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EVALUATING WATER SCARCITY VULNERABILITY LEVELS IN RURAL COMMUNITIES OF ISEYIN LOCAL GOVERNMENT AREA, OYO STATE, NIGERIA: AN INTEGRATED AND MULTIDIMENSIONAL APPROACH

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Abstract

Water is essential for life, yet water scarcity persists globally, driven by population growth, poor quality, and limited access. This study assesses water scarcity in 19 rural communities in Iseyin, Oyo State, Nigeria, using primary data from geodetic GNSS receivers and household estimates via Google Earth. A bespoke Water Scarcity Vulnerability Mapping (WSVM) software, developed by the researcher using VB Net 2022, combined with multi-criteria decision analysis using the Analytic Hierarchy Process (AHP) evaluated village vulnerability based on water availability, quality, drought resilience, and proximity to sources. The survey identified 32 water sources—including boreholes, wells, ponds, and rivers—revealing disparities: some villages have improved access, while others rely heavily on surface water, increasing their vulnerability. Villages were categorized into three levels: severe (7 villages, 37%), moderate (9 villages, 47%), and low (3 villages, 16%). Drought resilience and water quality were the main drivers of water insecurity, especially during dry seasons. An adaptive measure recommended is the installation of water infrastructures to enhance drought resilience of rural communities and ensure improved water quality.

Keywords: Water Scarcity, Vulnerability Assessment, Rural Communities, Water Infrastructure, Drought Resilience

1.0 Introduction

Water is an essential resource for sustaining life, supporting health, agriculture, sanitation, and economic activities [9]. Despite its critical importance, water scarcity remains a pressing global challenge, affecting over 2 billion people who lack access to safe and reliable water sources [8]. Rural communities are especially vulnerable due to inadequate infrastructure, dependence on surface water sources, and environmental pressures such as climate variability [6].

In Nigeria, water insecurity is a persistent problem that impacts socio-economic development and public health, particularly in rural areas where traditional water sources are increasingly unreliable [1]. Seasonal droughts, pollution, and population growth exacerbate water scarcity, leading to significant disparities in access and quality [7]. These vulnerabilities are often spatially heterogeneous and require detailed assessment to inform targeted interventions.

Previous research [4] has employed various methodologies to assess and categorize water scarcity vulnerability levels. Multi-criteria decision analysis (MCDA) techniques—such as the Analytic Hierarchy Process (AHP)—have been utilized to weight multiple socio-economic, environmental, and infrastructural factors influencing water scarcity even as I acknowledge that the spatial overlay analysis is a technique used to delineate high, medium, and low water scarcity vulnerability zones based on thematic layers like rainfall, groundwater depth, and infrastructure [11]. Additionally, composite vulnerability indices (CVIs) have been developed by aggregating indicators such as water availability, quality, and socio-economic parameters into a single score, which is then classified into categories like *severe*, *moderate*, and *low* vulnerability [5, 10]. Clustering algorithms, such as hierarchical clustering, have further aided in grouping communities with similar vulnerability profiles, facilitating targeted policy interventions. These approaches generally involve selecting relevant indicators, normalizing data, applying weighting schemes, and establishing thresholds or categories based on statistical or expert judgment. The resulting classifications enable stakeholders to prioritize areas for intervention, allocate resources efficiently, and develop resilient water management strategies.

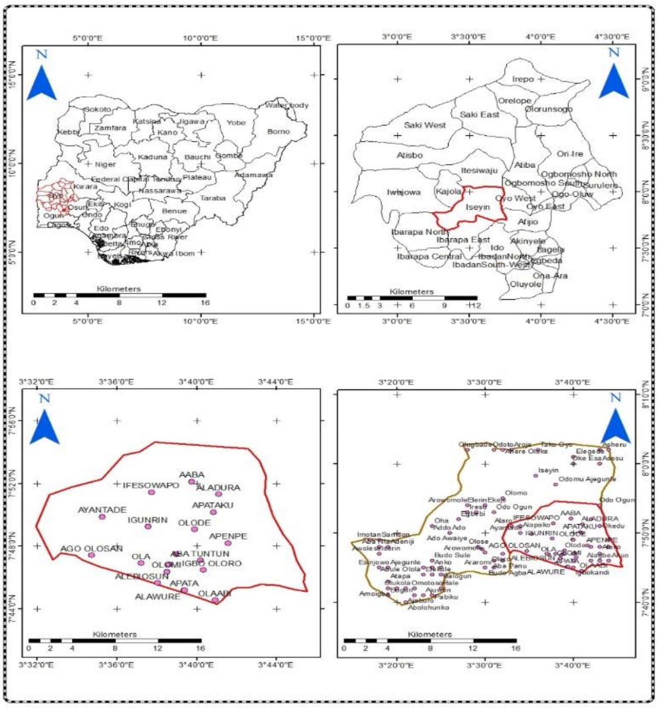
Building upon these methodologies, this study focuses on assessing water vulnerability in 19 rural communities within Iseyin, Oyo State, Nigeria. By employing GIS-based tools integrated with multi-criteria decision analysis—specifically, assigning weights to water availability, environmental, proximity, and climatic factors—and mapping the resulting vulnerability zones, the research aims to categorize communities into *severe*, *moderate*, and *low* vulnerability levels. This stratification will inform sustainable water management strategies and resilience-building efforts tailored to community-specific needs.

2. Materials and Methods

2.1 Study Area

Iseyin is a significant city in Southwest Nigeria, situated approximately 72 km north of Ibadan, with a population that grew from about 236,000 in 2005 to nearly 363,000 in 2011. Covering an area of 2,341 km², it is predominantly inhabited by the Yoruba people, with Oba Sefiu Oyebola Adeyeri III currently serving as the traditional ruler. The city is culturally rich, known for its history, traditions, and socio-cultural ties, including notable events like the Iseyin riots of 1916. Geographically, Iseyin extends from 7°55′N to 7°59′N and 3°33′E to 3°36′E, operating in the UTC+1 time zone. Its fertile soils historically attracted early farmers and hunters, making agriculture a central activity—producing crops such as yam, maize, cassava, plantain, and tobacco.

Iseyin is renowned as the home of Aso Ofi (Aso Oke), a traditional Yoruba fabric integral to cultural ceremonies like weddings and festivals. The weaving tradition, dating back about four centuries to Ile-Ife and linked to Oduduwa, is passed down through generations, with locals sourcing fibers locally and from neighboring states. The town celebrates its weaving heritage through the annual Aso-Ofi Festival, initiated in 2016 during World Tourism Day, boosting tourism and cultural pride.



Source: Author, (May, 2025)

Figure 1: Map of the Study Area

Apart from agriculture and weaving, Iseyin hosts various industries and institutions, including SAF Polytechnic, a government technical college, a milk processing center operated by Friesland Campina, and the Raji Oke-Esa Memorial Library. The city is also home to significant infrastructural sites like the Ikere Gorge Dam contributing to its economic and environmental landscape. Overall, Iseyin blends historical depth, cultural vibrancy, and economic activity, making it a notable city within Oyo State.

2.2 Data sources, collection and processing

Data collection is a fundamental element of scientific research, serving as the foundation for analysis and interpretation. The following outlines various types of data, their descriptions, sources, instruments, and procedures utilized for data acquisition in this study. Detailed information regarding the datasets collected is presented in Table 1. These datasets were gathered from credible sources or providers and encompass a comprehensive representation of the study area.

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Type	Description	Source	Software used
Google Earth Imagery	Estimation of number of households per village, etc.	Accessed via Google earth	Google Earth Pro
Village Data	Locational data (latitude and longitude—WGS84 datum), Number of houses, water demand, socio-economic activity, village name, etc	Contact Survey Method (CSM) using GNSS receiver and social survey.	Microsoft excel 2016 and WSVM 3.25
Demographic Data	Population data per village based on AHC (average head counts) per house.	Google earth data and estimation of AHC per household based on Demographic and Health Survey (Ethiopia, 2016).	Microsoft excel 2016 and WSVM 3.25
Water Source Data	Type of water source i.e. surface (pond, river/spring/stream, etc), groundwater (well and borehole), Locational data (latitude and longitude), calculated total water volume per day (at rainy and dry seasons), water quality, water source name, etc	Contact Survey Method using GNSS receivers, social survey, volume calculation formulae, and visual observation	Microsoft excel 2016 and WSVM 3.25
Attribute Data	Names of villages, predominant socio-economic activities of rural dwellers, etc.	Social Survey, google earth and direct (self) observations.	Microsoft excel 2016

Table 1: Details of Data types, Sources and software required for the research.

Satellite imagery was accessed through Google Earth Pro, enabling the extraction of crucial and pertinent data, such as the number of households in each village. The imagery offered significant visual context for analyzing the spatial distribution of residential structures and improved the data collection process. By utilizing high-resolution satellite images, the researcher was able to systematically identify and verify household counts across the various villages in the study area, thereby enhancing the reliability of the demographic information gathered. The population of each village was calculated by multiplying the number of households (HH) by an average of five persons per rural household based on Demographic and Health Survey (Ethiopia, 2016).

The formula used to determine the total population (P) for village (V_i) was expressed as follows:

Population ($P_{V(i=1-n)}$) = Number of Households (HH_{Vi}) × 5 …….. eqn. (1)

In the data processing phase, several crucial steps were taken to ensure data uniformity and compatibility. Initially, a careful data projection check was performed to confirm that all datasets shared the same geographic reference system (WGS84). These processing steps guarantee that all datasets are harmonized by projection and geographic reference frame, enabling accurate and seamless integration of various datasets (GMapControl—accessible via WSVM) for the subsequent geospatial analysis. The geographic coordinates were converted from degrees, minutes and seconds to decimal degrees, ensuring conformity to the format of the analysis tool (WSVM).

Calculation of Water Volume from various sources in the Study Area

Volume calculations for various water source types—such as ponds, boreholes, rivers, and wells—are essential for understanding the availability of water resources in a study area. Presented below in table 2 is a brief overview of how the volume for each type of water sources was calculated:

Table 2: Volume calculations for various water source types

SN	Water Source Type	Volume Formulae
1	Pond: Rectangular	Length × Width × Average Depth
	Irregular	Surface Area × Average Depth, where surface area was calculated using geocoordinates of edges picked using a GNSS receiver.
2	Borehole	π × r2 × h, where r is the radius of the borehole (in meters) and h is the depth of the water (in meters).
3	River	Cross-Sectional Area × Length. The cross-sectional area was calculated by measuring the width and average depth at various points and using an average.
4	Well (cylindrical shape)	π × r2 × h, where r is the radius of the well and h is the height of the water column inside the well.

Each of the above formulas was used to calculate water supply (W_s) by each water source type. W_s was used in the calculation of water stress index (WSI).

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Calculation Of Total Water Demand (TD)

The total water demand (W_d) for each village's total population was calculated using the following formula:

$$W\_d = DD + Lid + LD \text{ ....eqn. (2)}$$

Where,

- DD (Domestic Demand)= $\sum_{i=1}^{n}(N_i \times W_i)$
- Ni = Number of people in category i
- Wi = Water consumption per person in category i (litres/day)
- n = Total number of categories
- LID = Light Industrial Demand (Liters/day), which is a specified value.
- LD (Livestock Demand) = Na×Wa
- Na = Number of animals
- Wa = Water consumption per animal (litres/day)

Multi-Criteria Decision Analysis (MCDA)—AHP Technique by Saaty (1980)

This technique integrates multiple factors influencing water insecurity to prioritize areas for intervention. The Analytical Hierarchy Process (AHP) using a pairwise comparison technique was employed to assign weights to various criteria such as Water Availability (WA—0.3), Water Quality (WQ—0.25), Proximity to Water Sources (P—0.2), and Resilience to Drought (RD—0.25). The calculation was done using a module in WSVM software where each main criterion's sub-criteria were compared with others'.

Criteria Standardization

The criteria in this study were standardized to a uniform scale ranging from 0 to 1 to facilitate comparison.

Water Availability Index (WAI) (https://doi.org/10.1126/science.289.5477.284)

The formula for **WAI** considering only the water supply (**W_s**) and water demand (**W_d**) was:

$$WAI = W\_s / W\_d$$

Where,

W_s = Water supply

W_d = Water demand

Water Stress Index (WSI) was calculated using formula:

WSI = 1 – WAI (https://academicjournals.org/articles/j_articles/IJWREE)

Interpretation of the WSI

- **WSI = 1**: No supply available (highest severity).
- **0<WSI<1**: (moderate severity levels).
- **WSI = 0**: Water supply meets or exceeds demand (least severity).

Water Quality Index (0 to 1 Scale) by weighted arithmetic water quality index method [2]

- 0 indicates excellent quality—minimal impurities (safe for consumption and ecosystem health)
- 0.5 indicates moderate quality (suitable for some uses but with limitations)
- 1.0 indicates poor quality (generally unsafe for consumption and potentially harmful to ecosystems).

The Proximity Index (PI) with the minimum distance set to 500 meters and maximum set to 1000m and above (1km+), was calculated using the Min-Max Normalization (or Scaling) formular:

$$\text{PI} = (D - Dmin)/(\text{Dmax} - \text{Dmin})$$

Source: https://en.wikipedia.org/wiki/Feature_scaling#Rescaling_(min-max_normalization)

Where,

P.I. = Proximity Index
D = Village—Water distance in meters
Dmax = Maximum Distance in meters (1000)
Dmin = Minimum Distance in meters (500)

- **The Proximity Index scales from 0 (at the minimum distance of 500 meters) to 1 (at the maximum distance of 1000 meters and above).**
- **As the distance increases from 500 meters to 1000 meters, the PI increases linearly.**

Constant at PI = 1 for D>1000:

The Drought Severity Index (DSI) was calculated using formular:

DSI = 1 – DI (Drought Index) (https://doi.org/10.1080/02508068508686328)

Where,

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DI = Wsd/Wsr

W_{sd} = Water supply at dry season

W_{sr} = Water supply at rainy season

- DSI = 1: Extreme drought conditions (Water supply at dry season is significantly less than the rainy season supply or the ratio approaches zero).
- DSI = 0: minimal drought effect or impact (Water supply at dry season = water supply at rainy season).
- DSI = 0.5 indicates moderate drought conditions (supply at dry season falls to half the amount of rainy season supply).

Weighted Overlay (Criteria Combination)

The assignment of weights (Xi) to these criteria is a critical step in the research. These weights are determined based on their relative importance in decision-making. Using WSVM tools, a weighted overlay combined standardized criteria to produce a composite water scarcity map. These weights reflect the significance of each criterion and are determined using the Multi-Criteria Decision Method (MCDM) ensuring a systematic and data-driven approach to assessing levels of vulnerability to water scarcity.

The Vulnerability Index (VI) is calculated using equation below [3]:

$$VI = \sum_{i=1}^{m} \sum_{j=1}^{n} (X_{i.} W_{ij})$$

Where,

VI is the vulnerability index for villages.

X_i is the normalized weight of the ith feature (criterion). X_i pertains to the overall importance assigned to each criterion in the analysis. It is a single weight representing the significance of the entire criterion, considering all its classes.

W_{ij} is the normalized weight of the jth class of the thematic layer.

Pearson Correlation analysis was used to identify and categorize factors that most exacerbate water scarcity vulnerability in the study area.

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3 Results and Discussion

3..1 Results of Vulnerability Index Calculations

The assessment of water scarcity vulnerability across the studied rural communities revealed varying levels of susceptibility. Out of the total 19 communities surveyed, 3 (15.8%) were classified as highly vulnerable (severe), 9 (47.7%) as moderately vulnerable, and 7 (36.8%) as having low vulnerability.

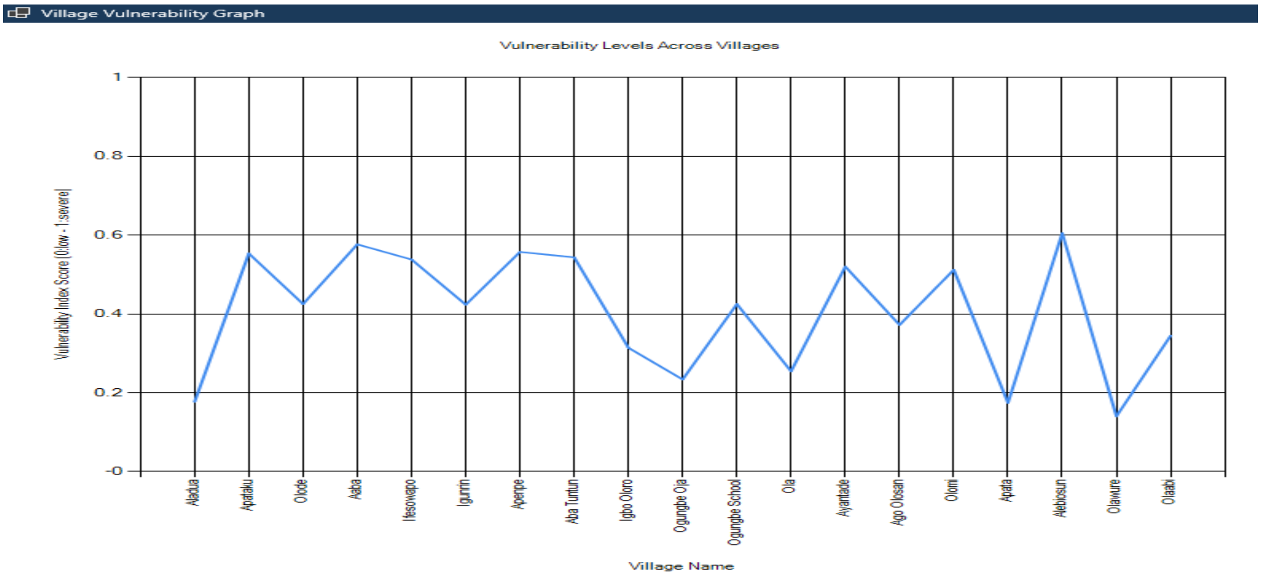
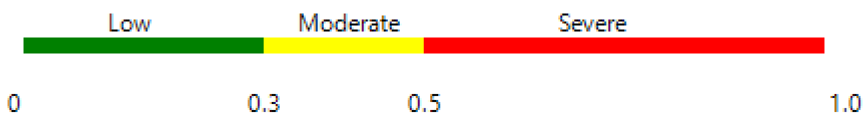


Figure 2: Line Graph Representing The Water Scarcity Vulnerability Index (WSVI) Values Across Sampled Villages: (a) Low Vulnerability (0—0.3), (b) Moderate (0.31—0.49) and (c) Severe Vulnerability (0.5—1).

Classification Thresholds Using Line Scale



The research classified the villages into three categories based on their Water Scarcity Vulnerability Index (WSVI) scores:

Figure 3 depicts the Vulnerability Index (VI) map of the surveyed villages in the study area

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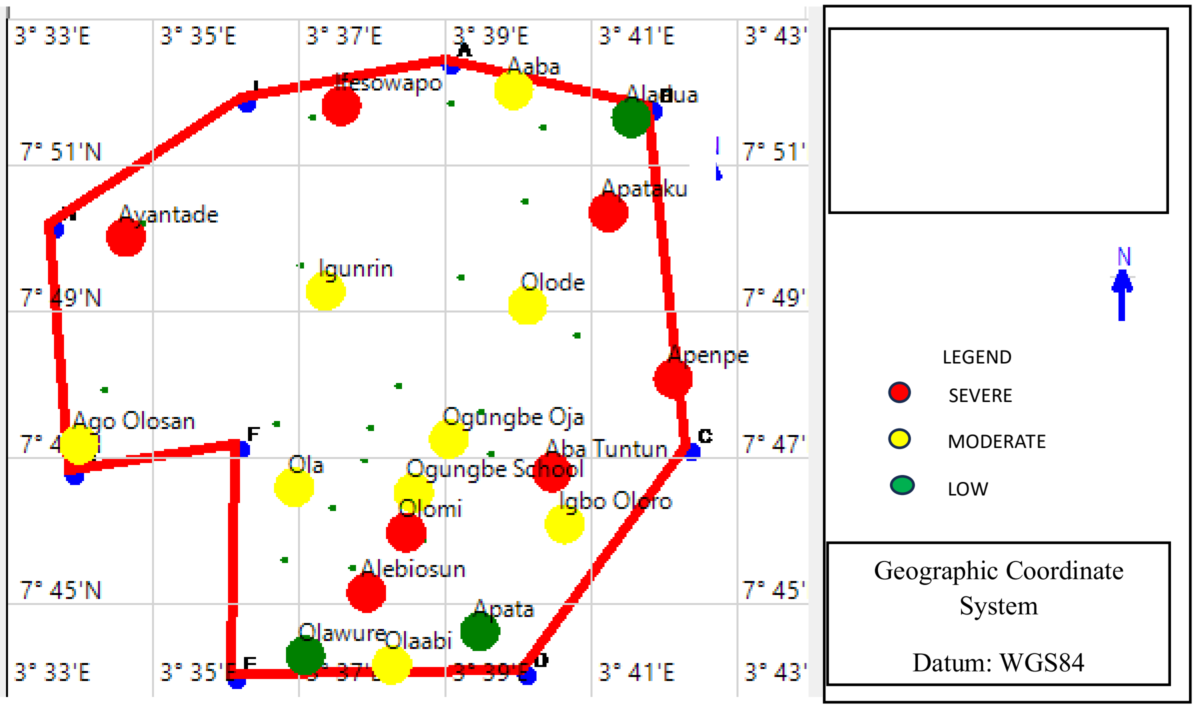

Figure 3: Water Scarcity Vulnerability (WSV) Map of the Study Area.

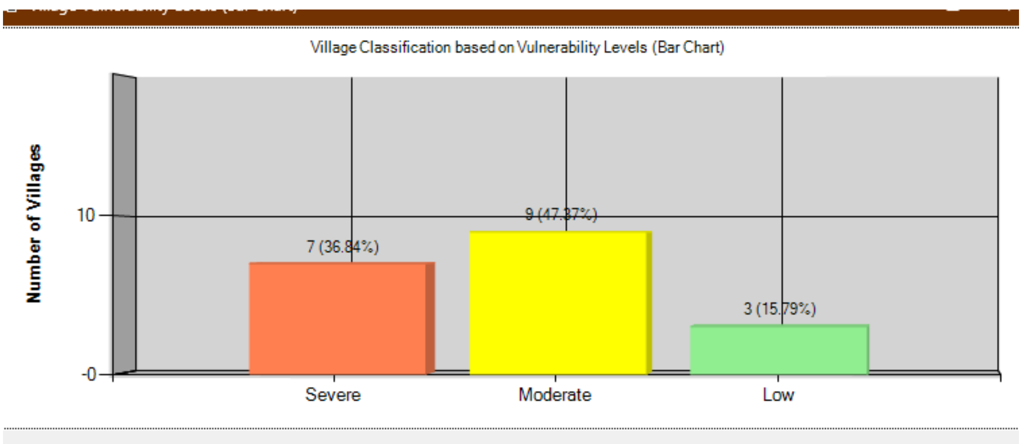

Figure 4: Bar Chart Of WSV Of The Study Area

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Table 3: Summary Of Results Of Each Village's VI Score Using MCDA by AHP

frmVI

Village Name	Water Availability (WA)	Water Quality (WQ)	Proximity (P)	Resilience to Drought (RD)	Vulnerability Index Value (TVV)	Level of Vulnerability (LOV)
Aladua	0	0.5	0	0	0.125	Low
Apataku	1	0.5	0	1	0.675	Severe
Olode	0	0.7	0	1	0.425	Moderate
Aaba	0	0.75	0	1	0.4375	Moderate
Ifesowapo	0.5	1	0.2	0.5	0.565000000000...	Severe
Igunrin	0.5	0.75	0	1	0.5875	Severe
Apenpe	1	0.5	0	1	0.675	Severe
Aba Tuntun	0	0.7	0.2	1	0.464999999999...	Moderate
Igbo Oloro	0	0.7	0.2	0.5	0.339999999999...	Moderate
Ogungbe Oja	0.5	0.5	0	0.5	0.4	Moderate
Ogungbe School	0	0.7	0	1	0.425	Moderate
Ola	0.5	0.666666666666...	0	0	0.316666666666...	Moderate
Ayantade	0	1	0.2	1	0.54	Severe
Ago Olosan	0	0.75	0	1	0.4375	Moderate
Olomi	0	1	0.2	1	0.54	Severe
Apata	0	0.7	0	0	0.175	Low
Alebiosun	0	1	0.2	1	0.54	Severe
Olawure	0	0.35	0	0	0.0875	Low
Olaabi	0	0.733333333333...	0	1	0.433333333333...	Moderate
Summary						
Severe	7					
Moderate	9					
Low	3					

Source: Author's Bespoke Software

Correlation Results Between Water Scarcity Vulnerability Scores and considered Factors across the nineteen villages.

Table 4: Correlation Results Between Vulnerability and Factors

Variable	Pearson Correlation Coefficient	Interpretation	Category
Water Availability	-0.31	Weak negative correlation	Weak/Moderate
Water Quality	-0.64	Moderate to strong negative correlation	Moderate/Strong
Resilience to Drought	-0.76	Strong negative correlation	Strong
Proximity	-0.45	Moderate negative correlation	Moderate

3.2 Discussion

The findings of this study underscore the complex and heterogeneous nature of water scarcity vulnerability among rural communities in Iseyin, Nigeria. The spatial analysis and vulnerability classification reveal that nearly half of the surveyed villages (47.7%) are moderately vulnerable, with a significant subset (15.8%) facing severe water scarcity challenges. This disparity highlights the multifaceted drivers of vulnerability, including water availability, quality, resilience to drought, and proximity to water sources, which collectively influence each community's capacity to access safe and reliable water.

The strong negative correlation between resilience to drought and the vulnerability index (-0.76) emphasizes that communities with higher drought resilience tend to be less vulnerable to water scarcity. This aligns with existing literature indicating that adaptive capacity, including infrastructural robustness and community preparedness, plays a crucial role in mitigating drought impacts (Mekonnen & Hoekstra, 2016; Hassan et al., 2018). Similarly, water quality demonstrated a moderate to strong negative correlation (-0.64) with vulnerability, suggesting that poor water quality significantly contributes to community vulnerability, potentially exacerbating health risks and reducing water usability.

Interestingly, water availability exhibited a weak to moderate negative correlation (-0.31), indicating that while availability is critical, other factors such as water quality and resilience may have more immediate impacts on vulnerability. The moderate correlation between proximity and vulnerability (-0.45) suggests that accessibility plays a role but is not the sole determinant—highlighting the importance of a holistic assessment encompassing multiple criteria.

4 Conclusion and recommendation

This study underscores the urgent need to improve water security in rural Iseyin by addressing key factors such as drought resilience and water quality. To reduce vulnerability, investments in water infrastructure, including boreholes and treatment facilities, are essential, alongside promoting climate-resilient practices like water harvesting. Regular water quality monitoring and community education can further enhance safety and sustainable use. Utilizing spatial vulnerability data to guide targeted interventions will optimize resource allocation, while ongoing assessment is vital for adaptive management. Implementing these strategies will bolster community resilience and ensure sustainable access to safe water sources.

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