# Assessment of Urban Water Resources System's Vulnerability in Birnin Kebbi, Northwestern Nigeria

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## Abstract

This study aimed to assess the vulnerability of the urban water resources system (UWRS) in Birnin Kebbi, Northwestern Nigeria. Multi-dimensional data were input into a modified Driving-Force, Pressure, State, Impact, and Response (DPSIR) framework. The Model consists of fifteen (15) evaluation factors/indicators relevant to the study area's peculiarities. UWRS' vulnerability grades were categorized from mild to extremely strong intensities. The intensity levels of factors were subsequently computed. Multivariate Principal Component Analysis (PCA) and Time Series Mantel correlogram techniques were employed to reduce the dimensionality of datasets, refine interpretability while minimizing information loss, and depict patterns of DPSIR sub-systems. Patterns of how each pair of factors behaved (from 1990 to 2020) were generated in the PAST3.2 environment. Results showed an increasing resilience trend in the post-2000 years. This suggests vulnerability transitions where not all factors moved in concert or concurrently across the decades, an indication of internal dynamics that push back against uniform change in the system. This implies Birnin Kebbi's UWRS's effective adaptive responses and vulnerability mitigation mechanisms despite periodic spikes in unmitigated pressures, states, and impacts in the pre-2000 period. The study contributed to explaining how climate change manifested impacts (drought/rainfall variability, aridity, and watershed degradation) combine with human–environmental factors to create UWRS vulnerability.

**Keywords**: DPSIR, Resilience trends, Vulnerability, Climate change, Water supply.

## Introduction

Water is a vital environmental resource essential for the nourishment and sustainable operations of both ecological and socioeconomic systems (Lu et al., 2022; Anandhi and Kannan, 2018; Vörösmarty et al., 2010). It is abstracted from sources such as surface and groundwater, which are accessible for use, provided they adequately meet quantity and quality needs and requirements within a specific time and location (Chen et al., 2021). A water resources system refers to the integrated structure through which water is sourced, managed, allocated, utilized, and conserved (Cardwell et al, 2006; Davis, 2007). This system connects hydrological, infrastructural, ecological, and societal elements and strives to meet objectives such as supply security, ecological conservation, quality control, equitable distribution, and resilience to climate change and extreme weather and climatic events such as drought and increased aridity (O'Connell, 2017).

Effective tackling of the challenges posing a threat to water resource sustainability requires assessing the vulnerability of water resource systems and their driving factors (Wu et al., 2023). This also involves analysis of biophysical stresses and human–environmental factors and their interactions that determine systems' resilience (McCarthy et al., 2001; Wisner et al., 2004). A substantial body of literature on both surface and groundwater has been conducted in the study area (the majority of the research works centered on quality and risks of surface water and groundwater (Yahaya et al., 2024), hydrochemistry/heavy metals toxicology of old town and environs (Wali et al., 2023), concentration and cytogenotoxicity of heavy metals and microorganisms in Labana Rice Mills wastewater, Birnin Kebbi (Yahaya et al., 2021). Another related study is a state-wide exploration on the access/coverage ratio of persons to public water sources among urban, semi-urban, and rural schemes (Wali et al. 2018). Lastly, there is a study on water production in Dikku (peri-urban Birnin Kebbi) Water works and the city boreholes network, especially from the perspective of long-term (up to 2050) scenario planning by Umar et al. (2025).

The aforementioned studies lack localized, integrated vulnerability assessments that account for dynamic environmental and socio-economic factors. The purpose of this study, therefore, is to bridge this existing research gap through undertaking vulnerability assessment of the UWRS of the study area using techniques such as Multivariate Principal Component Analysis (PCA) and Time Series Mantel correlogram to depict DPSIR sub-system contributions to the study area's vulnerability and patterns of how each pair of factors behaved (from 1990 to 2020). This study has adopted a modified DPSIR water resources vulnerability evaluation system to assess the UWRS vulnerability in Birnin Kebbi, Northwestern Nigeria. The study is guided by the DPSIR (Driving force–Pressure–State–Impact–Response) model, being a diagnostic and policy-support tool, especially its perspective on the interaction between catchments' water resources, human and natural resources systems.

This study was aimed at assessing the vulnerability of the urban water resources system in Birnin Kebbi, Northwestern Nigeria, using the modified DPSIR evaluation framework. The objectives of the study were to: (a) identify vulnerability factors/indicators under Drive-Pressure-State-Impact-Response or DPSIR framework and assess (evaluate) their intensities in the study area; (b) ascertain patterns (similarity or dissimilarity) on how each pair of DPSIR factor behaved over the 1990–2020 period (c) evaluate overall vulnerability of water resources system parameters over the time period in the study area and (d) suggest some resilience measures.

## Materials and Methods

### Study Area

The study area, Urban Birnin Kebbi, comprises areas within the city and peri-urban localities in its environs of Birnin Kebbi Local Government Area, which forms the capital city of Kebbi State, Nigeria. The city is located at the crossroads of Latitude 12◦ 24' 00" to 12◦ 30' 30" N and longitude 4◦ 10' 0" to 4◦ 15' 30" E. (Yauri et al., 2018). The climate of the area is of the tropical wet and dry type, coded Aw by W. Köppen classification. Vegetation around the study area consists of tropical grasslands of the Sudan and Sahel Savannas. This watershed is characterized by seasonal river flow fluctuations, high evapotranspiration rates, and acute water stress, posing serious risks to water supply, sanitation, and ecosystem health (Adamu et al., 2017; Umar and Adamu, 2019). It entails extensive livelihood-rich floodplains within which crucial surface water bodies like the River Rima traverse (Shuaibu and Murana, 2024; Aminu, 2022; Gada, 2014). Agriculture, the predominant livelihood activity in the study area, is of two categories: rain-fed and dry-season irrigation. Crops produced include millet, sorghum, rice, cowpea, soy beans, wheat, groundnut, sesame, and vegetables (Umar and Adamu, 2019; Umar et al., 2017).

**Data types and sources**

While constructing the modified DPSIR framework, multi-dimensional data and information have been collected from various institutions within Kebbi State, Nigeria, and other areas across the globe. The various categories of data/information and their sources of collection or generation are presented in Table 1. These data cover all those used in generating thirteen (13) out of the fifteen (2) indicators. Two (2) indicators were generated through the use of the Delphi method, where experts' opinions or value judgements were incorporated in assigning weights to the factors/indicators and validating them. Delphi is highly suited to solving complex problems where exact knowledge is not available, and the contribution of experts (drawn from academia, professionals, and other members of the community) helps in advancing understanding about the subject matter. The Delphi process was guided by Donohoe's (2011) guidelines, where seven (7) experts who are knowledgeable and have experience in the study area and were willing to participate were selected and incorporated in an online discussion that subsequently agreed on assigning weights to the two indicators over the time period and validation of secondary data that requires consistency vetting. Coefficients generated from weights assigned through the Delphi process were elaborated in Tables 2 to 4.

**Table 1. Categories of data/information and their sources**

| S/N | Data Type | Temporal Dimensions | Sources |
|---|---|---|---|
| 1 | Demographic (total population census headcounts, estimates, and projections) data of Birnin Kebbi | 1990, 2000, 2010, 2020 | National Population Commission, National Bureau of Statistics, National Planning Commission |
| 2 | Land-use and land cover data/ information (total areal dimension in hectares and square kilometres, built-up areas, percentage of vegetal cover) of Birnin Kebbi | 1990, 2000, 2010, 2020 | Review of related literature (Sources: Dantani, 2024; Abubakar & Sawa, 2020; Sadiq, 2016). |
| 3 | Climatic data (total annual rainfall and potential evapotranspiration) of Birnin Kebbi | 1915 to 2020 | FAO (n.d) Aquastat information website<br>Nigeria Meteorological Agency, Kebbi State Agricultural Development Project |
| 4 | Water Supply, Sanitation, and Hygiene (WASH) Sector data | 1990, 2000, 2010, 2020 | Kebbi State Water Board and the Delphi process to arrive at a consensus evaluation. |

| | | | |
|---|---|---|---|
| 5 | Water quality index | 1990, 2000, 2010, 2020 | Review of related literature (Sources: Wali et al., 2023; Yahaya et al, 2021) |

**Population and sampling procedure**

The Birnin Kebbi metropolis formed the research population of this study. The area was purposively sampled or selected because the city has been situated in an extensive livelihood enriched floodplains within which crucial surface water bodies like River Rima, traverse (Shuaibu and Murana, 2024; Aminu, 2022; Gada, 2014) where seasonal river flow fluctuations, high evapotranspiration rates, and growing human demands and frequent acute water stress, posing serious risks to water supply, sanitation and ecosystem health calls for examination and re-examination.

**Data analysis: construction of the modified DPSIR index system**

The DPSIR model evaluates threats to the region's water resources system security through exploration of natural hazards exposure, socioeconomic activities, and the human responses to these threats. The model has been modified to assess vulnerability of water resources systems by incorporating indices that entail areal natural hazards or endowment conditions and human activities in combination with the relationships that exist between factors or indicators that constitute the model. Table 2 shows that the DPSIR model consists of five subsystems, namely: Driving Force, Pressure, State, Impact, and Response. While the modified model created by this study entails fifteen (15) factors or indicators, which were assigned symbols from D1, D2, to P1, P2, up to R2. Each factor/indicator has a unit and an index of calculation (see Table 2).

**Table 2. Socio-economic, ecological, and human response factors employed in the DPSIR system**

| Subsystems | Factors/Indicators | Symbol | Unit | Meaning of Index and or Calculation |
|---|---|---|---|---|
| **DRIVING FORCE** | Population density | D1 | person/km2 | This implies the influence of population density on water supply resilience. Total population / total land area |
| | Urbanization rate | D2 | % | This depicts the effect of land-cover change on water resources security Built-up area /total land area |
| | Percentage of domestic water coverage | D3 | % | Total supplied water/total population. |
| | Rainfall variability | D4 | Coefficient | Water resources index formula : Z=(x-μ)/б |
| | Aridity Index | D5 | Coefficient | Water resources index formula: AI =P/pET |
| **PRESSURE** | Vegetated land cover | P1 | % | Percentage of Vegetated land cover |
| | Percentage of Non-residential water consumption | P2 | % | (Consumption total, lpcd - Consumption residential, lpcd) /Consumption total, lpcd x100 |
| | Percentage of persons having access to safe | P3 | % | Total volume of safely managed water consumption under residential use, lpcd |

| | | | | |
|---|---|---|---|---|
| | residential piped water consumption Percentage of Levels of water losses | P4 | % | **System Input Volume** (SIV) - **Authorised Consumption** = (theft, meter error, leakages, etc.) |
| **STATE** | Percentage of persons having access to improved sanitation. | S1 | % | Total households with improved sanitation facilities/total population x 100 |
| | Cost-recovery ratio (percentage of Revenue to Cost) | S2 | % | Bill Collection Efficiency |
| | Water quality index (based on WQI by Tyagi et al., 2013) | S3 | Coefficient | Index-based computation on WQI by Tyagi et al. (2013). |
| **IMPACT** | Percentage of groundwater to surface water abstraction | I1 | % | Total volume of groundwater output to total surface water production output |
| | Hours of operation/day (average) | I2 | Hours | Total hours that water is served daily divided by 24 |
| **RESPONSE** | Water conservation and facility maintenance | R1 | Qualitative | Experts' judgment/opinion on the effectiveness of the institutional response |
| | Improved regulations and enforcement on the vegetation conservation & WASH sector management, etc | R2 | Qualitative | Experts' judgment/opinion on the effectiveness of the institutional response |

Source: Authors' Data Collection & Analyses, 2025

The next step after the creation of the DPSIR System with its subsystems and factors/indicators, as well as the procedure of their assessment, is to set a vulnerability evaluation standard for the water resources system (measured through assessing DPSIR Sub-systems indicators). This is constructed in considerations to region's or area's meanings and laid down criteria for sustainable development and water resources system vulnerability. The extent of water resources vulnerability was divided into four grades, as follows: Grade I (extremely strong vulnerability), Grade II (strong vulnerability), Grade III (medium vulnerability), and Grade IV (mild vulnerability). The assessment index system of water resources system vulnerability and relevant grading criterion based on DPSIR are shown in Table 3.

**Table 3. Assessment index of UWRS vulnerability and relevant grading** criteria **based on DPSIR**

| DPSIR Sub-system | Evaluation index | Symbol | Vulnerability Intensity Grades/Levels | | | |
|---|---|---|---|---|---|---|
| | | | Grade I (extremely strong vulnerability) | Grade II (strong vulnerability) | Grade III (moderate vulnerability) | Grade IV (mild vulnerability) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Driving force | Total population/total land area | D1 | >10000/km$^2$ | 5000-9999/km$^2$ | 1000-4999/km$^2$ | <1000/km$^2$ |
| | Urbanization (Built-up land area /totalarea) | D2 | >0.75 | 0.50 - 0.75 | 0.10 - 0.49 | <0.10 |
| | Domestic water coverage | D3 | <20% | 20-49% | 50-74% | >75% |
| | Rainfall variability | D4 | < -2.00 | -1.00 to -1.99 | -0.99 to 1.49 | >1.50 |
| | Aridity Index | D5 | <0.05 | 0.05 to 0.49 | 0.50 to 0.65 | >0.65 |
| Pressure | Percentage of vegetal land-cover | P1 | <20% | 20-49% | 50-74% | >75% |
| | Percentage of Non-residential consumption | P2 | >0.75 | 0.50 - 0.75 | 0.10 - 0.49 | <0.10 |
| | Percentage of persons having access to safe residential piped water consumption | P3 | <20% | 20-49% | 50-74% | >75% |
| | Percentage of Levels of water losses | P4 | >50% | 16 - 49% | 15% | <15% |
| State | Percentage of persons having access to improved sanitation. | S1 | <0.10 | 0.10 - 0.49 | 0.50 - 0.75 | >0.75 |
| | Cost-recovery ratio (percentage of Revenue to Cost) | S2 | <0.10 | 0.10 - 0.49 | 0.50 - 0.75 | >0.75 |
| | Water quality index (based on WQI by Tyagi et al., 2013) | S3 | <75 | 51 to 75 | 26 to 50 | 0 to 25 |
| Impact | Percentage of groundwater to surface water abstraction | I1 | <20% | 20-49% | 50-74% | >75% |
| | Hours of operations/day(aver.) | I2 | <6 Hours | 6 to 11 Hours | 12 to 18 Hours | >18 Hours |
| Response | Water conservation and facility maintenance | R1 | Highly Ineffective | Ineffective | Effective | Highly Effective |

| | | | | | |
|---|---|---|---|---|---|
| Improved regulations and enforcement on vegetation conservation, WASH sector management, etc | R2 | Highly Ineffective | Ineffective | Effective | Highly Effective |

Source: Authors' Data Collection & Analyses, 2025

**Multivariate Principal Component Analysis (PCA) and Time Series Mantel correlogram techniques**

Multivariate Principal Component Analysis (PCA) and Time Series Mantel correlogram techniques were employed to reduce the dimensionality of datasets, refine (make clearer) interpretability while minimizing information loss, and depict patterns of DPSIR sub-systems. Patterns of how each pair of factors behaved (from 1990 to 2020) were generated in the PAST3.2 environment through the generation of a scalogram. This is a computer application-generated triangular heat-map that shows how similarly or dissimilarly each pair of DPSIR factors behaved over the 1990–2020 period based on the Mantel correlogram, visualizing correlation patterns among water resources system parameters.

## Results and Discussion

### Vulnerability factors/indicators under the DPSIR framework and their intensities

As stated in section 2.2, the DPSIR model entails five (5) sub-systems categorized as: Driving Force-Pressure-State-Impact-Response, also called the DPSIR framework. This model has been run on data and information collected or generated, which are explained in Table 1. The assessed vulnerabilities, including their various intensities over the time period (1990 to 2020), have been computed and presented in Table 4.

**Table 4. Factors/indicators under the DPSIR framework**

| Factors | Symbol | Values | | | |
|---|---|---|---|---|---|
| | | 1990 | 2000 | 2010 | 2020 |
| Population density | D1 | 41/km<br>IV | 2121/km<br>IIIIII | 2262/km<br>III | 2340/km$^2$ |
| Urbanization rate | D2 | 1.3%<br>IV | 3.3%<br>IV | 4.5%<br>IV | 6.2%<br>IV |
| Percentage of domestic water coverage | D3 | 26%<br>II , | 31%<br>II , | 32%<br>II, | 40%<br>II, |
| Rainfall variability | D4 | -0.21<br>III, | 0.1<br>III , | 1.8<br>IV, | 0.0<br>III, |
| Aridity index | D5 | 0.25 | 0.35 | 0.52 | 0.35 |

| | | | | |
|---|---|---|---|---|
| | | II, | II, II, | III, |
| Percentage of non-residential water consumption | P1 | 5.0% IV, | 7.0% 15.1% IV, III, | 10.4% III, |
| Percentage of persons having access to safe residential piped water consumption | P2 | 57% III, | 41% 31% II, II, | 33% II, |
| Percentage of levels of water losses | P3 | 9% IV, | 14% 22% IV, II | 15% III , |
| Percentage of persons having access to improved sanitation. | S1 | 32% II, | 34% 34% II, II, | 37% II, |
| Cost-recovery ratio (percentage of Revenue to Cost) | S2 | 42% II, | 44% 32% II, II, | 36% II, |
| Water quality index (based on WQI by Tyagi et al., 2013) | S3 | 76 I, | 53 40 II, III, | 41 III, |
| Percentage of groundwater to surface water abstraction | I1 | 68% III, | 71% 52% III, III, | 96% IV, |
| Hours of operation/day(average) | I2 | 0.8 III,. | 0.7, 0.5 II, II, | 0.7 II |
| Water conservation and facility maintenance | R1 | III, | II, II, | II, |
| Improved regulations and enforcement on vegetation conservation and WASH Sector management, etc | R2 | II, | III, III, | II, |

Source: Authors' Data Collection & Analyses, 2025

**Normalization of vulnerability factors/indicators values**

The vulnerability sub-systems' factors/indicators values are of different and varying units, scales, and indexes/coefficients. Because of this disparity, the values of vulnerability factors/indicators must be normalized. Common methods used in normalization of units/coefficients include the Min–Max method (see Equation 1), where individual factors/indicators to be aggregated have to undergo a normalization process:

$$X^i = \frac{(X - X_{min})}{(X_{max} - X_{min})} \qquad (1)$$

Where X means the original value of units/coefficients, $X_{min}$ means the minimum value in the data set, $X_{max}$ means the maximum value in the data set, and $X^{i}$ means the normalized value (which is generated between the range of 0 and 1, or sometimes between -1 and 1) (Mazziotta &Pareto, 2022). Alternatively, we used row normalise length under the transform menu of PAST3.2 Software (Hammer et al., 2001), where the vulnerability sub-systems' factors/indicators values under DPSIR shown in Table 4 were normalised and presented in Table 5.

**Table 5. Normalized vulnerability factors/indicators values under the DPSIR framework**

| | 1990 | 2000 | 2010 | 2020 |
|---|---|---|---|---|
| D1 | 0.017386988 | 0.051312819 | 0.111107095 | 0.99233054 |
| D2 | 0.153989097 | 0.390895401 | 0.533039183 | 0.73440954 |
| D3 | 0.398306672 | 0.474904108 | 0.490223596 | 0.61277949 |
| D4 | -0.115704675 | 0.055097464 | 0.991754354 | 0 |
| D5 | 0.328861976 | 0.460406766 | 0.684032909 | 0.46040676 |
| P1 | 0.370337351 | 0.518472292 | 0.770301691 | 0.02592361 |
| P2 | 0.682255655 | 0.490745296 | 0.394990116 | 0.37105132 |
| P3 | 0.28661839 | 0.445850829 | 0.477697316 | 0.70062273 |
| S1 | 0.46651989 | 0.495677383 | 0.539413623 | 0.49567738 |
| S2 | 0.541316225 | 0.567093188 | 0.463985336 | 0.41243141 |
| S3 | 0.697688268 | 0.486545766 | 0.37638446 | 0.36720435 |
| I1 | 0.462842133 | 0.483261639 | 0.653424188 | 0.35393810 |
| I2 | 0.550742713 | 0.481899874 | 0.481899874 | 0.48189987 |
| R1 | 0.381246426 | 0.533744996 | 0.533744996 | 0.53374499 |
| R2 | 0.575396456 | 0.410997468 | 0.575396456 | 0.41099746 |

Source: Authors' Data Collection & Analyses, 2025

**Principal Component Analysis (PCA) and identification of hidden patterns in data**

We have fifteen factors or indicators that measure vulnerability in the DPSIR framework model. Since these indicators are definitely cross- correlated, and because of this, the factors' dimensionality can be reduced in some fashion to fewer indicators (feature reduction), which capture as much as possible of the variation in the original data set. Through the use of Principal Component Analysis (PCA), this goal can be achieved. As can be seen, Table 6 presents PC Scores and Loadings. Each row represents one indicator/factor, and each column (PC1–PC4) is a principal component. The PCA scores represent the transformed data in terms of the four principal components (PC1, PC2, PC3, and PC4). These scores indicate how each observation (in this case, each time point from 1990, 2000, 2010, and 2020) relates to the hidden patterns in the data as identified by PCA. The scores also show how strongly each indicator contributes to each principal component.

**Table 6. Scores, Loadings, Eigenvalues, and Percentage variance of PCs**

| | **PC Scores Principal Components** | | | |
|---|---|---|---|---|
| **Factors/Indicators** | **PC 1** | **PC 2** | **PC 3** | **PC 4** |
| D1 | 0.72573 | -0.42478 | -0.16981 | -0.02823 |
| D2 | 0.23755 | -0.22543 | 0.14576 | 0.00138 |
| D3 | 0.14386 | 0.037547 | 0.072356 | 0.008577 |

| | | | | |
|---|---|---|---|---|
| D4 | -0.58046 | -0.67874 | -0.099709 | 0.021164 |
| D5 | -0.08673 | -0.063527 | 0.11521 | 0.032771 |
| P1 | -0.49549 | 0.0065904 | 0.0014645 | -0.09516 |
| P2 | -0.013257 | 0.31953 | -0.13743 | -0.00429 |
| P3 | 0.2306 | -0.072514 | 0.10922 | -0.00546 |
| S1 | 0.015233 | 0.10047 | 0.046398 | 0.014729 |
| S2 | -0.018436 | 0.2211 | 0.0015608 | -0.06023 |
| S3 | -0.0060877 | 0.33492 | -0.15544 | -0.00637 |
| I1 | -0.16427 | 0.07332 | 0.037785 | 0.029631 |
| I2 | 0.033987 | 0.17822 | -0.018796 | 0.026324 |
| R1 | 0.050744 | 0.04719 | 0.10518 | -0.03672 |
| R2 | -0.072974 | 0.14611 | -0.053741 | 0.1019 |
| **(%)Percent of Variance** | 51.34 | 41.458 | 6.0548 | 1.1472 |

**PC Loadings**

| | **PC 1** | **PC 2** | **PC 3** | **PC 4** |
|---|---|---|---|---|
| A | -0.053272 | 0.83396 | -0.22343 | 0.50175 |
| B | -0.082468 | 0.49568 | 0.68489 | -0.52766 |
| C | -0.57834 | -0.23442 | 0.5372 | 0.56744 |
| D | 0.80986 | -0.062074 | 0.43867 | 0.3845 |

**PC Summary**

| **PC** | **Eigenvalue** | **% variance** |
|---|---|---|
| 1 | 0.0916989 | 51.34 |
| 2 | 0.074047 | 41.458 |
| 3 | 0.0108143 | 6.0548 |
| 4 | 0.00204906 | 1.1472 |

The PCA method introduces a new set of variables (indicators), linear combinations of the original data set. The linear combination explains, or accounts for, the maximum amount of variation in the data set, otherwise called the dominant gradient. It is also called the first principal component because it is the single most important axis explaining vulnerability - indicators that push vulnerability up, as against those that stabilize the system. The first principal component (PC1) is given as: PC1 = 0.72573 (D1 or population density) +0.237554(D2 or urbanization) + 0.2306 (P3 or percentage of levels of water losses) + 0.14386 (D3 or percentage of domestic water coverage) + 0.050744 (R1 or water conservation and facility maintenance). Major vulnerability gradient for PC1 is: Driving Force, Pressures, and Responses. The second principal component (PC2) is then determined independently of the first one, so that it provides details as much as possible with regard to the remaining variability. Further components are then created one after another, every fresh component being free of the preceding ones. The PC2, as can be seen from Table 6, predominantly consists of vulnerabilities in the infrastructure's stress (State) against governance capacity. Thus, PC2= 0.33492(S3 or water quality index) +0.31953(P2 or percentage of persons having access to safe residential piped water consumption) + 0.2211(S2 or cost-recovery ratio) + 0.14611 (R2 or improved regulations and enforcement on vegetation conservation and WASH Sector management). Note that PC1 and PC2 explain or account for an overwhelming 92.8 per cent of the variability amongst the four components fundamentally. We deduce that the two PCs or years 1990 and 2000 had episodes with spikes in unmitigated vulnerabilities. Hence, the scatter plot (Figure 1a) only shows clusters (correlations) of dominant gradients, namely: PC1 and PC2, with the data structure. But the scree plot (Figure 1b) depicts the two dominant PCs and the other two residual components.

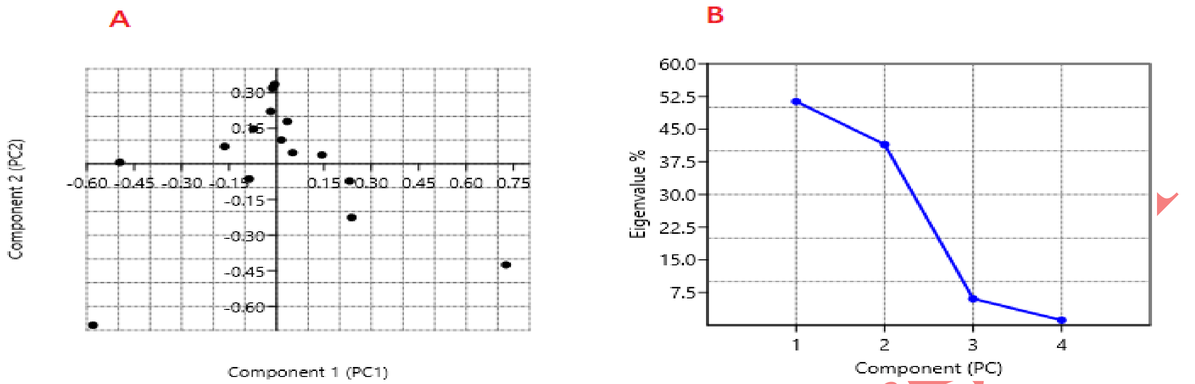


**Fig 1. a) Scatter plot of PC1 (x-axis) and PC2 (y-axis) and their loadings; b) Scree plot of PCs and their respective Eigenvalues**

## DPSIR factors' patterns over the 1990–2020 period

Analysis and interpretation of the scalogram (that is, Figure 2)revealed that indicators that are close together in the DPSIR chain (e.g., population density, urbanization rate, and domestic water coverage) had strong positive correlations (warm colours such as reddish and orange hues), meaning their vulnerabilities swung (rose and fell) together. This is called a Decay of Similarity with Distance as we move up the triangle to larger "Distance" values (eg, from D1 to P2 or from D4 to S3 near the top of the scalogram, representing a Driver vs a Response indicator separated by many positions). Near-related factors behaved alike, but distant ones deviated or swerved. In contrast, indicators that are farther apart (e.g., those of Drivers vs. Responses) show negative correlations (represented in blue colours), implying opposing behaviour -when drivers worsened, response factors improved - indicating feedback and management effects. The scores of PC1 under Driving Force (from D1 to D3) in Table 6 show descending order in positive scores (positions), while the most distant parts show either lower or negative scores. This pattern – transitioning from warm (positive correlation) at short distances to cool (negative correlation) at long distances – indicates that indicators that are conceptually distant in the DPSIR chain have inverse or dissimilar vulnerability patterns. In other words, there is negative spatial autocorrelation at large lags: widely separated factors tend to behave in opposite ways.

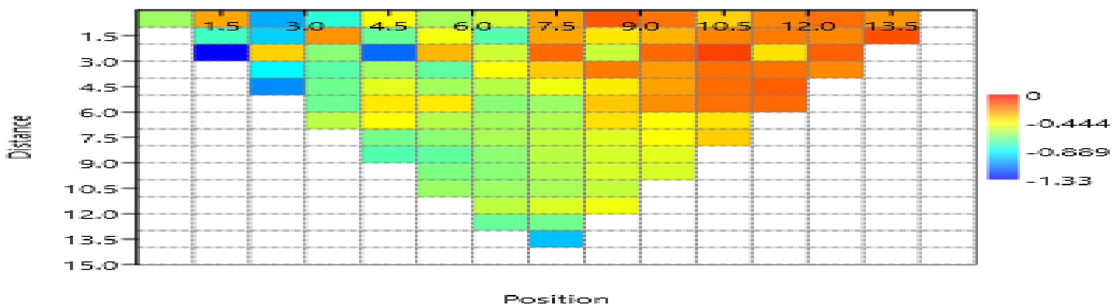

**Fig 2. Scalogram (triangular heat-map) showing patterns in DPSIR factors (Authors' Data Collection & Analyses, 2025)**

With regards to the magnitude of autocorrelation, the intensity of blue at the top (approaching correlation approximately ~ –1.3), rainfall variability (D4), and population density (D1) are very strongly negatively correlated. A correlation of around -1 implies that when one indicator's vulnerability is high, the other's is low (and vice versa) almost perfectly. Such strong inverse relationships occur between DPSIR categories that have a cause-and-effect counteracting relationship. For instance, population density (D1)'s low vulnerability in 1990 has coincided with high vulnerability of the water quality index (S3) in the same year. This is an indication that subsequent years of interventions in Response (such as improved regulations and enforcement on vegetation conservation and WASH sector management, etc) might have been effective. A related study by Aliyu and Umar (2016) in Gusau Metropolis (same drainage basin as the study area) has confirmed this scenario.

**Spatial autocorrelation patterns among indicators**

Spatial autocorrelation in this context refers to how the vulnerability of one factor (that is, an indicator, say for instance urbanization rate D2) is correlated with the percentage of levels of water losses (P3) as a function of their position in the DPSIR sequence. The scalogram reveals distinct patterns: strong local similarity (short distances), along the bottom of the triangle (where the vertical axis "Distance" = 1 or 2, D1, D2, D3, etc.), we observe warmer colors (reddish or orange hues). This indicates an existence of positive correlation as we navigate from D1 to D2, D3, and P1, P2 in the DPSIR chain, an exhibition similar to or nearly similar vulnerability trends over time (factors/indicators scores in Table 6 corroborate these). For example, D1, to, D4, and P1 to P3 vulnerabilities rise and fall in tandem during the pre-2000 years. This is an indication that underlying Driving Forces and Pressures collectively increase vulnerability, and all worsen concurrently. Figure 3 shows high positive values for lags such as 1.0 and 0.5 as well as spikes at certain lags (around 3 to 4), which implies cyclical patterns and/or underlying periodic trends in the data PC1 and PC2 (1990 to 2000). Also, percentage of non-residential water consumption (P1), percentage of persons having access to safe residential piped water consumption(P2), and percentage of persons having access to improved sanitation (S1) and water quality index (S3) ameliorate and degrade together when under stress and reform improvement conditions, respectively, over the (1990 – 2000) years. This suggests a clustered behavior where related factors reinforce each other, and that the series retains its positive trends over these periods.

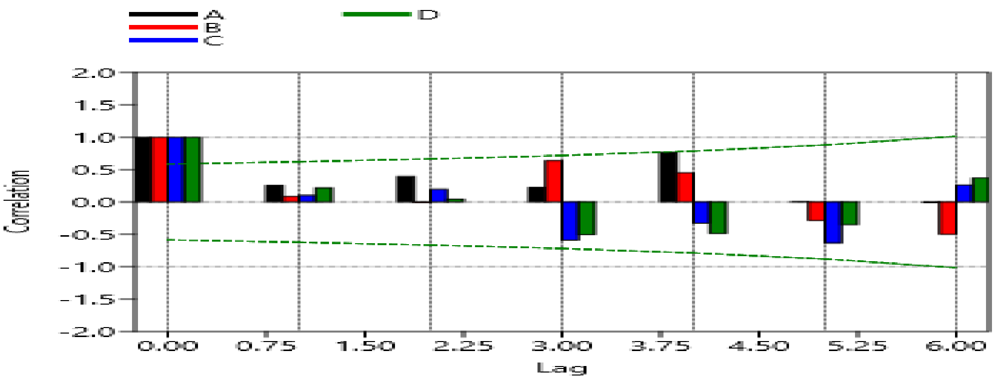


**Fig 3. Autocorrelation plot showing patterns**

**Clustering of correlation patterns by years and intensities**

The scalogram also went beyond the general distance-based trend analysis in revealing vulnerability intensity levels that lead to clustering in correlation patterns. The Year-Specific Patterns or the Temporal Clusters in the image have shown vulnerability time-series of certain DPSIR factors/indicators that experienced unique spikes or dips in specific years (1990 to 2000, and 2010 to 2020). These would affect their correlation with others primarily at particular distance lags. For example, as can be seen, there was a high intensity drought (D4 with a component score of -0.099709) in the year 2010. This caused the percentage of non-residential water consumption (P1 with a component score of 0.0014645) and the percentage of groundwater to surface water abstraction (I1 with a component score of 0.037785) to rise as the scalogram depicted such an event in the form of localized patches of other than red and blue colour tones involving the mentioned factors/indicators' cross-correlations. The image also shows a band of altered correlation values corresponding to comparisons that span temporal events. Correlation patterns "cluster" around periods, which means that before vs. after that year, relationships among indicators shifted. For instance, as can be seen in the scalogram, in pre-2000, all factors have trended upward uniformly (positive correlations), but post-2000, some factors leveled off or declined due to interventions, breaking the synchronicity. The PCA technique has shown how PC1 and PC2 explain or account for an overwhelming 92.8 per cent of the variability amongst the four components were the two PCs or years 1990 and 2000 had episodes with spikes in unmitigated vulnerabilities.

The findings produced mixed correlation signals in comparisons that include both pre- and post-2000 water resources system vulnerability of the study area. Intensity bands refer to ranges of vulnerability grades/levels. Anytime certain levels of vulnerability consistently produce particular correlation patterns, this appears as horizontal bands of color across the scalogram (Liu et al., 2022). This implies the study area's WRS vulnerability does not see large regions of high positive correlation (which would have shown bright yellow or red beyond 0). Instead, a baseline of mild positive correlation for nearby indicators and increasingly negative correlation for more distant ones exists. All the clustering of colors revolves around how quickly the colors shift as distance increases. For instance, urbanization rate (D2) and rainfall variability (D4), as well as percentage of persons having access to improved sanitation (S1) and percentage of groundwater to surface water abstraction (I1) see a rapid drop into negative correlation, that could indicate that after a certain point in the chain, factors stop co-varying

and start opposing each other – potentially a sign of a critical transition in how the system operates around those categories.
Part of the results of this study have corroborated the findings of Alizadeh &Moshfeghi (2023), who used an indicator-based model to assess urban water vulnerability in cities vulnerable to climate change, a case of Ahvaz in Iran, and found that there was no positive outlook and reliable capacity in terms of water resilience in Ahvaz. This scenario resembles what was obtainable in the study area from the years 1990 to 2000. In the same vein, Li et al. (2024) discuss the weight allocation of vulnerability assessment indicators. This study creatively proposed a data-based objective evaluation framework of water resource vulnerability, and applied it to the evaluation of water resource vulnerability in Hubei Province, China, using the analytical framework of the DPSIR model. Their research found that the model can deal with complex multi-index optimization problems, and is an effective way to solve the comprehensive evaluation of complex vulnerability, and the weighting method is important for the evaluation of water resources vulnerability.

**Conclusion**

The study assessed and evaluated the UWRS vulnerability in Birnin Kebbi, Northwestern Nigeria, using a modified DPSIR evaluation framework. Multivariate PCA and Timeseries Mantel correlogram techniques were employed to reduce the dimensionality of datasets, refine (make clearer) interpretability while minimizing information loss, and depict patterns of the DPSIR sub-system. Identified DPSIR vulnerability factors/indicators and their intensity patterns were ascertained and visualized using a triangular heat-map. The overall vulnerability of UWRS parameters over the time period in the study area showed evidence of resilience and Transition in the sense that the system has not been stuck in a vulnerability trap but has undergone transformation, or precisely a transitioning system where not all variables rise and fall together. The overall spatial autocorrelation findings from the scalogram suggest a gradient-like structure in the vulnerability data: closely related indicators share similar vulnerability trajectories, whereas distantly related indicators exhibit contrasting trajectories. This has been evident in a mix of positive and negative correlations across the board (ranging from red/orange to blue and other colours), including strong negatives, which implies the system has internal dynamics that push back against uniform change. This implies evidence of adaptive management and resilience, especially during the post-2000 years. But we call on future studies to confirm this. The policy implications with regard to our findings underscore the importance of Integrated Water Resources Management (IWRM) mainstreaming in the WASH Sector and climate change and urban development policy formulation and implementation to mitigate UWRS Vulnerability. Based on the foregoing, we therefore suggest as follows:

- There is a need to develop and maintain early warning systems and climate-resilient water resources infrastructure management.
- Authorities and Non-Governmental Organizations (NGOs) should flag off more campaigns and sensitizations that promote community-level water conservation practices.
- There is a need for more investment in water use reduction, recycling, and aquifer recharge where feasible.

- Governments should promote policies that integrate urban planning with water resource management.

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## Declaration of conflict of interest

We hereby declare that there is no conflict of interest in this study.

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