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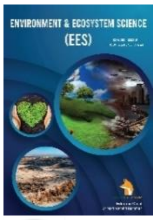

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RESEARCH ARTICLE

EVALUATING THE IMPACT OF COMMUNITY CHARACTERISTICS ON VULNERABILITY TO FLOODING: A CASE OF ILEMBE, KWAZULU NATAL PROVINCE, SOUTH AFRICA

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ABSTRACT

Flooding is a significant natural disaster that affects many communities around the world, including KwaZulu Natal Province in South Africa. Vulnerability to flooding is influenced by a variety of community characteristics, including social, environmental, and economic factors. Understanding the impact of these characteristics on vulnerability is essential for effective disaster risk reduction and management strategies. Therefore, this study aimed to evaluate the impact of community characteristics on vulnerability to flooding in the iLembe district municipality. Data were collected from 67 households using a survey questionnaire and analysed using multiple regression analysis. The results of the regression analysis revealed that social and economic characteristics significantly predicted vulnerability to flooding, while environmental characteristics did not have a significant effect. Specifically, social characteristics had a negative relationship with vulnerability, indicating that higher levels of social characteristics were associated with lower vulnerability to flooding. The results further suggest that poverty and economic insecurity may increase vulnerability to flooding in this community. Interestingly, the coefficient for environmental characteristics was not statistically significant, indicating that these factors do not have a significant impact on vulnerability score in this context. This finding may reflect the fact that the study was conducted in a relatively homogenous geographic region, where environmental characteristics may be relatively consistent across the community. Overall, these results highlight the importance of social and economic factors in understanding vulnerability to flooding in the KwaZulu Natal province of South Africa. Policymakers and practitioners should consider interventions that address poverty and economic insecurity, as well as promote social cohesion and support networks, to reduce vulnerability to flooding in this community.

KEYWORDS

Vulnerability; Flooding; Community characteristics; Social characteristics; Economic characteristics

1. Study Area Description

Ilembe District Municipality is a local municipality located in the KwaZulu-Natal province of South Africa. It was named after the Ilembe Mountain Range, which runs through the district (Mackie n.d.). The municipality covers an area of approximately 3,260 square kilometres and has a population of around 616,000 people according to the 2011 census. The district municipality is responsible for providing regional services such as water supply, sanitation, solid waste management, and regional planning and development. The district is predominantly rural, with a few urban centres such as KwaDukuza, Ballito, and Salt Rock (Mastrorillo et al., 2016). Agriculture, mainly sugar cane, is the primary economic activity in the area. There are also some manufacturing and tourism activities, particularly along the coastal areas. Ilembe District Municipality is known for its rich cultural heritage, with a significant Zulu influence. It is home to various historical sites, including the King Shaka Visitor Center and Shakaland, a traditional Zulu village. The district also boasts beautiful beaches and nature reserves, such as the Harold Johnson Nature Reserve, that offer hiking trails, birdwatching, and other outdoor activities. Ilembe District Municipality is prone to flooding due to its location and topography. The district is located in a coastal area and is surrounded by several rivers, including the Tugela and the Umvoti, which increase the likelihood of flooding during heavy rainfall. The municipality has experienced several floods in the past, causing significant damage to infrastructure and homes (Pharoah et al., 2014). In 2022, for example, heavy rains caused flooding in the KwaDukuza area, resulting in the displacement of hundreds of people and damage to infrastructure such as roads and bridges. Figure 1 shows one of the cases of flood damage in 2022. In addition to flooding, the district is also prone to other natural hazards such as coastal erosion and drought. The municipality has implemented measures such as the promotion of water conservation and the use of alternative energy sources to mitigate these risks (Bigara, 2012).

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Figure 1: Mhlali bridge on N2 road (Source: The north coast courier)

2. Introduction

The study was conducted between latitude 5º55'67'' and 5º37'12'' and Flooding is a significant hazard that affects many communities worldwide, causing loss of life, damage to infrastructure, and disruption to livelihoods (Ojo et al., 2021). In South Africa, floods are one of the most frequent and costly natural disasters, affecting millions of people every year. The Ilembe District Municipality in KwaZulu Natal province is one of the areas in South Africa that is particularly vulnerable to flooding. The district has experienced severe floods in the past, resulting in significant economic and social costs. Community characteristics are known to play a critical role in shaping the vulnerability of communities to flooding (Stephanus, 2013). For example, social capital, demographic factors, land use patterns, and infrastructure development are all factors that can affect a community's ability to cope with and recover from floods.

Understanding the relationship between these factors and vulnerability is essential for developing effective flood risk reduction strategies and promoting community resilience (Jansen, 2012). This study aims to evaluate the impact of community characteristics on vulnerability to flooding in the Ilembe District Municipality, with a particular focus on the factors that contribute to or mitigate vulnerability. The study draws on a wide range of literature related to community vulnerability to flooding and takes a case study approach to investigate the unique context of iLembe. The study begins with a literature review that explores the relationship between community characteristics and vulnerability to flooding. The review examines key factors that influence vulnerability, such as social capital, land use, and infrastructure, and discusses existing research on community vulnerability to flooding in South Africa. This review provides a foundation for the subsequent analysis of the data collected from the case study.

3. Literature Review

3.1 Relationship between community characteristics and flood vulnerability

Flooding is a natural hazard that can cause significant social and economic costs to communities (Sikhakhane, 2008). Vulnerability to flooding is influenced by a range of factors, including physical, social, and economic factors. Community characteristics, such as social capital, demographics, and infrastructure, can play a critical role in shaping the vulnerability of communities to flooding. Social capital refers to the social networks, norms, and trust that facilitate cooperation and collective action among individuals and groups. Social capital can influence vulnerability to flooding by enhancing community resilience and promoting collective action in response to flood events. For example, communities with high levels of social capital may be more likely to mobilize resources and engage in mutual aid during and after floods.

Demographic factors, such as age, gender, and income, can also affect vulnerability to flooding. For example, elderly people and young children may be more vulnerable to floods due to physical limitations, while low-income households may be more vulnerable due to lack of resources and access to information and services. Infrastructure, including buildings, roads, and drainage systems, can also affect vulnerability to flooding. Poorly designed or maintained infrastructure can exacerbate flood damage, while well-designed and maintained infrastructure can help mitigate the impact of floods (Thinda et al., 2020). Research has shown that community characteristics can play a significant role in shaping vulnerability to flooding. A study (Busayo et al., 2022). found that social capital can enhance the resilience of communities to flooding in Bangladesh, while a study by found that demographic factors such as age and income can influence vulnerability to flooding in China (Sikhakhane, 2008).

3.2 Factors influencing vulnerability, such as social capital, land use, and infrastructure

Vulnerability to flooding is influenced by a range of factors, including physical, social, and economic factors (Ngcobo, 2021). These factors interact to shape vulnerability in complex ways and understanding the key factors that influence vulnerability is critical for developing effective flood risk reduction strategies (Thinda et al., 2020). Social capital refers to the social networks, norms, and trust that facilitate cooperation and collective action among individuals and groups. Social capital can enhance community resilience and promote collective action in response to flood events. Communities with high levels of social capital may be more likely to mobilize resources and engage in mutual aid during and after floods. Land use is another key factor that can influence vulnerability to flooding. Land use practices, such as urbanization and deforestation, can increase the likelihood and severity of flooding by altering the hydrological cycle and reducing the capacity of ecosystems to absorb and regulate water (Ahmed, 2005). Land use practices can also affect the distribution of flood risks and impact vulnerable populations disproportionately. Infrastructure, including buildings, roads, and drainage systems, can also influence vulnerability to flooding. Poorly designed or maintained infrastructure can exacerbate flood damage, while well-designed and maintained infrastructure can help mitigate the impact of floods (Fortuin, 2022; Pharoah et al., 2014).

3.3 Community vulnerability to flooding in South Africa

Flooding is a frequent and costly natural disaster in South Africa, affecting millions of people every year (Ngcobo, 2021). Vulnerability to flooding is shaped by a range of factors, including physical, social, and economic factors, and understanding these factors is critical for developing effective flood risk reduction strategies in South Africa. Existing research has highlighted the significant impact of flooding on South African communities, particularly those in informal settlements and low-income areas. Infrastructure has also been identified as a key factor in shaping vulnerability to flooding in South Africa. A study by found that poorly designed and maintained stormwater drainage systems were a significant driver of flooding in Durban, while a study found that investment in flood infrastructure can significantly reduce flood vulnerability in South Africa (Tenza, 2018; Fortuin, 2022). In conclusion, existing research highlights the significant impact of flooding on South African communities and the importance of understanding the factors that shape vulnerability to develop effective flood risk reduction strategies. Social and economic factors, as well as infrastructure, are critical in shaping vulnerability to flooding in South Africa, and addressing these factors is essential to reduce the impact of flooding on vulnerable communities.

4. Methods and Materials

This study aims to evaluate the impact of community characteristics on vulnerability to flooding in the iLembe region of KwaZulu Natal province, South Africa. The study area has recently experienced floods that have caused significant loss of life and infrastructure. The methodology involved the selection of a sample size of 67 households, which were randomly selected for analysis.

The collected data was first analysed for demographics as a baseline analysis. Reliability testing was carried out using McDonald's ω and Cronbach's α. For the main analysis, multiple regression analysis (hierarchical) was used to evaluate the impact of community characteristics on vulnerability to flooding. The vulnerability equation adopted for the study was:

Vulnerability = Exposure * Sensitivity / Adaptive capacity (1)

Where:

Exposure refers to the likelihood or probability of being exposed to a hazard.

Sensitivity refers to the degree to which a system or community is affected by a hazard.

Adaptive capacity refers to the ability of a community or system to adapt and cope with the effects of a hazard (Ngcamu and Chari, 2020).

The vulnerability equation shows that vulnerability is a function of exposure, sensitivity, and adaptive capacity. A high level of exposure or sensitivity to a hazard, coupled with a low level of adaptive capacity, will result in a high level of vulnerability. Conversely, a low level of exposure or sensitivity, coupled with a high level of adaptive capacity, will result in a low level of vulnerability (Ojo et al., 2021). The independent variables used in the analysis were social characteristics, economic characteristics, and environmental characteristics. Normality testing was conducted using descriptive statistics and Q-Q plots.

A multicollinearity test was performed using correlation analysis. The dependent variable used in the analysis was the vulnerability to flooding. The vulnerability equation was used to determine the vulnerability score for each household. The independent variables used in the analysis were social characteristics, economic characteristics, and environmental characteristics. Social characteristics included factors such as age, education, and income. Economic characteristics included factors such as household income and employment status. Environmental characteristics included factors such as location of the household, land use, and distance from water bodies. Figure 2 show a conceptual framework to this study. The data was prepared by first detecting outliers. Composite scores were then calculated for each household using the vulnerability equation.

Hierarchical multiple regression is a statistical method used to evaluate the influence of multiple independent variables on a single dependent variable (Mark and Goldberg, 1988). This method is particularly useful when researchers want to test the effect of certain predictors while controlling for other variables that may also influence the outcome. In hierarchical multiple regression, predictors are entered into the model in a predetermined order, with each subsequent variable being entered after controlling for the previous variables. This approach helps to isolate the unique contribution of each predictor variable to the variance in the dependent variable, while accounting for the shared variance with other predictors. This method is commonly used in social sciences and other fields where researchers want to explore the effects of multiple variables on a particular outcome (Maxwell Scott, 2000). For example, in the study of vulnerability to flooding in KwaZulu Natal province, South Africa, hierarchical multiple regression was used to evaluate the impact of social, economic, and environmental characteristics on vulnerability scores. By entering the predictor variables in a specific order and accounting for shared variance, researchers were able to determine the unique contribution of each characteristic to vulnerability.

The study adopted sustainability theory. Sustainability theory is a multidisciplinary field of study that focuses on the development and implementation of sustainable practices for ensuring that resources are used in an environmentally, socially, and economically responsible way. Sustainability theory posits that humans need to take a holistic approach to development, one that integrates environmental, social, and economic considerations to promote long-term viability (Kolk and van Tulder, 2010).

At its core, sustainability theory recognizes the interdependence between human activities and natural systems and emphasizes the need to manage natural resources in a way that balances the needs of current and future generations. The theory is rooted in the concept of carrying capacity, which is the ability of an ecosystem to support a given level of human activity without degrading natural systems (Ashrafi et al., 2020). The concept of sustainability theory is highly relevant to the study at hand, which evaluates the impact of community characteristics on vulnerability to flooding in the iLembe district municipality of KwaZulu Natal province, South Africa.

The study seeks to understand the factors that contribute to vulnerability to flooding, with the ultimate goal of informing strategies to enhance the community's resilience to future floods. Sustainability theory emphasizes the need to maintain ecological, social, and economic systems in a state of balance to ensure long-term viability. The vulnerability of communities to environmental hazards, such as flooding, is a reflection of the complex interplay between social, economic, and environmental factors. The study considers these factors in assessing the community's vulnerability to flooding and seeks to identify areas where interventions can be made to promote sustainability.

The identification of social, economic, and environmental characteristics that influence vulnerability to flooding is crucial for developing effective and sustainable strategies for disaster risk reduction. This study contributes to the body of knowledge on vulnerability assessment and risk reduction by adopting the vulnerability equation, which incorporates exposure, sensitivity, and adaptive capacity. By identifying and addressing the factors that contribute to vulnerability, the study aims to enhance the community's capacity to adapt to future floods sustainably.

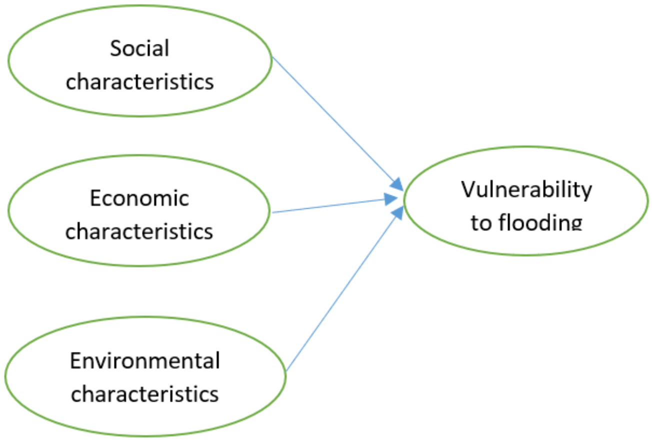


Figure 2: Conceptual framework

5. Results and Discussion

Table 1: Frequentist scale reliability statistics

Estimate	McDonald's ω	Cronbach's α	mean	sd
Point estimate	0.822	0.821	2.984	0.404
95% CI lower bound	0.812	0.810		
95% CI upper bound	0.833	0.831		

A frequentist scale reliability analysis was conducted to assess the internal consistency of the questionnaire as shown in table 1. McDonald's ω and Cronbach's α coefficients were calculated, with point estimates of 0.822 and 0.821, respectively. The 95% confidence intervals (CI) for both coefficients were also calculated, with the lower bounds at 0.812 and 0.810, and the upper bounds at 0.833 and 0.831, respectively. These results indicate that the scale has acceptable levels of internal consistency, with both coefficients exceeding 0.7 and their 95% CIs not overlapping with 0.5. The mean score on the scale was (M=2.984, SD = 0.404), providing information about the distribution of scores among participants.

Table 2: Contingency table, age and gender

	Gender		
Age	**Male**	**Female**	**Total**
18-25	7	3	10
26-35	10	9	19
36-45	7	12	19
46-55	7	9	16
56+	3	0	3
Total	34	33	67

Table 3: Chi-Squared Test, age and gender			
	Value	**df**	**p**
X^2	6.205	4	0.184
N	67		

A contingency table (table 2) was constructed to show the distribution of participants by age and gender. The results revealed that there were 34 male and 33 female participants, with varying numbers across age groups and gender categories. Chi-squared test was conducted to examine whether there was a significant association between age and gender. The results (Table 3) indicated that there was no significant association between age and gender ($X^2(4)$, N=67, p = 0.184).

Table 4: Contingency table, age and marital status

	Marital status				
Age	**Single**	**Married**	**Divorced**	**Widowed**	**Total**
18-25	3	3	3	1	10
26-35	7	8	4	0	19
36-45	5	13	1	0	19
46-55	6	8	0	2	16
56+	2	0	0	1	3
Total	23	32	8	4	67

Table 5: Contingency table, educational level and occupation

Educational level	**Occupation**					
	Employed	**Self-employed**	**Student**	**Unemployed**	**Other**	**Total**
Primary school	0	0	0	0	5	5
High school	1	7	1	3	0	12
College/University	23	4	6	0	0	33
Postgraduate	10	6	1	0	0	17
Total	34	17	8	3	5	67

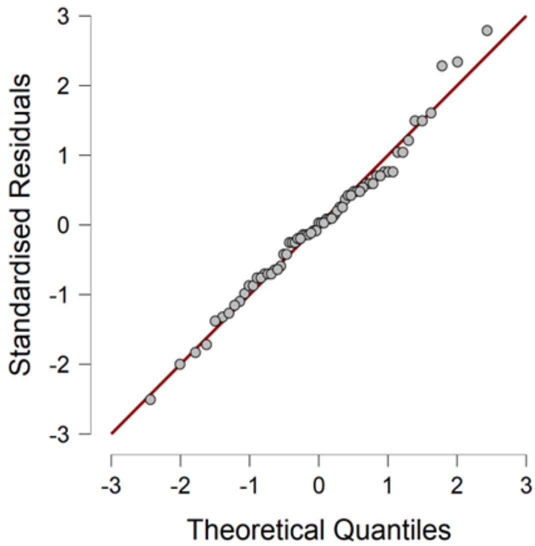
Table 4 displays a contingency table that shows the distribution of participants by age and marital status. The table indicates that of the 67 participants, 23 were single, 32 were married, 8 were divorced, and 4 were widowed. There were varying numbers of participants across age groups and marital status categories, with the youngest age group (18-25) having an equal distribution of singles, married, divorced, and widowed participants.

Table 5 presents a contingency table that shows the distribution of participants by educational level and occupation. The rows show different levels of education, ranging from primary school to postgraduate studies, while the columns show occupation, including employed, self-employed, student, unemployed, and other. The table reveals that of the 67 participants, 34 were employed, 17 were self-employed, 8 were students, 3 were unemployed, and 5 had other occupations. There were varying numbers of participants across educational levels and occupation categories. Finally, tables 4 and 5 provide information about the distribution of participants by age, marital status, educational level, and occupation. Table 4 indicates that the participants were mainly married, while Table 5 indicates that the majority were employed or self-employed, with college/university education being the most common level of education.

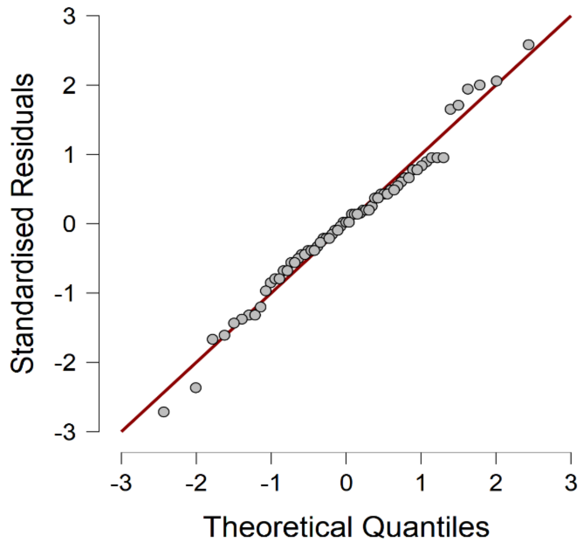
Table 6: Descriptive Statistics

Statistic	**Vulnerability score**	**Social characteristics**	**Environmental characteristics**	**Economic characteristics**
Valid	67	67	67	67
Mean	2.843	3.492	3.561	3.435
Std. Deviation	0.370	0.358	0.349	0.329
Shapiro-Wilk	0.984	0.982	0.987	0.979
P-value of Shapiro-Wilk	0.564	0.445	0.705	0.318
Minimum	1.917	2.521	2.646	2.521
Maximum	3.875	4.417	4.583	4.125

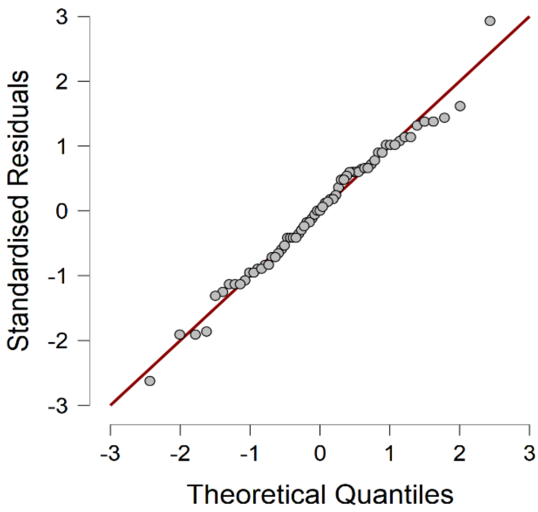
Table 6 displays the descriptive statistics for vulnerability score, social characteristics, environmental characteristics, and economic characteristics. The table shows that the mean vulnerability score and standard deviation were (M=2.843, SD= 0.370). The mean scores and standard deviations for social characteristics, environmental characteristics, and economic characteristics were M_{sc}= 3.492, SD_{sc}=0.358; M_{enc}=3.561, SD_{enc}= 0.349 and M_{ecc}=3.435, SD_{ecc}= 0.329 respectively. Normality tests were conducted using the Shapiro-Wilk test, with all variables having p-values greater than 0.05, indicating that they are normally distributed. Figure 3 further complemented the normality test showing Q-Q plot of all variables residuals normally distributed. The minimum vulnerability score was 1.917, while the maximum vulnerability score was 3.875. Overall, the results indicate that the participants had relatively low vulnerability scores, with mean scores ranging from 2.84 to 3.56 across the different characteristics.



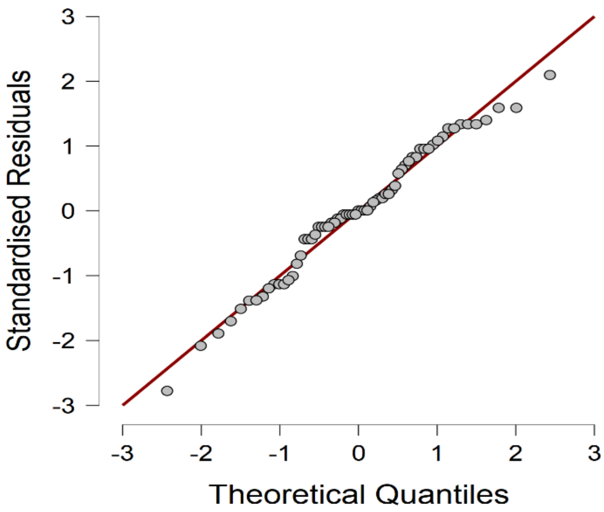
Vulnerability score



Social characteristics



Environmental characteristics



Economic characteristics

Figure 3: Q-Q Plots

Table 7: Pearson's Correlations

Variable		Vulnerability score	Social characteristics	Environmental characteristics	Economic characteristics
1. Vulnerability score	Pearson's r	—			
	p-value	—			
2. Social characteristics	Pearson's r	-0.456	—		
	p-value	< .001	—		
3. Environmental characteristics	Pearson's r	0.027	0.311	—	
	p-value	0.831	0.511	—	
4. Economic characteristics	Pearson's r	-0.386	0.273	0.084	—
	p-value	0.001	0.066	0.497	—

Table 7 shows the Pearson's correlations among the four variables of interest: vulnerability score, social characteristics, environmental characteristics, and economic characteristics. The correlation coefficients and corresponding p-values are presented. The correlation coefficient between vulnerability score and social characteristics is (r=-0.456, p < .001), indicating a moderate negative correlation. The correlation between vulnerability score and economic characteristics is (r=-0.386, p = .001), indicating a moderate negative correlation as well. The correlation between social characteristics and economic characteristics is (r=0.273, p = 0.066), indicating a weak positive correlation.

The correlation between vulnerability score and environmental characteristics is (r=0.027, p = 0.831), indicating no significant correlation. There is no evidence of multicollinearity between the independent variables in this study. Multicollinearity is a situation where two or more independent variables in a regression model are highly correlated with each other, leading to unstable and unreliable estimates of the regression coefficients. In this case, the correlation coefficients among the independent variables are relatively low, suggesting that they are not highly correlated with each other. Therefore, it is unlikely that multicollinearity will be a major issue in the regression analysis.

Table 8: Model Summary - Vulnerability score

Model	R	R^2	Adjusted R^2	RMSE	R^2 Change	F Change	df1	df2	p
H_0	0.000	0.000	0.000	0.370	0.000		0	66	
H_1	0.560	0.313	0.281	0.314	0.313	9.578	3	63	< .001

Table 9: ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	2.827	3	0.942	9.578	< .001
	Residual	6.199	63	0.098		
	Total	9.027	66			

A linear regression model was fitted to examine the relationship between vulnerability score and its predictors. Model summary statistics are presented in Table 8. The model included one predictor variable, and the model fit was evaluated using R-squared (R^2), adjusted R-squared, root mean square error (RMSE), R-squared change, F change, degrees of freedom (df), and p-value. The null hypothesis (H_0) stated that the predictor variable does not significantly predict vulnerability score, while the alternative hypothesis (H_1) stated that the predictor variable significantly predicts vulnerability score. The results showed that the model significantly predicted vulnerability score (F(3, 63) = 9.578, p < .001), accounting for 31.3% of the variance in vulnerability score (R^2 = .313). The adjusted R-squared was .281, and the RMSE was .314.An analysis of variance (ANOVA) was performed to assess the significance of the regression model. Table 9 presents the results of the ANOVA, including the sum of squares, degrees of freedom (df), mean square, F value, and p-value. The ANOVA results revealed that the regression model significantly accounted for a portion of the variance in vulnerability score (F(3, 63) = 9.578, p < .001). The regression model had a regression sum of squares of 2.827, a residual sum of squares of 6.199, and a total sum of squares of 9.027. The mean square for the regression was .942, and the mean square for the residual was .098.

Table 10: Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	2.843	0.045		62.928	< .001
H_1	(Intercept)	4.808	0.571		8.422	< .001
	Social characteristics	-0.451	0.118	-0.436	-3.835	< .001
	Environmental characteristics	0.197	0.116	0.186	1.694	0.095
	Economic characteristics	-0.318	0.122	-0.283	-2.609	0.011

The table 10 displays the coefficients for the model predicting vulnerability score based on social, environmental, and economic characteristics. Model H_0 has an intercept value of 2.843 with a standard error of 0.045. The intercept value is significantly different from zero (t = 62.928, p < .001) while model H_1 has an intercept value of 4.808 with a standard error of 0.571. The intercept value is significantly different from zero (t = 8.422, p < .001). For Model H_1, the coefficient for social characteristics is -0.451 with a standard error of 0.118 and a standardized coefficient of -0.436. The coefficient is significantly different from zero (t = -3.835, p < .001). For Model H_1, the coefficient for environmental characteristics is 0.197 with a standard error of 0.116 and a standardized coefficient of 0.186. The coefficient is not statistically significant (t = 1.694, p = 0.095). For Model H_1, the coefficient for economic characteristics is -0.318 with a standard error of 0.122 and a standardized coefficient of -0.283. The coefficient is significantly different from zero (t = -2.609, p = 0.011). These results suggest that social and economic characteristics are significantly associated with vulnerability score, while environmental characteristics are not.

6. Conclusion and Recommendations

In this study, the impact of community characteristics on vulnerability to flooding was evaluated, specifically in the iLembe district municipality. The regression results presented revealed that social and economic characteristics have a significant impact on vulnerability score, while environmental characteristics do not. Model H_0 had an intercept value of 2.843, which was significantly different from zero, indicating that there is a base level of vulnerability present in the community. Model H_1 had an intercept value of 4.808, which was also significantly different from zero, indicating that there are additional factors contributing to vulnerability beyond the base level. The coefficient for social characteristics was -0.451, which indicates that higher levels of social characteristics are associated with lower vulnerability scores. This result is consistent with previous research that has shown that social factors such as education and social support can play a protective role in disaster situations.

The coefficient for economic characteristics was -0.318, indicating that higher levels of economic characteristics are associated with lower vulnerability scores. This result suggests that poverty and economic insecurity may increase vulnerability to flooding in this community. Interestingly, the coefficient for environmental characteristics was not statistically significant, indicating that these factors do not have a significant impact on vulnerability score in this context. This finding may reflect the fact that the study was conducted in a relatively homogenous geographic region, where environmental characteristics may be relatively consistent across the community. Overall, these results highlight the importance of social and economic factors in understanding vulnerability to flooding in the KwaZulu Natal province of South Africa. Policymakers and practitioners should consider interventions that address poverty and economic insecurity, as well as promote social cohesion and support networks, to reduce vulnerability to flooding in this community.

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