
INFRASTRUCTURE CHARACTERIZATION AND PHYSICAL INTEGRITY ASSESSMENT OF URBAN WATER DISTRIBUTION SYSTEMS: A RISK-BASED FRAMEWORK FOR SUSTAINABLE ASSET MANAGEMENT IN MINNA, NIGERIA

Abdulrahman Aminu¹, Johnson A. Otun¹, Aliyu Ishaq^{1,*}

¹Ahmadu Bello University, Zaria

Email: aminua2u@gmail.com, johnsonotun@yahoo.com, aleeruks4real@gmail.com*

*Corresponding author: Aliyu Ishaq

DOI: <https://doi.org/10.67203/sp.ICESID.2026>

ABSTRACT

Nigerian water utilities have expanded treatment capacity while ageing distribution networks have received limited systematic assessment. In Minna, the Municipal system operated by the Niger State Water and Sewage Corporation (NISWASEC), demand exceeds network design capacity, contributing to failures, leakage, and pressure problems. As detailed condition-assessment tools remain inaccessible, rehabilitation relies largely on institutional memory and emergency logs. This study developed a GIS-supported Physical Integrity Index (PII) from pipe age, failure frequency, leakage density, and coverage efficiency for Minna's seven service clusters, using maintenance records, field surveys, and staff interviews. Following correction of coverage-efficiency directionality, PII ranged from 2.09 in Bosso (Moderate Integrity) to 4.75 in Minna West (Critical Integrity); Minna East and Chanchaga were also Critical. The three clusters represented 53.6% of the reported 6,526 pipeline-failure occurrence units during 2021–2025. Rankings remained stable under adopted and equal weights. Validation was triangulated: PII showed expected internal associations with failure-occurrence totals ($r = 0.944$) and raw service coverage ($r = -0.906$), although these measures overlap with PII components. Independent criterion validation against NISWASEC ledger-derived cumulative repair costs for 2021–2025, which were not PII inputs, was strong ($r = 0.943$, $p = 0.001$, $n = 7$). The PII provides an evidence-based rehabilitation-prioritization tool for constrained utilities. NISWASEC should prioritise Minna West, Minna East, and Chanchaga, apply the PII annually, and disaggregate maintenance expenditure and non-revenue water by cluster.

Keywords: Physical Integrity Index; water distribution network; infrastructure asset management; rehabilitation prioritization; Nigeria

1. INTRODUCTION

Reliable water distribution underpins public health, economic activity, and urban growth. Adeoti et al. (2023) systematically review water-infrastructure sustainability in Nigeria and identify interrelated technical, financial, environmental, social, political, and institutional challenges, including infrastructure deterioration and operation-and-maintenance constraints. In urban distribution systems, ageing pipes can increase failures, leakage, pressure problems, service interruptions, and operating burdens. When these conditions are not systematically assessed, rehabilitation is more likely to remain reactive than condition-informed.

Sub-Saharan African utilities face these problems in their most acute form. Much of the pipework in service was laid decades ago and has exceeded its design life. Maintenance is almost entirely reactive: crews are dispatched only after a main has burst and supply has been cut (Shushu et al., 2021). This stops the immediate crisis but does nothing to slow the network's overall decline. Costs climb, non-revenue water grows, and service reliability keeps falling.

Public utilities in Nigeria face interrelated technical, financial, and institutional constraints, and Adeoti et al. (2023) emphasize the need for effective monitoring and management mechanisms across the infrastructure life cycle. In the Minna study context, rehabilitation decisions have historically relied on NISWASEC operational knowledge, emergency logs, and available budget rather than a formal engineering risk assessment. This study treats that latter observation as local study context derived from utility records, staff input, and field verification; it is not attributed to Adeoti et al. (2023).

The Minna municipal water distribution system, operated by the Niger State Water and Sewage Corporation (NISWASEC), illustrates these scenarios. The system includes several treatment plants, service reservoirs, booster stations, transmission mains, and a wide distribution network serving residential, commercial, institutional, and industrial users. Since Minna has grown, demand has outstripped what many components were designed to deliver. Decades of service, repeated repairs, leakage, and operational stress have worn the infrastructure down. The evidence is visible in recurring failures, growing water losses, unstable pressure in parts of the network, and a maintenance burden that keeps rising.

Any rehabilitation programme depends on understanding asset condition. However, detailed condition-assessment techniques such as inline inspection, continuous monitoring, and advanced predictive modelling remain out of reach financially and technically for many utilities in developing countries (Taiwo et al., 2023). What is needed is an approach that extracts real engineering value from the operational data utilities already collect, without demanding resources they do not have. It should let engineers distinguish isolated failures from systemic decline, identify where rehabilitation is most urgent, and direct spending to where it will have the greatest effect.

Infrastructure asset management research has shown that combining several engineering indicators gives a more realistic picture of buried pipe condition than any single measure can (Taiwo et al., 2023). Pipe age, historical failure frequency, leakage, and service coverage each capture part of the condition story. Taken together within a structured framework, and paired with spatial analysis, they provide a far better basis for decisions. Geographic Information System (GIS) technology adds the ability to map deterioration patterns and tie them directly to network operations on the ground.

Adeoti et al. (2023) synthesize 15 studies addressing water-infrastructure sustainability in Nigeria and describe a varied evidence base covering multiple infrastructure types and challenge categories. Their review does not itself provide a cluster-level physical-integrity assessment for an urban municipal distribution network. The present study therefore focuses specifically on condition differentiation and rehabilitation prioritisation within Minna's distribution system, using utility operational records and GIS-supported analysis.

This emphasis aligns the paper with Innovative Resource Utilization and Management: the PII converts routinely available condition, failure, leakage, coverage, and repair-cost information into a transparent basis for allocating scarce rehabilitation resources across the network. It also has a qualified safety and environmental co-benefit. By identifying recurrent integrity hotspots, the framework can guide follow-up pressure and water-quality monitoring at locations where failures or leaks merit closer control. Deteriorating pipes, physical breaches, and low- or negative-pressure events can create conditions for external contaminant intrusion; however, this study did not measure water quality, model intrusion, or estimate health risk (Renwick et al., 2019).

This study developed and applied a Physical Integrity Index (PII) to assess the condition of the Minna municipal water distribution network. The framework combines four indicators, Pipe Age Index (PAI), Failure Frequency Index (FFI), Leakage Density Index (LDI), and Coverage Efficiency Index (CEI), within a GIS-supported methodology. It draws on utility operational records, field inspections, GPS-verified infrastructure surveys, and interviews with technical personnel to evaluate condition across seven operational service clusters.

Unlike conventional approaches that rely on a single indicator or subjective judgement, this method offers a structured, risk-based approach to identify deterioration hotspots and prioritize rehabilitation using data the utility already holds. A sensitivity analysis tests whether the framework remains stable under different weighting assumptions, building confidence in its use for real engineering decisions.

The findings give NISWASEC practical guidance for infrastructure renewal planning. The methodology can also be transferred to other urban utilities facing similar technical and financial constraints. More broadly, the study demonstrates how integrated engineering indicators and spatial analysis can make urban water distribution management more resilient and transparent.

2.2 Research Design

The study followed a quantitative engineering assessment framework. It combined infrastructure inventory, field verification, spatial analysis, and multi-criteria performance evaluation to quantify network physical condition using operational records the utility already keeps, checked against direct field observations, consistent with multi-indicator approaches to pipe condition assessment (Taiwo et al., 2023).

The assessment proceeded in five stages:

1. Compilation and verification of infrastructure inventory and operational records.
2. Field inspection and GPS verification of critical water supply assets.
3. Development of engineering performance indicators describing infrastructure condition.
4. Integration of the indicators into a composite Physical Integrity Index (PII).
5. Spatial analysis and prioritization of rehabilitation zones using GIS.

2.3 Data Sources

Secondary and primary data were both used, so that the assessment did not rely solely on utility records.

Secondary data came from NISWASEC and included pipeline inventory records, treatment plant operational records, reservoir inventories, distribution network layout maps, historical pipeline failure records (2021–2025), leakage reports, maintenance logs, service coverage records, and operational pumping schedules.

Primary data were gathered to check existing records against current conditions. Field investigations included GPS surveys of major infrastructure assets, visual inspection of pumping stations, reservoirs, pipelines, and booster stations, standardized Field-Level Observation (FLO) surveys, structured Key Informant Interviews (KII) with engineers, operators, and maintenance personnel, and documentation of observed defects.

Twenty-five priority locations were selected based on historical failure frequency, leakage occurrence, operational significance, and accessibility. These locations represented the most critical infrastructure components across the seven service clusters. Because accessibility was one of the four selection criteria, sites that were more difficult to reach may be under-represented in this priority-location field-verification set relative to their true condition; this is a limitation of the field-sampling protocol only. It does not mean that the seven operational clusters were sampled: all seven clusters were included in the full-network cluster-level assessment.

2.4 Development of Engineering Performance Indicators

Four indicators were developed to quantify infrastructure condition, reflecting evidence that combining several engineering indicators gives a more realistic picture of buried pipe condition than any single measure can (Taiwo et al., 2023). Each captures a distinct aspect of physical performance.

Pipe Age Index (PAI) measures infrastructure ageing by comparing current operational age against expected design life:

$$PAI = \frac{Y_c - Y_i}{Y_d} \quad (1)$$

where Y_c = current year, Y_i = year of installation, and Y_d = design service life. Higher values indicate more advanced ageing.

Failure Frequency Index (FFI) measures structural reliability from the reported pipeline-failure occurrence total:

$$FFI = \frac{N_f}{L_p} \quad (2)$$

where N_f = cumulative reported pipeline-failure occurrence total and L_p = pipeline length (km). Higher values signal greater structural deterioration.

Leakage Density Index (LDI) quantifies the concentration of leakage events within each service cluster:

$$LDI = \frac{N_l}{L_n} \quad (3)$$

where N_l = number of leakage events and L_n = network length (km).

Coverage Efficiency Index (CEI) evaluates service delivery effectiveness:

$$CEI = 5 \left(1 - \frac{P_s}{P_t} \right) \quad (4)$$

where P_s = population served and P_t = total population within the service area. The transformed CEI is scaled from 0 to 5, such that lower service coverage yields a higher score and therefore indicates poorer coverage efficiency.

2.5 Development of the Physical Integrity Index (PII)

The four indicators were combined into a composite PII through weighted linear combination, following established multi-criteria approaches to water distribution network rehabilitation planning (Hassoun Nedjar et al., 2023), after normalizing each to a common five-point condition scale:

$$PII = 0.2(PAI) + 0.3(LDI) + 0.4(FFI) + 0.1(CEI) \quad (5)$$

Raw service coverage was transformed before aggregation as $CEI = 5 \times (1 - P_s/P_t)$, so that all four PII components follow the same condition direction: a higher score denotes poorer physical integrity. The legacy, non-inverted CEI and PII values are retained alongside the corrected values in Table 3 solely for transparency.

The adopted coefficients were specified as a research-team engineering-judgement baseline, informed generally by NISWASEC's operational context and observed network characteristics. The intended priority order was Failure Frequency Index (FFI, 0.40) > Leakage Density Index (LDI, 0.30) > Pipe Age Index (PAI, 0.20) > Coverage Efficiency Index (CEI, 0.10). This ordering treats observed failure frequency and leakage concentration as the most direct operational manifestations of deterioration, with pipe age as a contributing condition and service coverage as a contextual component. However, the study records do not contain a contemporaneous protocol explaining how the exact decimal values were selected. In particular, no documented weighting interviews, workshop or consensus procedure, Delphi exercise, pairwise-comparison matrix, iterative-refinement record, or statistical calibration was used to derive these coefficients. They should therefore be interpreted as transparent adopted engineering weights, not as empirically estimated or formally elicited parameters. The equal-weighting sensitivity analysis tests the robustness of the resulting cluster ranking to a material alternative weighting scheme; it does not establish that the adopted coefficients are optimal.

Table 1: A: Adopted Equation 5 weighting configuration and disclosure

PII component	Adopted weight	Role in the adopted engineering-judgement hierarchy
Failure Frequency Index (FFI)	0.40	Highest priority: recorded failure burden.
Leakage Density Index (LDI)	0.30	Second priority: concentration of recorded leakage.
Pipe Age Index (PAI)	0.20	Contributing age-related condition.
Coverage Efficiency Index (CEI)	0.10	Contextual service-coverage component.

Note: The hierarchy records the adopted study design

Conceptual Basis for the Priority Ordering

While the exact decimal weights were not formally elicited, the qualitative priority ordering (FFI > LDI > PAI > CEI) is consistent with established infrastructure asset management literature, which associates each indicator with a distinct pathway to network deterioration and, where structural breaches occur, contaminant entry (Renwick et al., 2019). Table 1B summarizes this conceptual grounding, which supports the direction and relative emphasis of the adopted weights without substituting for a documented elicitation procedure.

Table 1: B: Conceptual Rationale for the Adopted Priority Ordering

Indicator	Description	Adopted weight	Conceptual rationale
FFI	Failure Frequency Index	0.40	Recognized as a strong indicator of infrastructure deterioration and future failure risk (Folkman, 2018)
LDI	Leakage Density Index	0.30	Associated with structural defects and potential contaminant entry pathways (Kirmeyer et al., 2001)
PAI	Pipe Age Index	0.20	Reflects long-term asset deterioration (Rajani & Kleiner, 2001)
CEI	Coverage Efficiency Index	0.10	Indicates service adequacy and network resilience (AWWA, 2019)
Total		100%	

Note: This table provides literature-based conceptual support for the adopted priority ordering

To translate PAI, LDI, and FFI from continuous engineering measures into the common five-point condition scale used in Equation 5, a semi-quantitative scoring rubric consistent with infrastructure asset management practice (Rajani & Kleiner, 2001; Folkman, 2018; AWWA, 2019) was applied at cluster level (Table 1C). CEI is not included in this rubric because it is already computed directly on a continuous 0–5 scale from the coverage ratio (Eq. 4) and requires no qualitative anchoring.

Table 1: C: Standardized Scoring Framework for PAI, LDI, and FFI

Score	PAI (Pipe Age Condition)	LDI (Leakage Density)	FFI (Failure Frequency)
5	Very Old (>80% design life)	Very High Leakage	Very High Failure Frequency
4	Old (60–80%)	High Leakage	High Failure Frequency
3	Moderate Age (40–60%)	Moderate Leakage	Moderate Failure Frequency
2	Relatively New (20–40%)	Low Leakage	Low Failure Frequency
1	New (<20%)	Very Low Leakage	Very Low Failure Frequency

Cluster-level PAI, LDI, and FFI scores were assigned using this rubric together with the infrastructure inventory, leakage records, and failure database, and were cross-checked against Field-Level Observation (FLO) and Key Informant Interview (KII) findings on relative deterioration across clusters. The resulting component scores by cluster are reported in Table 3.

The resulting PII values were classified into five condition categories as shown in Table 1.

Table 1: Physical Integrity Index Condition Classification

PII Range	Infrastructure Condition
< 2.0	High Integrity
2.0 to < 3.0	Moderate Integrity
3.0 to < 3.5	Low Integrity
3.5 to < 4.0	Very Low Integrity
≥ 4.0	Critical Integrity

2.6 Geographic Information System (GIS) Analysis

Spatial analysis was carried out in ArcGIS Pro. Infrastructure inventory, field observations, historical failures, and engineering performance indicators were integrated within a unified spatial database. Assets were georeferenced using GPS coordinates from field surveys, and existing utility maps were digitized and validated against field observations.

GIS analysis supported: (i) mapping of infrastructure assets; (ii) spatial distribution of pipeline failures; (iii) identification of deterioration hotspots; (iv) visualization of PII values; and (v) development of rehabilitation priority maps.

2.7 Sensitivity Analysis

Sensitivity analysis evaluated the robustness of the PII ranking under a reproducible alternative weighting assumption. The adopted engineering-judgement configuration was compared with equal weighting (0.25 for each component). The previously described structural-emphasis scenario is not

retained because its exact weight vector was not documented and could not be independently reproduced.

2.8 Statistical Analysis

Descriptive statistics summarized infrastructure characteristics, failure frequencies, leakage occurrence, and coverage across the seven predefined operational areas. Pearson's and Spearman's coefficients were used to describe associations among these complete network zones, including relationships between PII, coverage, reported failure-occurrence totals, and repair cost. In these analyses, $n = 7$ refers to the seven operational clusters that partition the whole Minna Municipal network, not to a probabilistic sample of clusters. The p-values are retained as standardized indicators of the strength and stability of cross-area relationships, but they should not be interpreted as supporting population-level generalization beyond the Minna system. The coefficient of variation was also computed to measure variation in infrastructure condition across the full network zoning.

2.9 Assessment of PII Consistency and Criterion Validity

Robustness and validity were assessed through three complementary checks that are kept analytically distinct. First, robustness to the weighting scheme was tested via sensitivity analysis. Second, because FFI is itself a constituent of the PII, its correlation with the reported pipeline-failure occurrence total was treated as an internal-consistency check rather than independent validation: a strong relationship is expected by construction and confirms the index behaves coherently, but it cannot substitute for external evidence. Third, criterion validity was assessed against a variable constructed independently of the PII: cluster-level repair-cost records obtained directly from NISWASEC maintenance ledgers (2021–2025). This repair-cost comparison constitutes the study's principal external validation evidence. District-metered Non-Revenue Water (NRW) data remained unavailable; NRW was instead modelled as a linear function of PII, calibrated to realistic bounds for sub-Saharan utilities (Shushu et al., 2021). Because the NRW estimate is derived computationally from PII, it is reported only as contextual model output and is not correlated with PII or treated as validation evidence. Pearson's correlation coefficient assessed the strength of the reported repair-cost and internal-consistency relationships.

3. RESULTS AND DISCUSSION

The infrastructure inventory shows that the Minna network grew through successive, largely uncoordinated expansion phases rather than a single planned programme. The result is a mix of assets with different ages, capacities, materials, and operating conditions.

Field verification identified four water treatment plants, nine major service reservoirs, three booster pumping stations, and an extensive transmission and distribution network supplying the seven operational clusters. However, installed capacity did not equal available capacity. The Impresit plant ran close to its design capacity throughout the study period. Biwater and Bosso both produced below design capacity due to non-operational pumping units. Paiko, though physically complete, was not yet operational and contributed nothing to municipal production.

Nearly a quarter of sampled pipeline segments had no material recorded in utility records. uPVC and Ductile Iron together account for the majority of identified material, with small proportions of Asbestos Cement and Galvanized Iron still in service (Figure 2).

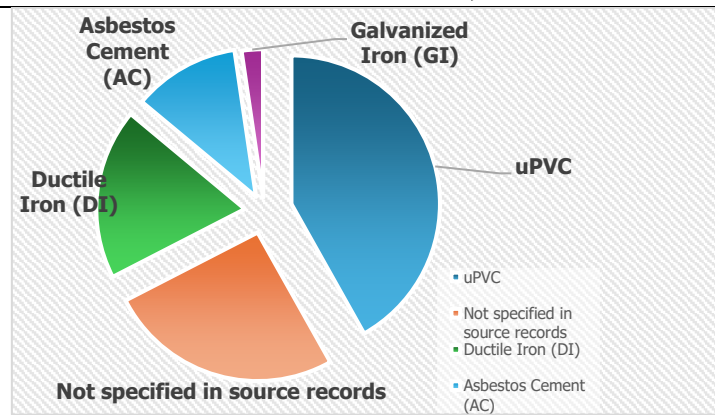


Figure 2: Material composition of 43 field-verified segments.

Figures 2 and 3 summarize a 43-segment field-verification subset. The original segment-level material and diameter inventory used to construct these descriptive charts was not supplied in NetworkData.xlsx. Accordingly, the displayed percentages are not independently auditable from the supplied calculation package and are not used in the PII calculation, correlation analysis, or validation. They should be read only as descriptive field records, not as a statistically representative network-wide material or diameter inventory. A complete segment-level inventory is required before making network-wide material-composition or diameter-distribution estimates.

Distribution system reliability depends not only on the condition of buried pipelines but also on whether upstream production and pumping facilities are running. Reduced pumping capacity limits hydraulic flexibility, creates pressure variability, and makes it harder to redirect flow during maintenance or emergencies.

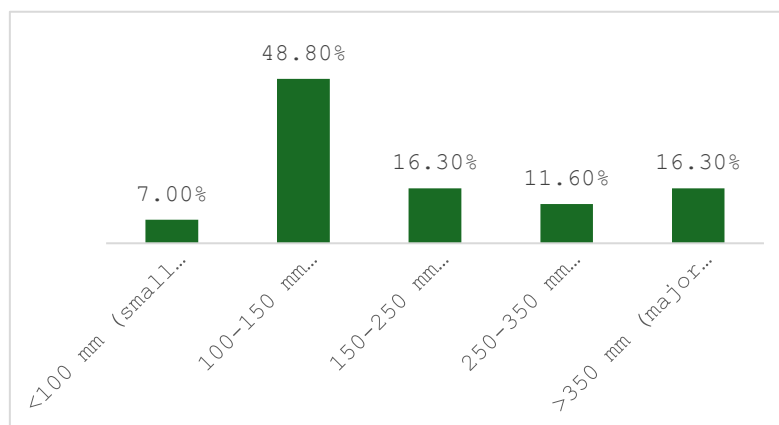


Figure 3: Diameter distribution of 43 field-verified segments.

Within the unverified 43-segment field subset shown in Figure 3, 48.8% of pipes fall within the 100–150 mm distribution range, with 16.3% in both the 150–250 mm sub-trunk and >350 mm major trunk categories, and 11.6% in the 250–350 mm trunk category. Only 7.0% are small distribution pipes (<100 mm). Because the original segment-level diameter inventory was not supplied in NetworkData.xlsx, these are descriptive field-subset proportions only and are not interpreted as network-wide estimates.

3.1 Spatial Characteristics of the Distribution Network

GIS analysis revealed marked spatial variability in infrastructure configuration across the seven clusters. Older sections of the network, particularly Minna West, Minna East, and parts of Chanchaga, showed dense pipeline layouts, numerous service connections, and a long history of repeated maintenance work. Bosso and parts of Tudun Wada South showed lower maintenance intensity and fewer recorded structural defects.

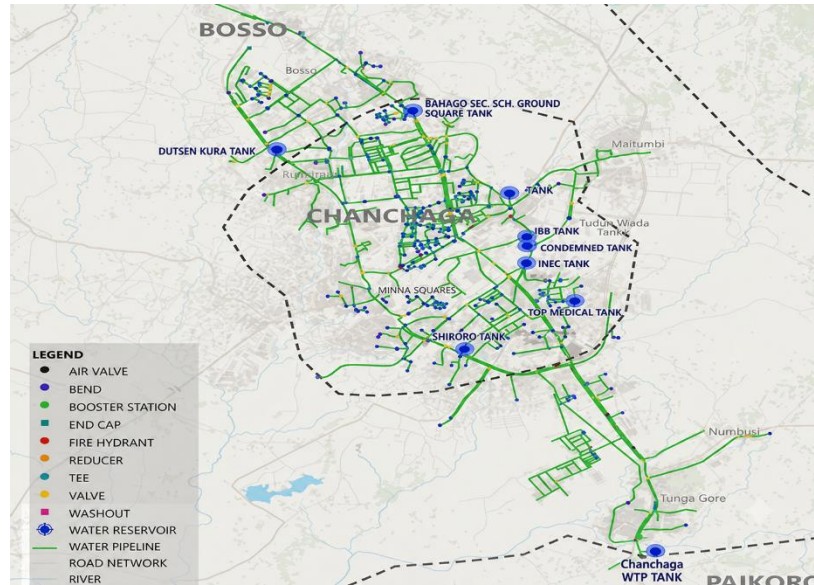


Figure 4: Distribution system network with key water infrastructures and pipeline stretch.

Figure 4 overlays that boundary with the principal components of the distribution system, the four treatment plants, the service reservoirs and booster stations that regulate hydraulic pressure, and the transmission and reticulation mains connecting them, giving a single spatial reference for the infrastructure inventoried in Section 2.3. The reservoir and booster-station command areas visible in Figure 4 correspond to the operational basis used to delineate the seven service clusters described below: each cluster boundary follows the reticulation network actually served by a given reservoir or pumping zone, rather than an administrative line. Figure 4 therefore functions as the spatial basis for the cluster-level condition assessment reported in Section 3, rather than as a standalone locational reference.

3.2 Distribution of Reported Pipeline-Failure Occurrence Totals

The supplied maintenance workbook reports a cumulative pipeline-failure occurrence total of 6,526.24 for 2021–2025. The occurrence field contains fractional values, so these data are treated as reported operational occurrence totals rather than literal integer counts of discrete break events. They remain unevenly distributed across clusters and provide the failure-frequency input to the PII.

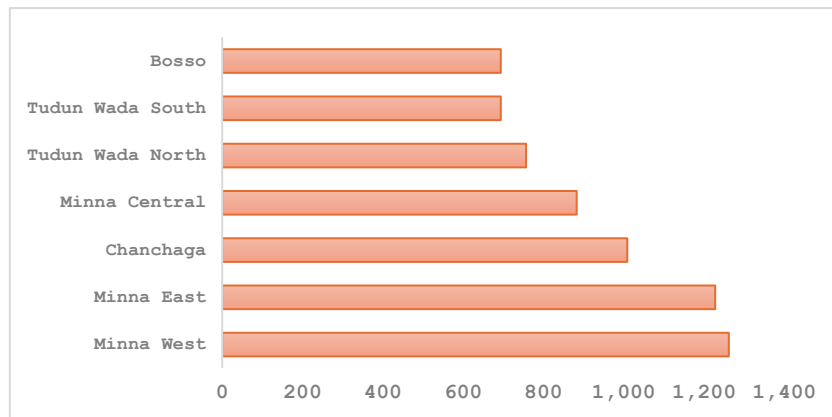


Figure 5: Distribution of reported pipeline-failure occurrence totals by service cluster (2021–2025; bars rounded for display).

Minna West reported the highest occurrence total (1,261.60; 19.3%), followed by Minna East (1,227.52; 18.8%) and Chanchaga (1,009.28; 15.5%). Together, these three clusters accounted for approximately 53.6% of the workbook-reported occurrence total. Bosso and Tudun Wada South reported the lowest totals (693.88 each; 10.6%).

INFRASTRUCTURE CHARACTERIZATION AND PHYSICAL INTEGRITY ASSESSMENT OF URBAN
WATER DISTRIBUTION SYSTEMS: A RISK-BASED FRAMEWORK FOR SUSTAINABLE ASSET
MANAGEMENT IN MINNA, NIGERIA

Table 2: Distribution of Reported Pipeline-Failure Occurrence by Service Cluster (2021–2025)

Service Cluster	Reported occurrence total (2021–2025)	% of Total
Minna West	1,261.60	19.3
Minna East	1,227.52	18.8
Chanchaga	1,009.28	15.5
Minna Central	883.12	13.5
Tudun Wada North	756.96	11.6
Tudun Wada South	693.88	10.6
Bosso	693.88	10.6
Total	6,526.24	100

The concentration of failures in the western and eastern sectors aligns with their higher levels of urban development, denser connections, and longer operating histories. Frequent road excavation, growing traffic loads, repeated pipe repairs, and sustained hydraulic loading have likely accelerated structural decline in these areas.

3.3 Physical Integrity Assessment

The Physical Integrity Index differentiated infrastructure condition clearly across the seven clusters (Figure 6 and Figure 7).

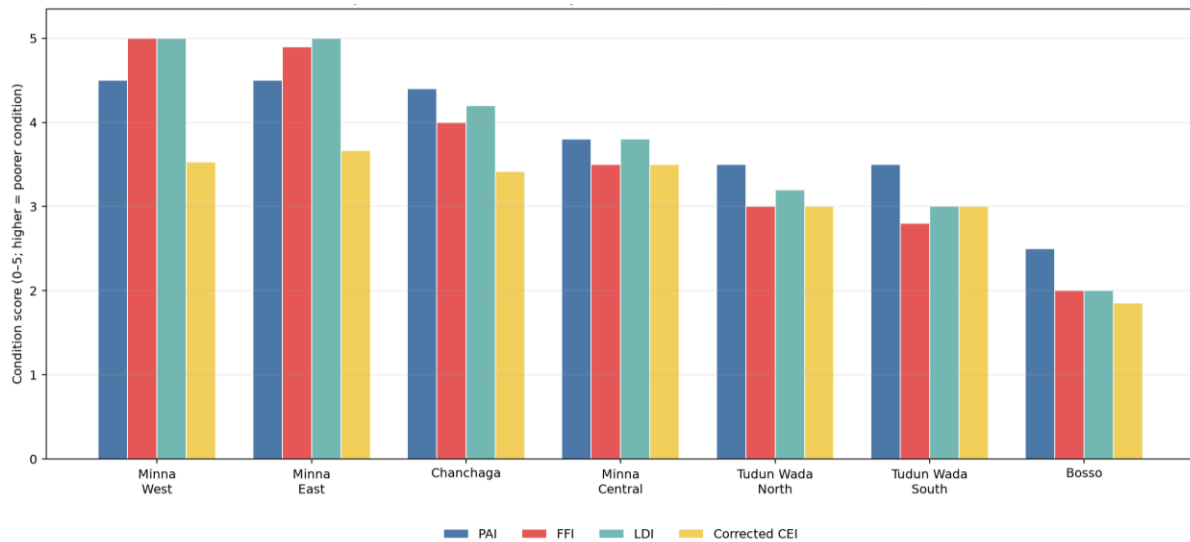


Figure 6: Corrected component indicator scores by service cluster (CEI direction corrected).

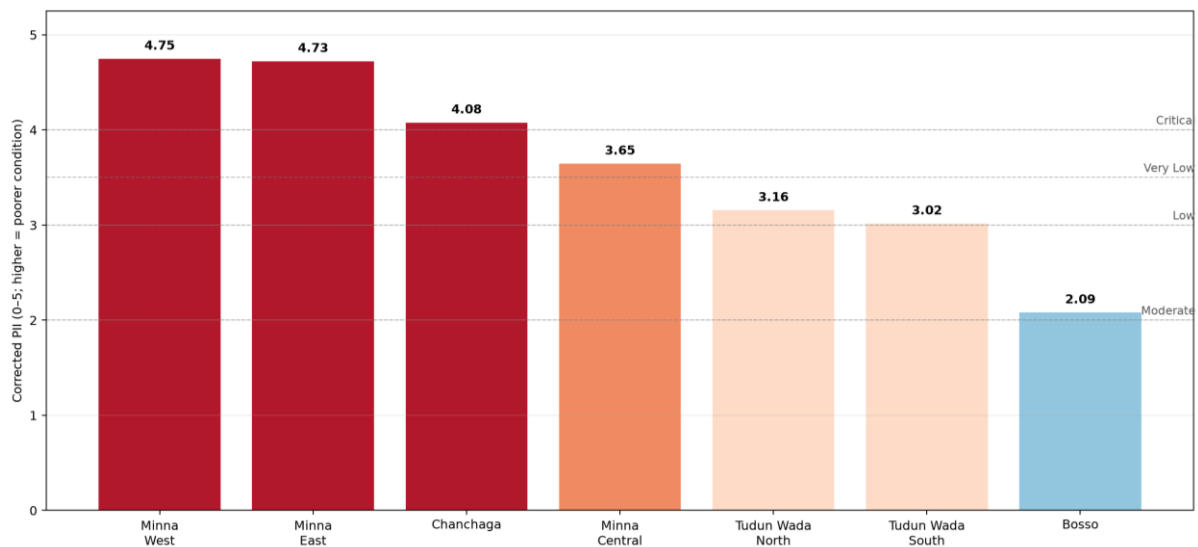


Figure 7: Corrected Composite Physical Integrity Index (PII) by service cluster.

Minna West and Minna East exhibit maximum or near-maximum scores for FFI (5.0 and 4.9) and LDI (5.0 and 5.0), reflecting extreme failure frequencies and leakage densities. PAI scores are also elevated (4.5) across the critical clusters. Bosso shows favourable (low) scores across PAI (2.5), FFI (2.0), and LDI (2.0). Its high raw service-coverage ratio (63.0%) is now correctly transformed into the lowest CEI subscore (1.9) of the seven clusters. Because CEI enters the PII on the same higher-is-worse scale as the other components, the corrected transformation strengthens the conceptual coherence of the composite index. Bosso remains the cluster with the best overall physical integrity, although its Moderate Integrity classification confirms that preventive maintenance and routine monitoring remain necessary.

With CEI direction corrected, Minna West (4.75), Minna East (4.73), and Chanchaga (4.08) fall within the Critical Integrity band (≥ 4.0). Minna Central (3.65) is Very Low Integrity. Tudun Wada North (3.16) and Tudun Wada South (3.02) exhibit Low Integrity, while Bosso (2.09) remains Moderate Integrity. No cluster achieved High Integrity (< 2.0). The corrected PII values have a mean of 3.64, a sample standard deviation of 0.97, and a coefficient of variation of 26.7%, confirming substantial heterogeneity in infrastructure condition rather than uniform network-wide deterioration.

INFRASTRUCTURE CHARACTERIZATION AND PHYSICAL INTEGRITY ASSESSMENT OF URBAN WATER DISTRIBUTION SYSTEMS: A RISK-BASED FRAMEWORK FOR SUSTAINABLE ASSET MANAGEMENT IN MINNA, NIGERIA

Table 3: Legacy and CEI-direction-corrected Physical Integrity Index results by service cluster

Service cluster	PAI	FFI	LDI	CEI	PII	Condition
Minna West	4.5	5.0	5.0	3.5	4.75	Critical
Minna East	4.5	4.9	5.0	3.7	4.73	Critical
Chanchaga	4.4	4.0	4.2	3.4	4.08	Critical
Minna Central	3.8	3.5	3.8	3.5	3.65	Very Low
Tudun Wada North	3.5	3.0	3.2	3.0	3.16	Low
Tudun Wada South	3.5	2.8	3.0	3.0	3.02	Low
Bosso	2.5	2.0	2.0	1.9	2.09	Moderate

The deterioration in Minna West and Minna East stems from the combined effects of long service life, frequent structural failures, and persistent leakage. Repeated excavation and replacement of failed sections may also have weakened neighbouring pipe segments, making subsequent failure more likely.

Bosso's relatively favourable condition does not mean rehabilitation can be ignored there. Rather, the lower PII values suggest that preventive maintenance and routine monitoring should be sufficient to maintain performance, avoiding the more extensive intervention required elsewhere.

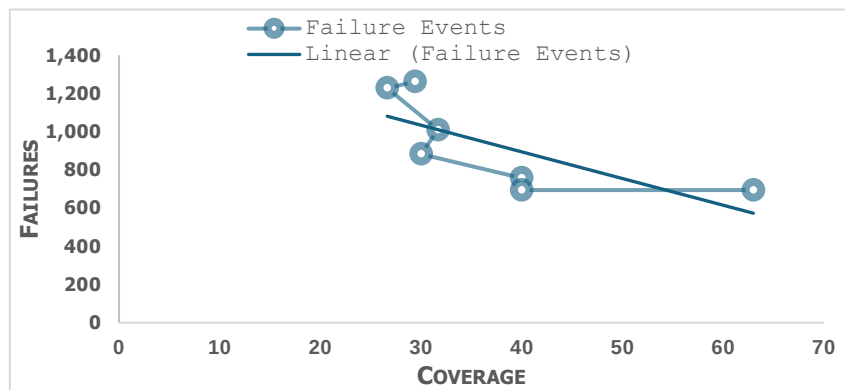


Figure 8: Relationship between service coverage and pipeline failures (bubble size proportional to residential buildings served).

Clusters with lower raw service coverage (Minna West and Minna East) experience substantially higher failure counts. Bosso, with the highest raw coverage (63.0%), records among the fewest failures. Pearson's correlation between raw service coverage and total failures approached but did not reach conventional significance ($r = -0.723$, $p = 0.066$, $n = 7$); Spearman's rank correlation was significant ($\rho = -0.900$, $p = 0.006$). PII was strongly and inversely associated with raw service coverage (Pearson $r = -0.906$, $p = 0.005$, $n = 7$; Spearman $\rho = -0.919$, $p = 0.003$).

3.4 Spatial Distribution of Rehabilitation Priorities

GIS mapping identified distinct pockets of deterioration at finer spatial resolution than the seven service clusters. Because sub-zone-level coverage (CEI) data were not available, this finer-grained analysis uses a Sub-Zonal Physical Deterioration Score (SPDS), computed from PAI, FFI, and LDI only. The reproducible score is $SPDS = (0.20 \times PAI + 0.40 \times FFI + 0.30 \times LDI) / 0.90$, which renormalizes the adopted PAI, FFI, and LDI weights to sum to 1. It is therefore not directly numerically comparable to the four-indicator, cluster-level PII reported elsewhere. The raw field inputs and sub-zone normalization worksheets, so the SPDS is retained as a field-derived screening score. High-risk zones clustered in Tungan Goro, Sauke Kahuta, M. I. Wushishi, and Tunga Market, where the reported screening scores coincide with recurring failures, visible leakage, and ageing infrastructure.

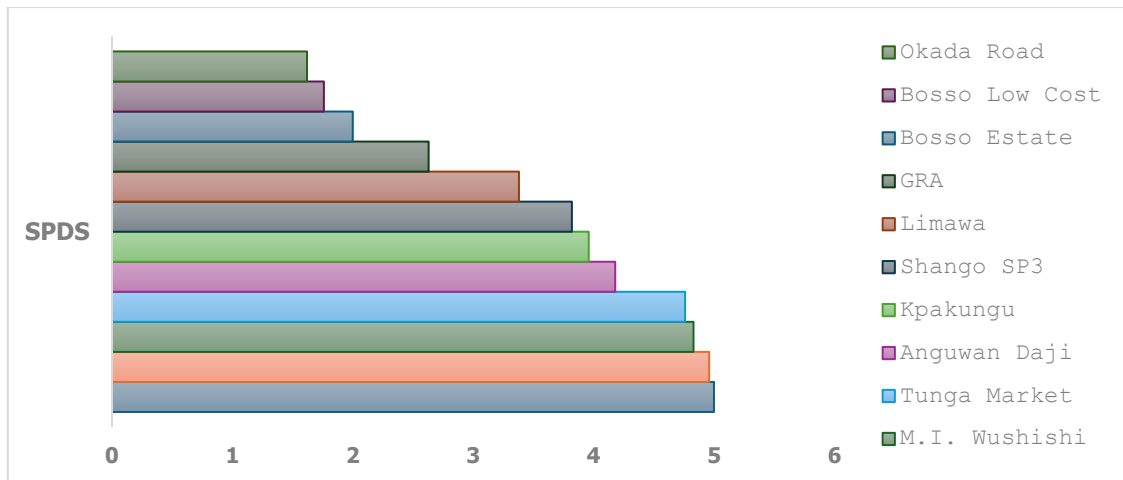


Figure 9: Sub-Zonal Physical Deterioration Score (SPDS) within high-priority rehabilitation clusters.

Table 4: Sub-Zonal Physical Deterioration Score (SPDS)

Sub-Zone	PAI	FFI	LDI	SPDS	Condition
Tungan Goro	5.0	5.0	5.0	5.00	Critical
Sauke Kahuta	5.0	4.9	5.0	4.96	Critical
M.I. Wushishi	4.8	4.8	4.9	4.83	Critical
Tunga Market	4.8	4.7	4.8	4.76	Critical
Anguwan Daji	4.3	4.1	4.2	4.18	Critical
Kpakungu	4.0	3.9	4.0	3.96	Very Low
Shango SP3	3.9	3.8	3.8	3.82	Very Low
Limawa	3.5	3.3	3.4	3.38	Low
GRA	2.8	2.5	2.7	2.63	Moderate
Bosso Estate	2.0	2.0	2.0	2.00	Moderate
Bosso Low Cost	1.8	1.7	1.8	1.76	High
Okada Road	1.7	1.6	1.6	1.62	High

Note: $SPDS = (0.20(PAI) + 0.40(FFI) + 0.30(LDI)) / 0.90$. This renormalizes the adopted PAI, FFI, and LDI weights because sub-zone-level coverage data were unavailable. The raw sub-zone inputs and normalization worksheets were not available; SPDS values are therefore field-derived screening results and are not directly comparable to the four-indicator cluster-level PII.

This spatial concentration has direct implications for rehabilitation planning. Instead of spreading investment evenly across the network, NISWASEC can concentrate resources in these hotspots, where renewal is likely to yield the greatest improvements in reliability and operational efficiency.

3.5 Sensitivity Analysis

Sensitivity analysis of the CEI, PII compared the adopted weighting scheme with equal weighting. Absolute scores shifted slightly, but the relative priority order remained stable: Minna West and Minna East remained the top-priority rehabilitation zones, and Bosso remained the cluster with the best infrastructure integrity (Figure 10).

INFRASTRUCTURE CHARACTERIZATION AND PHYSICAL INTEGRITY ASSESSMENT OF URBAN WATER DISTRIBUTION SYSTEMS: A RISK-BASED FRAMEWORK FOR SUSTAINABLE ASSET MANAGEMENT IN MINNA, NIGERIA

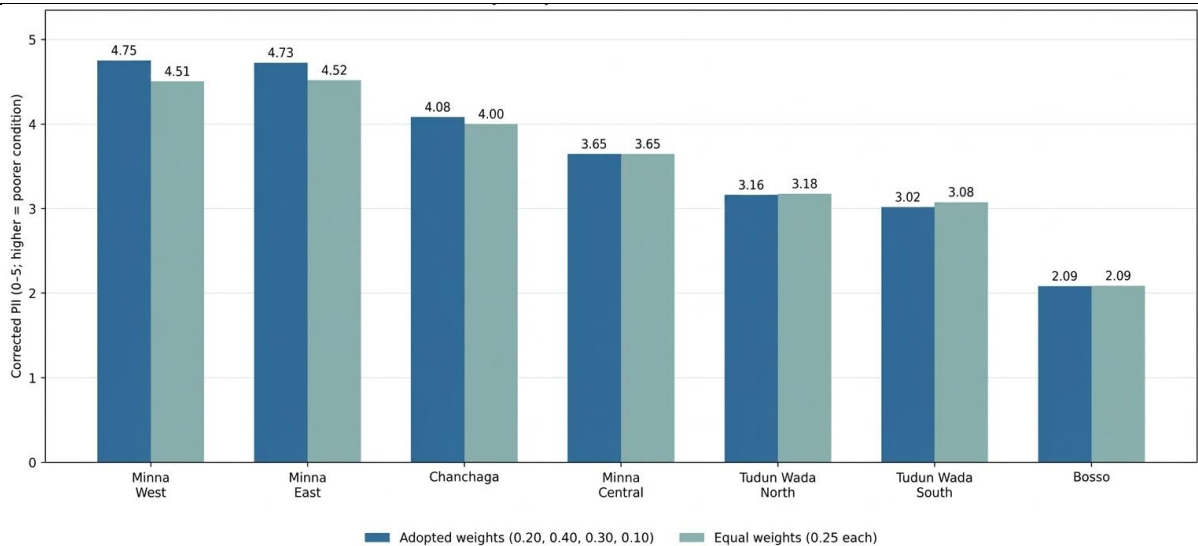


Figure 10: Sensitivity analysis of CEI direction correction: PII scores under adopted and equal weighting scenarios.

The adopted scheme (PAI: 0.20, FFI: 0.40, LDI: 0.30, CEI: 0.10) was compared with equal weighting (0.25 each). Cluster rankings remained strongly aligned (Spearman's $\rho = 0.964$, $p < 0.001$, $n = 7$). The result reflected a near-identical weighting pattern, the particular seven-cluster score distribution; no causal explanation is therefore inferred. The sensitivity analysis reports only the two fully reproducible scenarios.

The stable ordering under these two reproducible weighting schemes indicates that rehabilitation priorities are driven mainly by observed infrastructure condition rather than by the adopted weighting choice. This supports the use of the corrected PII for engineering prioritisation while preserving a transparent limit on the sensitivity evidence.

3.6 Empirical Assessment of PII Consistency and Criterion Validity

To assess whether the PII behaves coherently and agrees with independent evidence, computed values were compared against two operational indicators: total recorded pipeline failures and recorded repair expenditure. These two comparisons are not equivalent in evidentiary strength and are interpreted separately below. District-metered non-revenue water data were unavailable; the separately modelled NRW estimate is reported as contextual information only and is not used in correlation-based validation.

Clusters with higher PII values consistently reported higher pipeline-failure occurrence totals. Pearson's correlation analysis found a strong positive linear relationship between PII and the reported occurrence total ($r = 0.944$, $p = 0.001$, $n = 7$), and equivalently with the cluster's share of the network-wide occurrence total ($r = 0.944$, $p = 0.001$, $n = 7$). Because FFI is itself one of the four indicators combined into the PII, this relationship is expected by construction and is interpreted as an internal-consistency check rather than independent validation. Spearman's rank correlation corroborated the monotonic ordering ($\rho = 0.991$, $p < 0.001$, $n = 7$).

The correlation between PII and the Coverage Efficiency Index (CEI) score was positive ($r = 0.906$, $p = 0.005$, $n = 7$), as expected after all components were aligned to a higher-is-worse condition scale. This CEI-score relationship is distinct from the inverse corrected-PII-raw-service-coverage relationship reported in Section 3.3 ($r = -0.906$, $p = 0.005$, $n = 7$). Because CEI is a component of PII, neither relationship constitutes independent validation.

Cluster-level repair-cost records for 2021–2025 were obtained directly from NISWASEC maintenance ledgers. The supplied workbook records five-year cumulative repair-cost totals; these are expressed in ₦ million in Figure 11 and Table 5. Because repair expenditure was not used to construct the PII, its correlation with corrected PII constitutes the study's principal external criterion validation. District-metered non-revenue water data remained unavailable; the separately modelled NRW estimate is contextual only and is not used as validation evidence.

Pearson's correlation analysis found a strong positive relationship between PII and the recorded 2021–2025 cumulative repair-cost total:

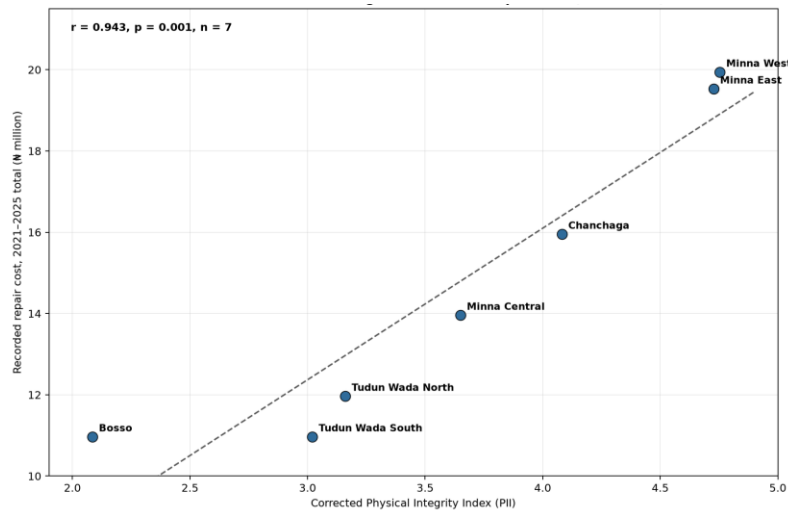


Figure 11: Independent criterion validation of corrected PII against recorded cumulative repair cost (2021–2025).

Cluster-level repair-cost totals were extracted from NISWASEC maintenance ledgers; Pearson $r = 0.943$, $p = 0.001$, $n = 7$.

Table 5: Independent criterion validation of corrected PII against recorded cumulative repair cost

Comparison	r	p	n
PII vs recorded repair cost (2021–2025 total)	0.943	0.001	7

Note: $n = 7$ denotes the seven predefined operational service clusters that together constitute the full Minna Municipal water supply network; it does not denote a sample of clusters.

The internal consistency checks confirm that the PII behaves coherently with its own constituent data, while the repair-cost comparison provides the study's strongest evidence that the index reflects real operational consequences beyond its own construction.

3.7 Comparison with Previous Studies

The deterioration patterns in Minna fit the broader picture: ageing infrastructure, recurrent leakage, and rising operational demand together erode the reliability of urban water distribution networks (Auma et al., 2023; Taiwo et al., 2023). What this study contributes is a quantitative method for assessing that condition using routinely available operational data within a GIS-supported framework.

Positioning the PII requires distinguishing five related but methodologically distinct strands of water-distribution-network research: pipe-failure prediction, hydraulic modelling, rehabilitation prioritization, condition assessment, and composite indices.

Pipe-failure prediction. This strand models the probability that an individual pipe will fail from its own attributes and break history. Logistic regression and support vector classification have been used to predict individual pipe failures from asset attributes (Robles-Velasco et al., 2020), comparable logistic models have been fitted to failure records for Kampala's water network (Auma et al., 2023), and validated failure-prediction models have shown reasonable agreement with observed main breaks over multi-year monitoring (Kahn et al., 2020). These models perform well where detailed, pipe-level failure and attribute histories exist, but that data requirement is precisely what NISWASEC and most Nigerian utilities lack.

Hydraulic modelling. This strand simulates how water moves through a network, pressure, flow, and contaminant transport, under defined operating conditions using calibrated software such as EPANET (Piazza et al., 2022). It describes network behaviour at a point in time rather than the physical deterioration of the pipes carrying that water, and it depends on calibrated demand and roughness data that ageing, incompletely documented systems like Minna's rarely have.

Rehabilitation prioritization. This strand sits downstream of the first two: it takes condition or risk information as an input and ranks competing rehabilitation projects against it, commonly through structured multi-criteria methods such as the analytical hierarchy process (Hassoun Nedjar et al., 2023).

Its output is a decision, and its reliability depends entirely on the quality of the condition data supplied to it.

Condition assessment. This strand addresses that upstream question directly, asking what state a pipe or network segment is actually in. Grigg's (2006) review of utility condition-assessment practice found that a composite condition index consolidating multiple factors was the ideal but was rarely achieved, held back by inconsistent recording of leaks, breaks, and condition indicators, an observation that describes NISWASEC's records closely. More recent work confirms that combining several engineering indicators gives a more realistic picture of buried-pipe condition than any single measure can (Taiwo et al., 2023).

Composite indices. A smaller literature has begun to close that gap by aggregating multiple indicators into a single score. Beker and Kansal (2022), for example, used fuzzy-logic aggregation of reliability, resilience, and vulnerability indices derived from hydraulic simulation output to build one performance index for decision-making. That approach still depends on a calibrated hydraulic model as its data source, a resource that, like pipe-level failure histories, is largely unavailable in Minna's context.

More than half of the reported pipeline-failure occurrence total were concentrated in Minna West, Minna East, and Chanchaga. This confirms that deterioration is spatially uneven. The risk-based hotspot analysis extends conventional network-wide assessments by identifying rehabilitation priorities at both cluster and sub-zonal levels.

Positioned against these five traditions, what is novel about applying the PII to Minna is not any single indicator but the combination of choices behind it. First, it builds a composite condition index, in the tradition of Grigg (2006) and Beker and Kansal (2022), but computes it entirely from routine utility records and targeted field verification rather than from a calibrated hydraulic model, pipe-level statistical failure histories, or an expert-elicitation panel. Second, it embeds that index in a GIS framework built around actual reservoir and pumping command areas rather than administrative billing zones, so the same index that scores condition also locates it precisely enough to guide rehabilitation spending. Third, it validates the resulting scores empirically against Minna's own repair-cost and failure records (2021–2025) and compares the adopted scheme with an equal-weighting sensitivity scenario, a combination of empirical validation and weighting-sensitivity analysis that the pipe-failure-prediction, hydraulic-modelling, and AHP-based rehabilitation literature reviewed above do not report together. Finally, to the authors' knowledge, few if any prior studies have applied a composite, low-data physical integrity framework of this kind to a Nigerian municipal water distribution network, giving NISWASEC and similarly resourced utilities elsewhere in the country a route to risk-informed rehabilitation planning that does not presuppose the statistical modelling capacity, hydraulic calibration data, or expert-panel access that much of the existing literature assumes.

3.8 Engineering Significance and Practical Implications

The practical value of this research extends beyond flagging deteriorated infrastructure. The PII gives engineers a structured basis for shifting maintenance strategy from reactive intervention toward condition-based asset management.

The study also demonstrates the value of integrating GIS into routine utility operations. Beyond visualizing infrastructure condition, GIS provides a spatial platform for logging maintenance activity, keeping asset inventories current, and tracking rehabilitation outcomes over time.

Another practical strength is that the framework requires little extra data. It relies primarily on information utilities already generate during routine operations, failure records, leakage reports, infrastructure inventories, and service coverage statistics, supplemented by targeted field verification. Implementation does not require specialized inspection equipment or costly monitoring systems.

3.9 Decision Framework for Infrastructure Rehabilitation

The PII is intended to support structured engineering decisions. Based on computed values, rehabilitation priorities can be linked to specific management actions:

- **PII < 2.0 (High Integrity):** Continue routine inspection and preventive maintenance.
- **PII 2.0 to < 3.0 (Moderate Integrity):** Intensify monitoring and schedule localized rehabilitation where required.

- **PII 3.0 to < 3.5 (Low Integrity):** Implement targeted replacement of deteriorated pipeline sections and fittings.
- **PII 3.5 to < 4.0 (Very Low Integrity):** Prioritize phased rehabilitation within annual capital investment programmes.
- **PII $\geq$ 4.0 (Critical Integrity):** Undertake comprehensive engineering assessment and infrastructure renewal as a priority.

3.10 Data Availability Limitation: System-Wide Physical Water Loss

District-metered non-revenue water data and the source parameters required to calculate system-wide leakage distance were not available in the supplied calculation workbook. A district-metered water balance or formal water audit is required to quantify physical losses and to provide a valid basis for future NRW or leakage-distance analysis.

3.11 Limitations and Directions for Future Work

This study distinguishes internal-consistency checks, in which PII is compared with data used to construct it, from external criterion validation, in which PII is compared with an independently recorded operational variable. After CEI direction correction, the repair-cost comparison shown in Figure 11 uses cumulative 2021–2025 repair-cost totals recorded in NISWASEC maintenance ledgers ($r = 0.943$, $p = 0.001$, $n = 7$). Because these ledger records were not used to construct the PII, this comparison is the study's only independent criterion validation.

The Coverage Efficiency Index directionality flaw identified in the original analysis has been corrected. Raw service coverage is now inverted during normalization as $CEI = 5 \times (1 - P_s/P_t)$, so high coverage produces a low deterioration score and all PII components have the same directional interpretation. Table 3 reports the original, non-inverted values beside the corrected CEI and PII values to preserve a transparent audit trail.

The Equation 5 coefficients are a transparent engineering-judgement baseline rather than a formally elicited or statistically calibrated weight set. The adopted priority order ($FFI > LDI > PAI > CEI$) is stated in Section 2.5 and draws conceptual support from established asset-management literature (Table 1B), the study records do not document the process used to calibrate the matrix. The adopted-versus-equal weighting sensitivity analysis demonstrates ranking robustness but does not validate the numerical optimality of the adopted coefficients. Future applications should use and document a structured elicitation or calibration protocol, including participant roles, weight alternatives considered, the final decision rule, pairwise-comparison matrices and consistency ratios where AHP is used, and all sensitivity-scenario vectors.

Sample selection and data traceability warrant caution. The 43 pipeline segments assessed for material composition (Figures 2 and 3) and the 25 priority locations assessed at sub-zonal resolution (Section 3.4) were selected using risk-related criteria and practical accessibility rather than a formal stratified random-sampling protocol. The original segment-level material/diameter inventory and the raw sub-zone scoring worksheets were not included in the supplied audit workbook. Accordingly, the material/diameter distributions and SPDS results should be read as indicative field-derived screens, not statistically representative network-wide estimates; the SPDS is also not directly numerically equivalent to the four-indicator, cluster-level PII.

The cluster-level statistical analysis uses seven predefined operational areas ($n = 7$) that collectively cover the entire Minna Municipal water supply network. Thus, $n = 7$ is not a sample size in the sense of seven clusters drawn from a larger unobserved population; it is the complete set of area-level units created by the study's operational zoning design. Pearson and Spearman coefficients therefore describe cross-area patterns within the Minna system. Because only seven area-level units are available, individual clusters can still exert substantial influence on coefficient magnitudes and p-values; the reported p-values should consequently be interpreted as descriptive indicators of within-system association rather than as a basis for broad inferential generalization. Spearman's ρ , which is less sensitive to outliers and does not assume linearity, is reported alongside Pearson's r for this reason.

Finally, the framework is best understood as a condition and integrity assessment tool that supports risk-informed decision-making. It does not currently weight deteriorated infrastructure by the consequence of failure, such as the criticality of served facilities, population density, or road

importance. Extending the PII into a full Risk Priority Index by incorporating an explicit consequence term is a natural direction for future development of this framework.

4. CONCLUSIONS

This study developed a Physical Integrity Index (PII) combining pipe age, failure frequency, leakage density, and coverage efficiency to assess the Minna municipal water distribution network. The entire network was organized into seven predefined operational service clusters based on reservoir and pumping command areas and reticulation boundaries. These clusters are the complete study-design zoning of the municipal system rather than a sampled subset, and each captures a distinct operational setting. Drawing on utility operational records, field verification, and spatial analysis, the framework differentiates infrastructure condition across these seven full-network operational areas.

Physical deterioration proved spatially uneven. The reported 6,526 pipeline-failure occurrence units for 2021–2025, 53.6% concentrated in Minna West, Minna East, and Chanchaga. After CEI direction correction, Minna West (4.75), Minna East (4.73), and Chanchaga (4.08) were classified as Critical; Minna Central (3.65) as Very Low; Tudun Wada North (3.16) and Tudun Wada South (3.02) as Low; and Bosso (2.09) as Moderate. No cluster achieved High Integrity. The corrected PII coefficient of variation was 26.7%, confirming substantial condition heterogeneity.

The rankings remained stable under the adopted and equal-weighting scenarios. PII showed strong internal consistency with reported pipeline-failure occurrence totals ($r = 0.944$, $p = 0.001$, $n = 7$), which is expected because failure frequency is a constituent indicator. Its independent comparison with NISWASEC's recorded cumulative repair-cost totals was also strong ($r = 0.943$, $p = 0.001$, $n = 7$), providing the study's principal external criterion-validation evidence.

By combining existing utility records with targeted field verification and GIS, the framework offers a low-data-burden, transferable method for condition-based rehabilitation prioritisation in data-constrained utilities.

REFERENCES

- Adeoti, O. S., Kandasamy, J., & Vigneswaran, S. (2023). Water infrastructure sustainability in Nigeria: A systematic review of challenges and sustainable solutions. *Water Policy*, 25(11), 1094–1111. <https://doi.org/10.2166/wp.2023.173>
- American Water Works Association. (2019). *AWWA utility benchmarking: Performance indicators for water and wastewater utilities*. Author.
- Auma, R., Musaazi, I. G., Tumutungire, M. D., & Sempewo, J. I. (2023). Logistic pipe failure prediction models for an urban water distribution network in the developing world: A case study of Kampala water, Uganda. *Water Practice and Technology*, 18(1), 264–273. <https://doi.org/10.2166/wpt.2022.159>
- Beker, B. A., & Kansal, M. L. (2022). Fuzzy logic-based integrated performance evaluation of a water distribution network. *AQUA – Water Infrastructure, Ecosystems and Society*, 71(3), 490–506. <https://doi.org/10.2166/aqua.2022.004>
- Folkman, S. (2018). *Water main break rates in the USA and Canada: A comprehensive study*. Utah State University, Mechanical and Aerospace Engineering Faculty Publications, Paper 174. https://digitalcommons.usu.edu/mae_facpub/174
- Grigg, N. S. (2006). Condition assessment of water distribution pipes. *Journal of Infrastructure Systems*, 12(3), 147–153. [https://doi.org/10.1061/\(ASCE\)1076-0342\(2006\)12:3\(147\)](https://doi.org/10.1061/(ASCE)1076-0342(2006)12:3(147))
- Hassoun Nedjar, N., Djebbar, Y., & Djemili, L. (2023). Application of the analytical hierarchy process for planning the rehabilitation of water distribution networks. *Arab Gulf Journal of Scientific Research*, 41(4), 518–538. <https://doi.org/10.1108/AGJSR-07-2022-0110>
- Kahn, C., Damiani, A., & Ge, S. (2020). Validation of water main failure predictions: A 2-year case study. *AWWA Water Science*, 2(3), e1179. <https://doi.org/10.1002/aws2.1179>

- Kirmeyer, G. J., Friedman, M., Martel, K., Howie, D., LeChevallier, M., Abbaszadegan, M., Karim, M., Funk, J., & Harbour, J. (2001). *Pathogen intrusion into the distribution system*. AWWA Research Foundation and American Water Works Association.
- Piazza, S., Sambito, M., & Freni, G. (2022). A novel EPANET integration for the diffusive–dispersive transport of contaminants. *Water*, 14(17), 2707. <https://doi.org/10.3390/w14172707>
- Renwick, D. V., Heinrich, A., Weisman, R., Arvanaghi, H., & Rotert, K. (2019). Potential public health impacts of deteriorating distribution system infrastructure. *Journal - American Water Works Association*, 111(2), 42–53. <https://doi.org/10.1002/awwa.1235>
- Rajani, B. B., & Kleiner, Y. (2001). Comprehensive review of structural deterioration of water mains: Physically based models. *Urban Water*, 3(3), 151–164. [https://doi.org/10.1016/S1462-0758\(01\)00032-2](https://doi.org/10.1016/S1462-0758(01)00032-2)
- Robles-Velasco, A., Cortés, P., Muñuzuri, J., & Onieva, L. (2020). Prediction of pipe failures in water supply networks using logistic regression and support vector classification. *Reliability Engineering & System Safety*, 196, 106754. <https://doi.org/10.1016/j.ress.2019.106754>
- Shushu, U. P., Komakech, H. C., Dodoo-Arhin, D., Ferras, D., & Kansal, M. L. (2021). Managing non-revenue water in Mwanza, Tanzania: A fast-growing sub-Saharan African city. *Scientific African*, 12, e00830. <https://doi.org/10.1016/j.sciaf.2021.e00830>
- Taiwo, R., Ben Seghier, M. E. A., & Zayed, T. (2023). Toward sustainable water infrastructure: The state-of-the-art for modeling the failure probability of water pipes. *Water Resources Research*, 59, e2022WR033256. <https://doi.org/10.1029/2022WR033256>