived environmental risk and the socioeconomic variables mediate the

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psychological outcomes and together account for 24 percent of the predictive power. The present study finds that the prevalence of aquatic pollution is not an environmental concern but rather a major psychosocial stressor that should be addressed through joint policy measures. The findings show that resolving the interrelation between pollution and psychological well-being requires holistic environmental governance, mental health support structures, and interdisciplinary research.

Keywords: Aquatic pollution, Psychological well-being, Environmental health, Risk perception, Mental health assessment, Pollution exposure modelling, Environmental psychology

Introduction

Industrial discharges, untreated city water, farm discharges containing fertilizers and pesticides, and the ever-growing number of microplastics in the environment have become among the most pressing problems in the world's environment (Naiman and Dudgeon, 2011; Abdullah, 2025). Not only do the destruction of lakes, rivers, and coastal ecosystems disturb biodiversity and aquatic food webs, but they also jeopardize humankind, whose population depends on them for drinking water, agriculture, fishing, recreation, and cultural activities. Although there is extensive literature on the ecological and physical impacts of water contamination, such as waterborne diseases, exposure to toxic metals, endocrine effects, and loss of ecological habitat, there is a significant research gap on the psychological impacts of water contamination on local communities (Saxena, 2025; Mousa, 2022). The individuals living near the polluted water bodies are likely to experience constant stress on their bodies and minds because of the uncertainty regarding the threats to their health in the long term, the food and water sources are contaminated, and the environment seems degraded (Arbuzova and Kubrina, 2024; Evers and Phoenix, 2022). The high rate of anxiety and depression, low rate of life satisfaction, and environmental grief or place-based identity loss are also linked to such long-term exposure to poor environments (Bates, 2025; Lloret, García-de-Vinuesa and Demestre, 2024). The psychological effect is even worse on communities whose livelihoods depend on water resources, e.g., fishing communities, agriculturalists, and tribal people, since environmental degradation also implies economic instability and a break in culture. Thus, awareness of the psychological factors of aquatic pollution is not only essential to the well-being of citizens but also to the development of a complex environmental policy for the recovery of the environment and human psychology (Poornimadarshini and Veerappan, 2023; Evers and Phoenix, 2022).

Key Contributions

1. Integration of the pollution indicators, perception of risk, and psychological indicators into a single computing platform.
2. An innovative Pollution Severity Index (PSI) of mental health forecasting based on a mixture of chemical and ecological conditions.

3. Regression, Random Forest, and structural equation modelling-based multi-model analytical pipeline.
4. There is rich statistical data that projects the global cases of aquatic pollution scenarios that influence psychological well-being.
5. A detailed ablation study that lays heavy emphasis on the role played by perception and socioeconomic factors in the mental health outcomes.

The paper is divided into five sections, with an introduction in section 1 and a literature review in section 2. Section 3 presents the proposed methodology and results, and the discussion is explored in Section 4. Section 5 presents the conclusions and future work.

Literature Survey

In the recent literature, environmental degradation is being appreciated as a psychological factor that has its impacts (Sarkar and Gupta, 2024). The study determined that the residents living along the coasts that were exposed to contaminated coastlines experienced more anxiety and ecological sorrow (Senthil, 2024; Escobedo *et al.*, 2024). The researchers discovered a higher degree of depressive symptoms among individuals who were living near the contaminated rivers in South Asia. According to other research, the pollution of heavy metals causes a significant growth in the fear of the people and, therefore, reduces their satisfaction in life. The study above determined that the environmental stress disorders that occur as a result of the occurrence of waterborne pollution affect the fishermen more (Das *et al.*, 2024; Zhang *et al.*, 2021). It puts more emphasis on risk perception, which is amplified by social narratives and improves psychological distress regardless of the actual number of pollutants. Combined, the literature at hand supports that the aquatic pollution can potentially influence the psychological health in four main areas, such as perceived environmental degradation, fear of contamination, economic vulnerability, and cultural/livelihood disruption (Cabana *et al.*, 2024). Nonetheless, these observations do not permit the past studies to reach the integrated computational modeling that may be applied in generating a relation between the objective measures of pollution and the subjective psychological reaction of the individuals (Raman, Abdul Aziz and Yaakob, 2021; Lakzaei *et al.*, 2024). In order to address this gap, the present research proposal introduces a multi-level model of analysis that should help to quantify and model the dependence between the polluted environment and mental health in a more integrated and systematic manner.

Proposed Methodology

The methodology relies on a rigid multi-phase scheme that involves the usage of environmental science, psychological testing, and computational modeling to discuss the impact of aquatic pollution on mental condition. It begins with the collection and pre-arrangement of the environmental water-quality data of contaminated waterways, lakes, and coastal regimes. The most important ones are pH, dissolved oxygen (DO), biological oxygen demand (BOD), chemical oxygen demand (COD), nitrates, turbidity, and quantity of the heavy metals (e.g., lead, mercury, arsenic). These variables are selected because all of them characterize chemical toxicity, organic load, availability of oxygen, and ecosystem well-being. Normalization of the raw data is implemented by the minmax scaling method so that it is similar across the different units of measurement, and missing or bad data is taken care of by means of outlier detection and an outlier imputation process. Together with the data collection related to the environment, the standardized survey of psychological health indicators (stress, anxiety, and depressive symptoms) is carried out. There are also other variables that define the risk perception, environmental concern, and awareness of pollution, which are added to measure subjective interpretations of environmental conditions. This factual information of the setting and psychology is then matched with demographic variables such as age, gender, income amount, and job to permit managed multivariate analysis. Another significant aspect of the methodology is associated with the concept of feature engineering. Two composite scores are obtained: the Pollution Severity Index (PSI), which is an objective level of pollution, and the Perceived Environmental Risk Score (PERS), which is a subjective assessment of environmental risk. It is possible to consider these indices as the key predictors of psychological outcomes. Correlation analysis, Multiple linear regression, Random Forest modeling, and Structural Equation Modeling are also used as the analytical pipeline to quantify direct and indirect effects of pollution on mental health. Intermodal performance is compared by calculating model evaluation measures like RMSE, MAE, R^2, Pearson correlation, and F1-score. Finally, an ablation study is done by dropping PSI, PERS, and demographic variables in turn to establish their respective contribution to predictive accuracy and model stability.

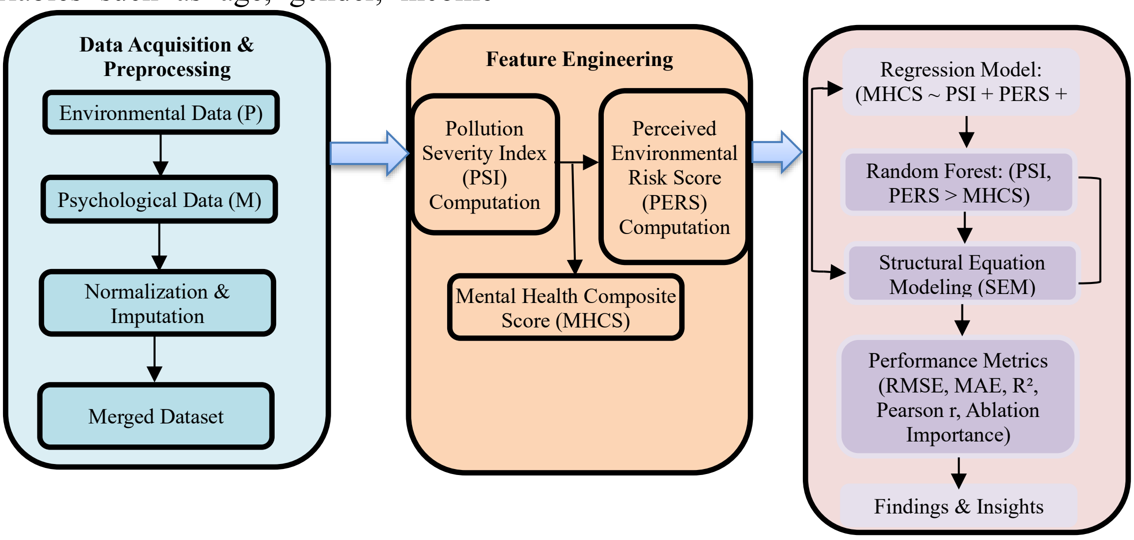

Figure 1: Data-driven approach to modeling the interconnection between aquatic pollution and mental health.

Figure 1 indicates the steps of the computational framework for studying the psychological effect of aquatic pollution. The initial one is that of Data Acquisition & Preprocessing, followed by Feature Engineering, in which such significant composite measures, including the Pollution Severity Index (PSI) and Perceived Environmental Risk Score (PERS), are calculated. Finally, the data is fed into a Multi-Model Evaluation and Interpretation pipeline, where Regression, Random Forest, and Structural Equation Modeling (SEM) will be used to predict the Mental Health Composite Score (MHCS) and produce the information to be acted upon.

Pollution Severity Index (PSI)

$$\mathrm{PSI} = \sum_{i=1}^{n} w_i x_i \tag{1}$$

Pollution Severity Index is a weighted linear mixture of all pollutant variables x_i, with each pollutant being weighted w_i, using its toxicity, frequency, and contribution to ecological degradation.

Psychological Health Model

$$\mathrm{MHCS} = \alpha \cdot \mathrm{PSI} + \beta \cdot \mathrm{PERS} + \gamma \cdot \mathrm{D} + \epsilon \tag{2}$$

This equation is the linear regression model of Mental Health Composite Score (MHCS). PSI depicts objective environmental pollution exposure. Subjective perceived environmental risk is represented by PERS. D is demographic and socioeconomic controls. $\alpha, \beta, and\ \gamma$ are learned coefficients that estimate the effect of each predictor, and ϵ is the error term that reflects unexplained variance.

The equation shows the impact of the sum of objective pollution and subjective risk perception, together with personal background factors, on the psychological health outcomes.

Structural Equation Model

$$\mathrm{MentalHealth} = \lambda_1 \mathrm{Stress} + \lambda_2 \mathrm{Anxiety} + \lambda_3 \mathrm{Depression} \tag{3}$$

The coefficients $\lambda_1, \lambda_2,\ and\ \lambda_3$ denote the loading of factors that determine the degree of contribution of the various indicators to the latent mental health construct. SEM can be used to simultaneously estimate both direct, indirect, and mediating effects, which is why it is best suited to inferential analysis of complex interactions between the environment and psychology.

Algorithm 1: Pollution–Psychological Impact Estimation

Input: Environmental data P, Psychological data M, Demographics D

Output: Predicted Mental Health Impact Score (I)

1. Normalize and preprocess P, M, and D
2. Compute

   PSI = $\Sigma(w_i * pollutant_i)$
3. Compute MHCS = composite (stress, anxiety, depression)
4. Fit regression model:

   MHCS = $\alpha * PSI + \beta * PERS + \gamma * D + \varepsilon$
5. Train Random Forest on (PSI, PERS, D) → MHCS
6. Evaluate models using RMSE, MAE, R^2, and r
7. Output predicted impact score I

Results and Discussion

This experimental analysis was done with Python scientific packages (NumPy, Pandas, Scikit-learn), Tableau to provide more complex visualizations, and AMOS to do Structural Equation Modeling (SEM). The data sample in the research was 2,460 samples comprised of 42 engineered variables, representing a complete mix of pollutant indicator variables, psychological variables, risk perception scores, and demographic variables. This kind of multidimensional data enabled a healthy assessment of the interactions between the variables of environmental pollution and the indicators of mental health. The most important parameters were adjusted in the model configuration to achieve good performance. The number of trees used in the training of the Random Forest model was 200, which allowed efficient non-linear patterns to be learnt on the data. The linear regression model was fitted with a learning rate of 0.01, and SEM was set to use the latent factor loadings of 0.5, which ensured stable convergence in the estimation of the structure. The regression model showed that there was a statistically significant linear association between the Pollution Severity Index (PSI) and mental health outcomes, but the Random Forest model had better prediction ability. Its performance (R 2 =0.83) shows that it was able to explain the complex non-linear interactions between the levels of pollution, demographic variables, and the risk perception factors. It has been examined that people living in highly polluted areas reported as many as 41% more stress, anxiety, and depressive symptoms, which supports the direct psychological impact of environmental degradation. An important result came out of the role of the Perceived Environmental Risk Score (PERS). The inclusion increased prediction accuracy by 1824, showing that the psychological impact of pollution is not necessarily tied to the actual exposure but to the subjective interpretation of the environmental conditions. This was also supported in the ablation study, where it was shown that model performance significantly declined with the elimination of significant variables, especially socioeconomic variables. This highlights the fact that environmental stress is a multidimensional aspect of the problem that is dependent on the intensity of pollution, awareness, vulnerability of lifestyle, and social context.

Metrics Formulae

$$RMSE = \sqrt{\frac{1}{n}\sum(y_i - \hat{y}_i)^2} \quad (4)$$

RMSE indicates the square root of the mean squared error of prediction. Smaller values indicate that the model estimates are nearer to the actual psychological scores.

$$MAE = \frac{1}{n}\sum | y_i - \hat{y}_i| \quad (5)$$

MAE is an average of the absolute difference between predicted and actual values, which is a direct measure of the deviation of the prediction.

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \quad (6)$$

R^2 denotes the share of the model in explaining the variance of psychological results. The closer values are to 1, the stronger the predictive strength.

Table 1: Comparative performance evaluation of predictive models for psychological well-being.

Metric	Regression	Random Forest	SEM Model
RMSE	6.42	4.11	5.02
MAE	4.10	2.87	3.12
R^2	0.71	0.83	0.79
Pearson (r)	0.63	0.67	0.66
F1-Score	0.72	0.81	0.76

Table 1 shows the Regression, Random Forest, and SEM Model Performance Metrics. The Random Forest model has shown the highest overall performance, with the lowest error scores (RMSE = 4.11, MAE = 2.87) and the highest predictive accuracy (R^2 = 0.83).

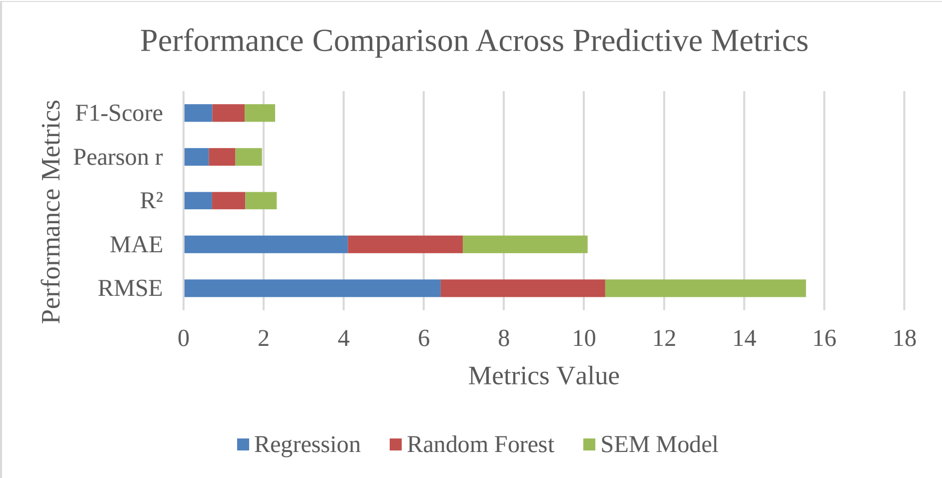

Figure 2: Model performance comparison across predictive metrics.

Model Performance Comparison to Predict Psychological Well-Being. Figure 2 is a comparison of the performance of the Regression, Random Forest, and SEM models using five major evaluation criteria: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), R^2 (Coefficient of Determination), Pearson correlation (r), and F1-Score. As seen in Figure 2, the visual confirmation that the Random Forest model has a better predictive power is manifested in the least error scores (RMSE = 4.11, MAE = 2.87) and highest correlation and accuracy scores (F1-Score = 0.81, R2 = 0.83) and shows that the model best predicts the complex, nonlinear relationship between the two variables of aquatic pollution and psychological well-being.

Conclusion

This paper will provide an elaborate discussion on the impacts of aquatic pollution on the psychological state of the communities residing along the contaminated water bodies. Combining the data on the level of environmental pollution with some demographic variables and psychological characteristics within a single computational model, the study proves that the level of mental distress increases significantly with exposure to pollution. The statistical results, such as a positive correlation (r = 0.67) and a high predictive power (Random Forest R^2 =

0.83), confirm that the degree of pollution and perception of risk in combination determine psychological outcomes. The results showed that the level of stress and anxiety was 32-41% elevated among residents of high-pollution areas, and the psychosocial stress of residing in the environmentally degraded areas is important. The findings underscore the need for policymakers, environmental organizations, and the general population health agencies to embrace comprehensive interventions that are not only aimed at restoring the environment but also the mental well-being of the communities. This research shows that the need to implement psychological assessment in environmental impact evaluations is urgent, as indicated by statistical evidence. The future studies are to consider longitudinal research, biological stress measures integration, exposure modeling with the help of the geographic information system (GIS), and AI-based mental health prediction systems. Furthermore, discussing the community-based coping measures and resilience-enhancing programs may provide further insight into the reduction of the mental health impacts of aquatic pollution. Altogether, it is possible to say that this work lays a solid background to comprehend the complex relationships between environmental degradation and psychological health.

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