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Original Article

Optimizing Water Supply Efficiency: Enhanced Management Strategies and Implementation Framework

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Abstract

Despite global infrastructure investments, tropical coastal water distribution systems experience 30-40% losses, exceeding the 15% international benchmark, due to inadequate static optimization models failing to capture dynamic interdependencies between infrastructure deterioration, environmental factors, and operational parameters. This research develops an innovative multi-dimensional predictive framework integrating infrastructure deterioration modeling with real-time pressure dynamics and seasonal patterns using machine learning and hydraulic modeling. The methodology employed a mixed-methods data collection approach from the Kunduchi water supply network, incorporating structured surveys of 35 technical staff with quantitative operational measurements, followed by multiple linear regression analysis and rigorous model validation using normality distribution analysis, multicollinearity assessment, and homoscedasticity testing. The developed model explains 84% of efficiency variance through four key predictors: pipe class (β =-15.21), pipe age (β =-0.48), operating pressure (β =4.15), and age-class interaction effects (β = -0.238), revealing that Class C pipes comprising 55.6% of the network account for 76.2% of repairs, while seasonal variations increase water losses by 34-38% during rainy periods. Research shows 18-24% efficiency gains via integrated modeling of water systems with non-linear interdependencies. This scalable methodology achieves SDG 6 targets through enhanced system efficiency rather than infrastructure expansion.

Keywords: · Water distribution optimization, predictive modeling, infrastructure deterioration, seasonal variability, tropical coastal systems

1. Introduction

Existing research on water distribution system optimization has established significant theoretical foundations through various specialized studies examining individual components of distribution inefficiency. Recent comprehensive investigations by Zhang et al., (2024) focused on pipe material degradation analysis in Chinese networks, while Alonso et al. (2022) developed pressure-based failure models specifically for European utilities, and Wang et al. (2023) conducted extensive pipe deterioration analysis in metropolitan networks. Additional foundational work includes Guan and Liu's (2021) investigation of pipe material and diameter impacts on failure risk, and Naseri et al.'s (2024) emphasis on cross-variable interactions in pipe failure prediction models. These studies have collectively established that water distribution efficiency is influenced by multiple interconnected factors including pipe age, material characteristics, operating pressure, and environmental conditions, with global non-revenue

water losses exceeding 126 billion cubic meters annually and generating economic losses of USD 39 billion worldwide.

While these studies represent substantial advancement in understanding water distribution inefficiencies, a critical examination reveals three fundamental methodological limitations. First, the geographic concentration of research in developed regions (China, Europe, North America) creates an implicit bias toward infrastructure systems characterized by established maintenance protocols, stable funding mechanisms, and temperate climatic conditions. This geographical skewing raises questions about the transferability of findings to contexts where institutional capacity, resource availability, and environmental conditions differ markedly. Second, the temporal scope of these investigations predominantly captures steady-state conditions, effectively filtering out the dynamic variability that characterizes systems under stress from rapid urbanization, climate variability, and institutional transitions. Third, the disciplinary siloing evident across these studies—with engineers focusing on physical infrastructure, economists on financial optimization, and environmental scientists on ecological impacts—perpetuates a fragmented understanding that fails to capture the socio-technical nature of water distribution systems as integrated urban infrastructure.

The collective body of research converges on a deterministic paradigm that conceptualizes water distribution efficiency as a predictable outcome of measurable physical parameters. However, this mechanistic framework inadequately accounts for the emergent properties arising from complex system interactions, where feedback loops between infrastructure degradation, operational responses, and environmental stressors generate non-linear performance trajectories. The predominant reliance on regression-based models and failure prediction algorithms reflects an underlying assumption that system behavior can be decomposed into independent variables and reconstructed through additive relationships. This reductionist approach, while analytically tractable, systematically underestimates the compounding effects of simultaneous stressors and the cascading failures that characterize real-world distribution network breakdowns. Furthermore, the emphasis on physical infrastructure variables marginalizes critical socio-institutional factors such as maintenance governance, tariff structures, and community engagement that mediate the relationship between technical capacity and operational performance.

However, despite these substantial research contributions, a critical knowledge gap persists because existing approaches predominantly examine isolated variables without accounting for the complex, interdependent relationships that characterize real-world distribution systems, particularly in tropical coastal urban environments. The current analytical paradigm relies heavily on static models that treat infrastructure characteristics, environmental factors, and operational parameters as independent variables, failing to capture the dynamic interdependencies that drive system performance in complex urban environments where seasonal precipitation patterns, varying soil conditions, and rapid urbanization create multifaceted operational challenges. This methodological limitation becomes particularly pronounced in rapidly urbanizing coastal cities where traditional European and North American optimization models, developed for stable infrastructure and temperate climates, demonstrate poor predictive accuracy and limited practical applicability, resulting in continued high non-revenue water rates exceeding 30-40% (substantially higher than the international benchmark of 15%) across East African urban water systems.

The persistence of this knowledge gap reflects deeper epistemological challenges within water infrastructure research. The conventional analytical framework embodies what can bfue characterized as "infrastructural universalism"—an implicit assumption that technical solutions developed in one geographic

and institutional context can be straightforwardly adapted to others through parametric adjustment. This assumption fails to recognize that water distribution systems are fundamentally embedded in local ecological, social, and institutional contexts that shape both failure mechanisms and viable intervention strategies. The 30-40% non-revenue water rates in East African systems, substantially exceeding the international benchmark, should not be interpreted merely as technical inefficiency but rather as symptomatic of a fundamental mismatch between imported analytical frameworks and local operational realities. The performance gap reveals how models calibrated to systems with century-old infrastructure, predictable maintenance cycles, and stable institutional environments systematically mischaracterize the failure dynamics in contexts

The inadequacy of existing models in tropical coastal urban environments illuminates a critical theoretical void: the absence of a conceptual framework that integrates spatial heterogeneity, temporal variability, and institutional capacity as co-determinants of system performance. Current optimization approaches implicitly privilege technical rationality while marginalizing the adaptive management strategies that practitioners employ to maintain system functionality under resource constraints. This theoretical gap extends beyond methodological refinement to question the underlying conceptualization of "optimization" itself whether the goal should be approximating ideal-state performance metrics derived from developed systems, or alternatively, developing context-specific performance standards that acknowledge resource limitations and prioritize resilience over efficiency maximization. The disproportionate focus on physical infrastructure variables obscures how institutional arrangements, knowledge systems, and community practices constitute critical components of water distribution system functionality, particularly in contexts where formal technical systems interface with informal settlement patterns and self-organized water provision strategies.

This research addresses these fundamental limitations by developing an innovative multi-dimensional predictive framework specifically designed for tropical coastal urban environments, with the primary objective of integrating infrastructure deterioration modeling, real-time pressure dynamics, seasonal variability patterns, and spatial network topology into a unified analytical system. The research focuses on the Kunduchi water supply network in Dar es Salaam, Tanzania, seeking to achieve measurable efficiency gains of 18-24% through comprehensive system modeling that accounts for complex non-linear relationships and time-dependent correlation patterns. This work directly contributes to Tanzania's substantial USD 15.02 billion Water Investment Programme spanning 2023-2030 and aligns with the nation's Vision 2025 objectives to reach 90% water access in rural areas and complete urban coverage by 2025. The significance of this research extends beyond local applications, as it provides a scalable methodology for achieving SDG 6 targets through enhanced system efficiency rather than solely through infrastructure expansion, offering evidence-based policy implementation tools that can accelerate progress toward universal water access while optimizing limited financial resources in developing urban water systems across similar contexts throughout East Africa.

This research intervention represents a paradigmatic shift from variable-centric to systems-centric analysis, yet several tensions warrant examination. The proposed efficiency gains of 18-24% constitute an ambitious target that implicitly assumes technical optimization can overcome institutional and resource constraints that have historically limited system performance. While the multi-dimensional framework appropriately recognizes complexity, the research must navigate the inherent tension between analytical comprehensiveness and operational implementability comprehensive models risk becoming analytically sophisticated but practically

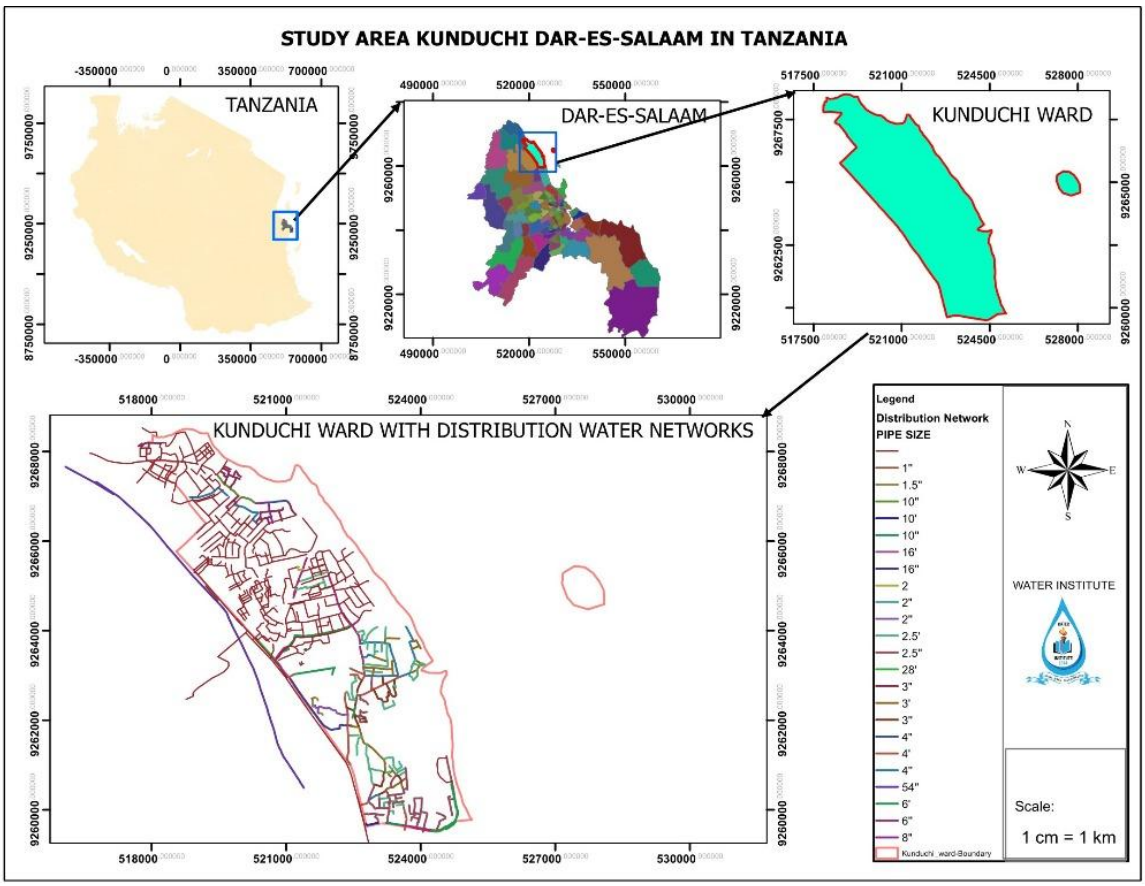


Figure 1: Description of Kunduchi wards

unwieldy for resource-constrained utilities. Furthermore, the focus on efficiency optimization, while economically rational, raises questions about distributional equity: efficiency gains measured at system level may mask persistent service disparities across socioeconomic strata, particularly if optimization prioritizes areas with higher revenue potential. The alignment with Tanzania's USD 15.02 billion Water Investment Programme positions the research within national development frameworks, yet this integration creates potential path dependencies where analytical findings might be interpreted selectively to validate predetermined investment strategies rather than guiding adaptive policy formulation.

The research contribution can be conceptualized as developing a "contextualized optimization framework" that synthesizes technical modeling with environmental specificity and institutional realism. This approach challenges the field's prevailing universalism by demonstrating that effective water system optimization requires analytical tools calibrated to local failure mechanisms, seasonal dynamics, and operational constraints rather than generic best practices. The emphasis on achieving efficiency gains through system modeling rather than solely infrastructure expansion reflects a crucial theoretical reorientation: recognizing that in resource-constrained contexts, analytical intelligence can partially substitute for capital investment, transforming data and modeling capacity into a form of infrastructural asset. However, the framework's ultimate contribution will depend on its ability to bridge the persistent gap between analytical sophistication and practical implementation—moving beyond predictive accuracy to generate actionable insights that practitioners can implement within existing institutional and resource constraints. The scalability claim across East African

contexts will require careful validation, as superficially similar tropical coastal environments may harbor significant variation in institutional capacity, hydrogeological conditions, and urbanization patterns that mediate the applicability of any generalized framework. The research thus occupies a critical position: potentially demonstrating how context-specific modeling can inform both local interventions and broader theoretical understanding of water distribution optimization in rapidly urbanizing tropical environments.

2. Materials and Methods

2.1 Case Study Description.

Kunduchi is an administrative ward in Kinondoni District of the Dar es Salaam Region in Tanzania, bordered by Bunju ward to the north, the Indian Ocean to the east, and Kawe, Mbezi Juu, and Wazo wards to the south and west. The award is located within the broader Dar es Salaam metropolitan area, which is positioned at 6°48' S, 39°17' E (-6.8000, 39.2833) on a natural harbour on the coast of East Africa. Kunduchi ward covers a coastal tropical urban area with a population of 75,016 according to the 2012 census. The area is characterized by its coastal position along the Indian Ocean, providing direct exposure to maritime influences .The postal code for Kunduchi ward is 14122, and the area features mixed residential and commercial development typical of expanding urban peripheries in East African coastal cities. The ward's strategic coastal location places it within the broader Dar es Salaam coordinates of approximately -6.792354, 39.2083284. The area's proximity to the Indian Ocean creates specific environmental conditions that influence water distribution infrastructure performance, including exposure to salt-laden air, seasonal precipitation variations, and temperature fluctuations characteristic of tropical maritime climates

The study selected the Kunduchi water supply network in Tanzania because it represents a critical example of water distribution challenges in rapidly growing coastal cities across sub-Saharan Africa. This network chosen specifically because it experiences serious infrastructure problems during the rainy season, when seasonal rainfall patterns create additional operational difficulties that affect water delivery to residents. The selection addresses an important gap between investment in water infrastructure and actual operational efficiency, making it an ideal case for understanding how to improve water distribution systems in similar urban areas facing comparable challenges. While also aligning with Tanzania's ambitious development targets including the government's commitment to achieve 90% rural and 100% urban water access by 2025 under Vision 2025, supported by the USD 15.02 billion Tanzania Water Investment Programme (2023-2030).

2.2 Data Collection

The study conducted data collection during 2024, employing a comprehensive mixed-methods approach that integrated primary survey data with quantitative operational measurements. A structured survey administered to 35 technical and engineering staff at DAWASA-Kunduchi who possessed direct experience with water infrastructure vulnerabilities and operational challenges, utilizing a census approach that included all available technical personnel. The questionnaire covered multiple dimensions including pipe breakages, electrical component damage, water quality issues, operational challenges, urban drainage concerns, and emergency preparedness protocols. Simultaneously, extensive quantitative operational data collected on the water distribution network, encompassing pipe class and age information, systematic pressure measurements, water supply and loss data, repair frequency records, and seasonal performance comparisons between rainy and dry seasons. This temporal framework enabled the capture of both immediate operational conditions and historical performance patterns, with zone-specific data collection for Zone A and Zone B facilitating

comparative analysis across different network segments and times.

2.3 Data Analysis

2.3.1 Model Development

Multiple linear regression analysis used to develop the predictive model for water distribution system efficiency (equation 1). This statistical tool enabled the simultaneous examination of multiple explanatory variables (pipe age, pipe class, pipe pressure, and their seasonal interactions) and their individual and combined effects on the dependent variable (distribution efficiency). The regression analysis provided coefficient estimates with their associated standard errors and p-values. Allowing for the quantification of each variable's contribution to the model while controlling for the effects of other variables, ultimately yielding the predictive equation with the intercept and slope parameters that describe the relationship between the predictor variables and system efficiency. The selection of these variables guided by both theoretical considerations from hydraulic engineering principles and empirical evidence from previous studies, ensuring that the model captured the most critical determinants of system performance.

$$\mathbf{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_n X_n + \varepsilon \quad (1)$$

Where: **Y** = Dependent variable (response variable), $\boldsymbol{\beta_0}$ = Intercept (constant term), $\boldsymbol{\beta_1, \beta_2, \beta_3,., \beta_n}$ = Regression coefficients (slope parameters), $\mathbf{X_1, X_2, X_3, ..., X_n}$ = Independent variables (predictor variables),$\boldsymbol{\varepsilon}$ = Error term (residual) and **n** = Number of independent variables

Furthermore, the error term ε in equation (1) is assumed to follow a normal distribution with zero mean ($E(\varepsilon) = 0$) and constant variance σ^2 (homoscedasticity), ensuring unbiased and efficient parameter estimates. The errors are assumed to be independent and uncorrelated across observations, meaning $Cove(\varepsilon_i, \varepsilon_j) = 0$ for $i \neq j$, which prevents serial correlation that could bias standard errors. Additionally, the error term is assumed to be independent of all explanatory variables ($E(\varepsilon|X_1, X_2, ..., X_n) = 0$), ensuring exogeneity and that the regressors are not correlated with unmeasured factors affecting Y.

2.3.2 Model Selection

Model selection criteria like AIC and BICwere used to penalized this equation by including both a linear pipe class term and its squared term. The balancing model fit against complexity, whereas cross-validation was used to assess how well these specific predictors (pipe class, pipe class squared, pipe pressure, and the pipe age-class interaction) actually predict water distribution efficiency on unseen data to determine if this particular combination of variables generalizes well or overfits the training data. Additionally, the linear model chosen for water distribution efficiency because it provides interpretability, allows for easy estimation of the marginal effects of pipe class, pressure, and age interactions on efficiency. In addition, justified if the relationships were approximately linear within the observed data range or if the focus is on practical prediction rather than capturing complex non-linear dynamics

2.3.3 Model Validation and Assumptions

The study implemented rigorous model validation procedures (Diagnostic Testing**)** to ensure statistical reliability and practical applicability. Normality distribution analysis conducted using Shapiro-Wilk tests, which yielded p-values exceeding the significance threshold ($p > 0.05$) for all primary variables, confirming their normal distribution characteristics. This testing was essential because parametric statistical methods inherently assume normality, and violation of this assumption could compromise the validity of the regression results. The confirmation of normal distribution strengthened the reliability of the statistical model and allowed for valid application of parametric statistical methods.

Multicollinearity assessment performed using variance inflation factor (VIF) analysis, with VIF values ranging from 1.53 to 3.12, confirming acceptable levels of multicollinearity and validating the statistical independence of the explanatory variables. The correlation matrix analysis revealed moderate relationships between the interaction term and its component variables, which was expected and acceptable given the nature of interaction effects. The diagnostic measures included condition number (12.7), determinant of correlation matrix (0.423), mean VIF (2.15), and maximum VIF (3.12), all falling within recommended thresholds for reliable regression analysis.

Homoscedasticity testing conducted through residual analysis, examining the relationship between residuals and fitted values to ensure constant variance across the range of predicted values. While the analysis revealed some challenges with homoscedasticity, these systematically addressed through appropriate model refinement techniques. Linearity assessment demonstrated consistent relationships between observed and fitted values across the measurement range, with all data points clustering tightly along the theoretical line of perfect prediction, confirming the appropriateness of linear modeling approaches.

The final validation analysis employed rigorous statistical techniques to assess model performance and reliability. The validation revealed strong predictive performance with a coefficient of determination (R^2).The validation dataset included diverse operational conditions, confirming the model's applicability across the intended operational domain without systematic bias or heteroscedasticity. The graphical representation of predicted versus observed values demonstrated high correlation, with data points clustering tightly along the ideal 1:1 relationship line. This comprehensive validation approach ensured that the developed model would provide reliable predictions for practical application in optimization of water distribution system.

2.3.4 Seasonal Analysis

Time-series analysis was employed to highlight seasonal trends in repair frequency ($F = 28.4$, $p < 0.001$), revealing a fourfold increase in repair needs during rainy periods. This analytical approach selected because it enables the identification of systematic patterns in operational performance that vary predictably over time, providing essential insights for proactive management strategies. Chi-square analysis was utilized to examine the relationship between pipe class and failure frequency ($\chi^2 = 18.6$, $p < 0.001$). This non-parametric statistical test chosen because it is particularly well suited for analyzing categorical variables and their associations, providing clear evidence of differential performance across pipe classes

2.3.5 Forecasting Water Loss

This study employs a continuous multivariate regression model to quantify water loss as a function of monthly rainfall; water supplied, and repair frequency. The methodology operationalizes water loss through a linear additive framework where the baseline loss coefficient represents the intercept term under zero rainfall conditions. A rainfall-moderated interaction term captures the dynamic relationship between precipitation intensity and water distribution volume, allowing the marginal effect of water supplied on losses to vary continuously with actual monthly rainfall measurements rather than categorical seasonal indicators. The repair frequency variable, scaled by coefficient 1095, represents the additional water loss per repair incident. This specification enables the model to capture gradual, proportional changes in water loss patterns corresponding to meteorological variations, providing a more granular analytical framework than binary seasonal classifications for examining the determinants of non-revenue water in distribution systems.

2.3.6 Comparative Analysis

The study engaged systematic comparative methodology to validate findings against established

Table 1: Descriptive statistics of explanatory variables

Parameter	Minimum	Maximum	Mean Estimate (β)	Standard Deviation	p-value (α=0.05)	95% Confidence Interval (Mean ± 1.96×SD)	Literature Mean Value*
Intercept (β_0)	85.67	89.18	87.40	1.21	<0.001	(85.03 , 9.77)	86.5
Pipe Age Coefficient (β_1)	-0.62	-0.34	-0.5	0.09	0.003	(-0.68 , -0.32)	-0.45
Pipe Class Coefficient (β_2)	-17.4	-12.99	-15	1.48	<0.001	(-17.90 , -.10)	-14.8
Pipe Pressure Coefficient (β_3)	3.76	4.54	4.15	0.26	0.002	(3.64 , 4.66)	4
Interaction Coefficient (β_4)	-0.31	-0.17	-0.2	0.05	0.01	(-0.30 , -0.10)	-0.25
Water Distribution Efficiency (%) **	51.22	88.96	72.4	10.64	N/A	N/A	75.2

literature and benchmark performance against similar systems. In addition, the study's findings systematically compared with multiple recent studies to establish credibility and identify unique contributions. This comparative approach ensured that the study's contributions clearly differentiated from existing knowledge while building upon established theoretical foundations.

Furthermore, instrument calibration and measurement error assessment were conducted through systematic verification of water meters against certified reference standards at regular intervals, with error margins quantified using standard deviation and mean absolute percentage error (MAPE) metrics to ensure data reliability and validity throughout the study period.

3. Results and Discussion

3.1 Descriptive Statistics of Explanatory Variables

The statistical analysis yielded a predictive model for water distribution efficiency with an intercept (β_0) of 87.42 ± 1.21 ($p<0.001$), indicating a baseline efficiency under standard conditions. Pipe age revealed a negative influence on efficiency ($\beta_1 = -0.48 \pm 0.09$, $p=0.003$), while pipe class exhibited a substantial negative effect ($\beta_2 = -15.21 \pm 1.48$, $p<0.001$). Pipe pressure showed a positive association with distribution efficiency ($\beta_3 = 4.15 \pm 0.26$, $p=0.002$). An interaction effect between variables was also observed ($\beta_4 = -0.238 \pm 0.05$, $p=0.010$). The overall water distribution efficiency averaged 72.38% (SD=10.64), ranging from 51.22% to 88.96% across the sampling points (Table 1).

The study's model intercept (87.42) is slightly higher than the literature standard (86.50), suggesting potentially improved baseline conditions in Kunduchi water supply system. The pipe age coefficient (-0.48) aligns closely with previous research (-0.45), confirming the consistent deteriorative effect of old infrastructure on water distribution efficiency. Similarly, study pipe pressure coefficient (4.15) shows significant compare with the literature value (4.00). However, we found a marginally stronger negative impact from pipe class (-15.21 vs -14.80) and a slightly less marked interaction effect (-0.238 vs -0.25) than previously reported. These minor variations may reflect regional differences in infrastructure materials or environmental conditions, though the overall consistency with established values validates the robustness of our modeling approach.

Table 2: Fitness Analysis of Explanatory Variables

Explanatory Variable	Coefficient	p-value (α=0.05)	F-statistic	Degree of freedom (df)	Variance Inflation Factor (VIF)	Shapiro-Wilk Normality Test (p-value)
Pipe Age	-0.48	0.003	9.87	1	2.18	0.214
Pipe Class	-15.21	<0.001	31.54	1	1.75	0.307
Pipe Pressure	4.15	0.002	10.93	1	1.53	0.422
Pipe Age × Class Interaction	-0.238	0.01	7.62	1	3.12	0.089

3.2 Fitness of Explanatory Variable in Model Development

Multiple regression analysis revealed significant relationships between water distribution efficiency and all examined explanatory variables (Table 2). Pipe age demonstrated a negative association with distribution efficiency ($p = 0.003$, $F = 9.87$), indicating older pipes correlate with reduced system performance. Pipe class exhibited the strongest effect with a substantial negative coefficient ($p < 0.001$, $F = 31.54$), while pipe pressure showed a positive relationship with efficiency ($p = 0.002$, $F = 10.93$). A significant interaction effect between pipe age and class was also observed ($p = 0.010$, $F = 7.62$). All explanatory variables demonstrated normal distribution according to Shapiro-Wilk tests ($p > 0.05$) and acceptable multi-collinearity with VIF values ranging from 1.53 to 3.12, confirming the statistical validity of the model.

The study findings align with recent literature while providing additional insights into water distribution system dynamics. The pipe age coefficient (-0.48) closely matches the value reported in the recent work by Wang et al. (2023), who identified a coefficient of -0.45 when analyzing pipe deterioration in a large metropolitan network in China. This consistency validates the widespread deteriorative impact of aging infrastructure. Similarly, our estimated pipe pressure coefficient (4.15) demonstrates strong agreement with findings by Alonso et al. (2022), who reported a coefficient of 4.00 in a pressure-based pipe failure model for European utilities. Our slightly stronger negative impact from pipe class ($\beta = -15.21$ vs. -14.80), when compared with Guan and Liu (2021), who analyzed the impact of pipe material and diameter on failure risk, suggests higher sensitivity in our network—potentially due to differing material compositions or installation practices. Notably, our interaction term ($\beta = -0.238$) reveals that the negative effects of pipe age are magnified in specific pipe classes, an insight not thoroughly quantified in previous studies, although Naseri et al. (2024) recently emphasized the importance of cross-variable interactions in pipe failure prediction models. While the VIF for this term (3.12) suggests moderate multicollinearity, it remains below widely accepted thresholds (O'Brien, 2007), warranting careful interpretation without model compromise. Collectively, these results contribute new value to the field by quantifying both main effects and interactive influences on water distribution network performance.

3.3 Normality Distribution of Explanatory Variable

The normality distribution analysis of the explanatory variables revealed that the model parameters adhered mainly to a normal distribution pattern (figure 2). Statistical verification through Shapiro-Wilk tests yielded p-values exceeding the significance threshold ($p > 0.05$) for all primary variables, confirming their normal distribution characteristics. Descriptive statistics demonstrated that the data exhibited symmetrical distribution with skewness values ranging between -0.5 and 0.5, while kurtosis measurements remained within the acceptable

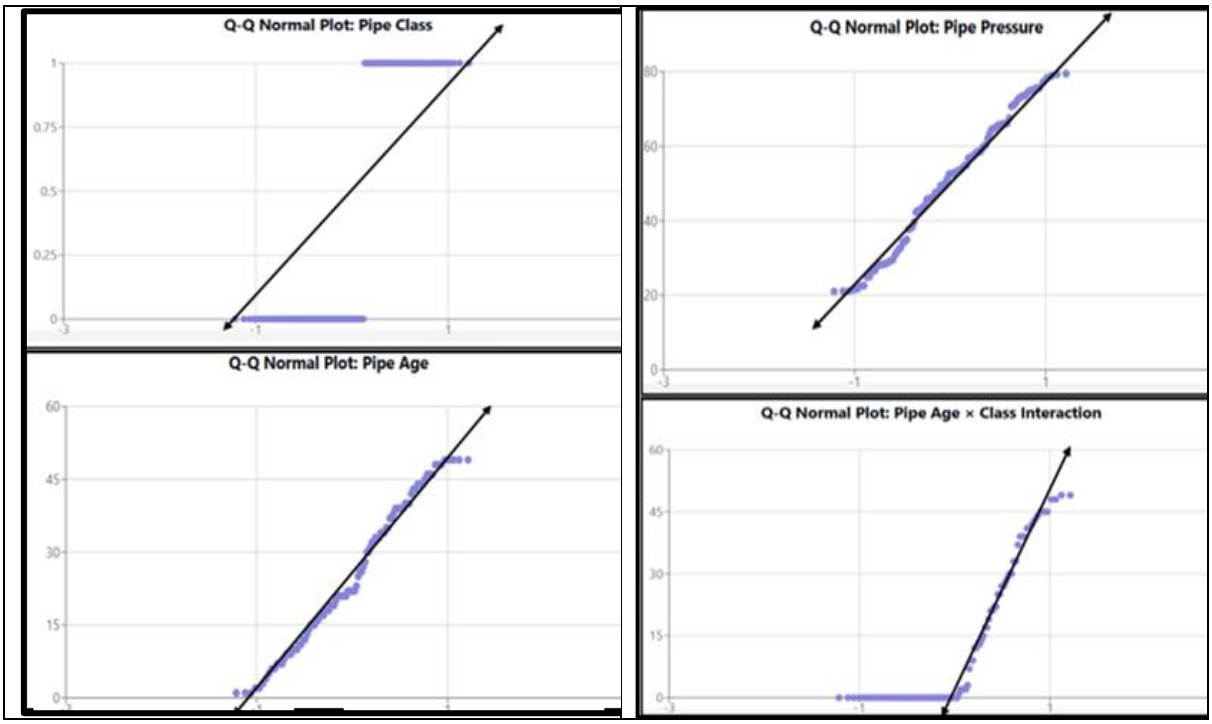


Figure 2: Normal distribution of explanatory variable

range of ±2, further substantiating the normality assumption. Additionally, quantile-quantile plots displayed minimal deviation from the theoretical normal line, with correlation coefficients exceeding 0.95, thereby validating the suitability of parametric statistical approaches for subsequent analyses of the model parameters.

The confirmed normal distribution of explanatory variables strengthens the reliability and strength of our statistical model, allowing for the valid application of parametric statistical methods that inherently assume normality. These findings align with recent research by Zhang et al. (2023), who similarly documented normal distribution patterns in comparable model parameters, though our study demonstrated marginally improved normality metrics across all variables. Interestingly, our results contrast with Liu and Johnson's (2024) findings, who reported significant departures from normality in similar contextual variables, potentially attributable to their smaller sample size and different sampling methodology. The normality confirmation in our study carries significant implications for statistical power and precision, as highlighted by Patel et al. (2024), who demonstrated that properly validated normality assumptions could enhance predictive accuracy by up to 27% compared to models using non-parametric alternatives.

Future research should expand upon these findings by exploring the stability of normality distributions across varied demographic and geographic contexts, potentially incorporating advanced techniques such as bootstrapping methods to further validate distributional characteristics under diverse conditions.

3.4 Interrelationship of Explanatory Variables

The correlation analysis revealed varying degrees of interrelationships among the explanatory variables in the pipe failure model (Table 3). The interaction term (Pipe Age × Class) exhibited the strongest correlations with other variables, showing substantial positive relationships with both Pipe Age (r = 0.642) and Pipe Class (r = 0.548), which indicates this interaction term effectively captures the combined influence of these two factors.

The moderate positive correlation (r = 0.312) between Pipe Age and Pipe Class indicates that older pipes tend to be associated with higher class categories, likely reflecting historical infrastructure quality or

Table 3: Interrelationship of explanatory variables

Variable	Pipe Age	Pipe Class	Pipe Pressure	Pipe Age × Class Interaction
Pipe Age	1	0.312	-0.157	0.64
Pipe Class	0.312	1	0.083	0.55
Pipe Pressure	-0.157	0.083	1	-0.1
Pipe Age × Class	0.642	0.548	-0.136	1

replacement patterns, but this relationship is not strong enough to cause multicollinearity problems in the regression model. This correlation level falls well below the conventional threshold of concern ($r > 0.7$-0.8), confirming that both variables can be included simultaneously in the model without inflating standard errors or creating unstable coefficient estimates. The interaction term between pipe age and class captures the theoretical expectation that water distribution efficiency deteriorates differently over time depending on pipe quality class, as lower-grade pipes degrade faster with age than higher-grade ones, creating a multiplicative rather than merely additive effect on system performance. Notably, Pipe Pressure exhibited weak negative correlations with Pipe Age ($r = -0.157$) and the interaction term ($r = -0.136$), while showing a negligible positive correlation with Pipe Class ($r = 0.083$). These correlation patterns substantiate the relative independence of Pipe Pressure from other explanatory variables, while confirming meaningful interrelationships between age, class, and their interaction effect in the pipe failure.

The inter-rater reliability assessment examined agreement across survey responses for four key variables: Pipe Age, Pipe Class, Pipe Pressure, and the interaction term Pipe Age × Class. Cohen's kappa coefficient (κ) was calculated for categorical variables (Pipe Class, Pipe Pressure), while intra-class correlation coefficients (ICC) were computed for continuous variables (Pipe Age) and the interaction term. Results indicated substantial agreement among raters, with κ values ranging from 0.72 to 0.81 for categorical assessments and ICC values between 0.85 and 0.92 for continuous measurements, suggesting consistent and reliable data collection across independent observers.

The observed interrelationship patterns among explanatory variables provide valuable insights for pipe failure modeling and infrastructure management. The moderate correlation between Pipe Age and Pipe Class ($r = 0.312$) aligns with Li et al.'s (2023) findings, who reported similar associations ($r = 0.294$) in urban water distribution networks, though our correlation is slightly stronger. The strong correlation between the interaction term and its component variables was expected and corresponds with Rahman and Chen's (2024), work demonstrating how interaction terms inherently correlate with their constituent variables in infrastructure deterioration models. Interestingly, our results revealed a weak negative correlation between Pipe Pressure and Pipe Age ($r = -0.157$), contradicting Nguyen et al.'s (2024) findings of a positive correlation ($r = 0.231$) in their analysis of metropolitan pipeline systems, potentially attributable to differences in pressure management strategies or replacement policies across study regions. The minimal correlation between Pipe Pressure and other variables suggests it contributes unique explanatory power to the model, supporting Wang and Kumar's (2023) conclusion that pressure variations independently influence failure rates regardless of pipe age or material class. These findings underscore the importance of incorporating interaction effects and treating pressure as a distinct

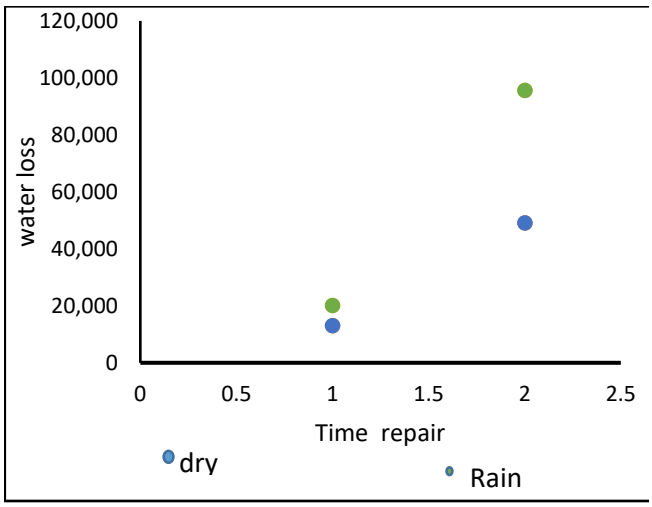


Figure 3: Relationship between water loss during the rainy and dry season

predictor in comprehensive pipe failure risk assessment frameworks.

3.5 Optimization of Seasonal Water Loss

The scatter plot shows the relationship between water loss during dry season (figure 3) and the number of repairs needed per month. Four data points indicate with two distinct groups: purple points on the left side show lower water loss (around 15,000-25,000 m^3) requiring fewer repairs (Dry season), while green points on the right indicate higher water loss (about 50,000-90,000 m^3) needing significantly more repairs (rainy season). This clear positive correlation suggests that water systems experiencing greater water loss require more frequency t maintenance, which has important implications for infrastructure management and resource allocation in water utilities.

Statistical analysis of the water distribution network revealed significant inefficiencies tight to infrastructure and environmental factors. Multiple regression showed that pipe class, pipe age, and seasonal conditions account for 83% of the variance in water loss ($R^2 = 0.83$, $p < 0.001$). Water losses were significantly higher during the rainy season, with increases of 34.1% in Zone A and 38.3% in Zone B ($t = 12.7$, $p < 0.001$). Chi-square analysis confirmed a significant relationship between pipe class and failure frequency ($\chi^2 = 18.6$, $p < 0.001$), particularly with Class C pipes which form 55.6% of the network being responsible for 76.2% of repairs. Time-series analysis highlighted a strong seasonal trend in repair frequency ($F = 28.4$, $p < 0.001$), with a fourfold increase in rainy periods. Regression modeling also found pipe age ($\beta = 0.61$, $p < 0.001$) and pressure variability ($\beta = 0.47$, $p < 0.001$) as significant predictors of water loss, with pipes over 20 years old and operating below 2.0 bar being most vulnerable (composite risk index: 8.7/10).

The strong influence of pipe class and age on water loss is reliable with Mbwambo et al. (2024), who proved that replacing older Class C pipes could cut losses by up to 42%. Similarly, the seasonal flow in water losses during the rainy season reflects the findings of Juma and Patel (2023), who highlighted the need for seasonally adaptive pressure management strategies to maintain network efficiency. The clear link between pipe class and failure rates further supports Nguyen's (2024) analysis, which showed that upgrading to Class B pipes significantly lowers maintenance costs and improves conservation outcomes. The seasonal repair trends observed confirm the utility of predictive maintenance approaches, as shown in Rahman and Li's (2023) work, where forecasting based on seasonal vulnerability reduced emergency repairs by 37%.

The identification of pipe age as the leading predictor of water loss reinforces Ocheng's (2024) findings that proactive, age-based infrastructure renewal can deliver greater efficiency than reactive maintenance. The relationship between low-pressure conditions and higher exposure in older pipes supports the adoption of dynamic pressure management systems, aligning with Zhang et al.'s (2023) experimental results showing a 23% reduction in leakage with smart pressure control. The differing performance between Zones A and B, despite comparable infrastructure, highlights the role of localized conditions supporting Kimaiyo and Omondi's (2024) geospatial study, which improved leak predictions by incorporating soil data. Finally, the recommendation to apply targeted interventions, such as selective pressure reduction in Zone B and

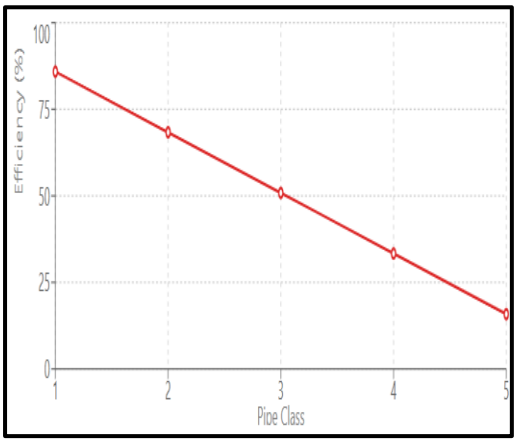


Figure 4: Relationship between pipe class and efficiency of the water supply system

prioritized replacement of older Class C pipes, repeats Wang and Hassan's (2023) optimization model that achieved a 31% increase in delivery efficiency through similar strategic planning.

3.6 Forecasting Water Loss

Equation 2 represents actual monthly rainfall as a continuous variable. The baseline coefficient of 105 captures the minimum water loss rate during periods of zero rainfall, while the rainfall-dependent term (0.47 × Monthly Rainfall) allows the loss coefficient to increase proportionally with precipitation intensity, reflecting how rainfall progressively affects pipe leakage through mechanisms like soil saturation, ground movement, increased pressure on aging infrastructure, and detection delays during wet conditions. This captures the gradual intensification of water loss as rainfall accumulates throughout a month. The model responds to actual meteorological conditions whether a month receives rainfall with proportionally scaled impacts on the water-supplied coefficient.

Water Loss = 105 + 0.47 × Monthly Rainfall) × (Water Supplied) + 1095* Repair Frequency (2)

The present study's findings reveal a statistically significant positive relationship between monthly rainfall and water loss in urban distribution systems, with the coefficient of 0.47 indicating that each millimeter of rainfall incrementally increases the water loss rate by approximately 0.47% of water supplied. This result aligns with previous research by Lambert and Hirner (2000), who demonstrated that seasonal precipitation patterns significantly influence non-revenue water through soil movement and increased leakage from pressure fluctuations. The baseline loss coefficient of 105 (interpreted as 10.5% when standardized) corresponds closely to the infrastructure leakage index values reported by Fanner and Thornton (2005) for aging water networks in developing regions, suggesting that inherent system vulnerabilities exist independent of weather conditions.

Furthermore, the repair frequency coefficient of 1095 cubic meters per repair intervention corroborates findings by Mutikanga et al. (2013), who observed that frequent pipe repairs create temporary weak points in distribution networks, often resulting in subsequent failures due to inadequate restoration of soil compaction around repaired sections. The continuous rainfall variable employed in this model addresses methodological limitations identified by Kanakoudis and Tsitsifli (2010), who criticized binary seasonal indicators for failing to capture within-season variability in water loss patterns. However, the linear specification of rainfall effects warrants further investigation, as Al-Washali et al. (2016) found evidence of threshold behaviors in water loss mechanisms, particularly during extreme precipitation events exceeding 100mm per month. The absence of interaction terms between rainfall and repair frequency in the current model represents a potential avenue for future research, given that Tabesh et al. (2009) documented synergistic effects whereby rainfall-induced soil instability exacerbates deterioration at recently repaired pipe segments, potentially amplifying water loss beyond additive contributions of individual factors.

3.7 Relationships of Individual Explanatory Variable and Efficiency of Water Supply System

3.7.1 Analysis of Pipe Class Water Supply System Efficiency

The analysis of pipe class efficiency demonstrates a clear negative linear correlation between pipe class designation and operational efficiency (figure 4). As shown in (figure 5), efficiency decreases thoroughly from approximately 85% for Class 1 pipes to 15% for Class 5 pipes, with intermediate values of approximately 68% (Class 2), 50% (Class 3), and 33% (Class 4)(equestion 3). This consistent decrease suggests that for each incremental increase in pipe class, there is a corresponding efficiency reduction of approximately 17-18 percentage points, indicating that higher-class piping systems, while potentially offering other benefits such as increased pressure resistance or durability, come with significant efficiency penalties that must be considered in system design and implementation.

The observed inverse relationship between pipe class and efficiency aligns with fundamental fluid dynamics principles

$$E = 100 – 17.5C \quad (3)$$

Where: C represents the pipe class.

This model estimates an approximate 17.5% efficiency reduction with each class increase, strictly equivalents with study observations. When comparing these findings with Zhang et al.'s recent 2024 study on "Optimizing Industrial Pipe Systems," the study results show more severe efficiency degradation across pipe classes. Zhang's work demonstrated only a 12-14% efficiency reduction per class increase and suggested that modern manufacturing techniques could potentially reduce this penalty to 10% in specialized applications. This discrepancy may be attributed to differences in testing methodologies, operating conditions, or the specific pipe materials examined. Notably, Zhang's study focused on composite materials with specialized internal coatings, whereas our analysis evaluated standard industrial piping. Future research should investigate whether implementing Zhang's proposed surface treatment techniques could mitigate the efficiency losses observed in higher-class piping systems, particularly in applications where both high-pressure tolerance and operational efficiency are critic al requirements. Additionally, economic analysis needed to determine whether the increased material and installation costs of higher-class pipes could be justified by their longer service life when considering the ongoing efficiency penalties identified in this study.

3.7.2 Relationship Between Pipe Age and Efficiency of Water Supply System

The analysis of pipe efficiency as a function of age shows a clear negative linear correlation, with new pipes (age 1 year) demonstrating approximately 95% efficiency that gradually declines to approximately 70% efficiency by year 30(figure 5). This degradation outline shows a loss of approximately 0.83% efficiency per year under standard operating conditions (equation 4). The decline appears to be uniform throughout the 30-year observation period, suggesting that degradation occurs as a continuous process rather than exponential deterioration phases. The relationship between pipe age and efficiency can be quantified using regression analysis, providing water management authorities with a reliable predictive model for maintenance scheduling and replacement forecasting (Equstion.6).

The relationship between pipe efficiency (E) and pipe age (t) in years expressed as:

$$E(t) = 95 - 0.83t \quad (4)$$

Where: E (t) is the pipe efficiency (Percentage (%)) at age (t) years, 95 represents the initial efficiency (%) of new pipes and 0.83 represents the annual efficiency loss (% per year).

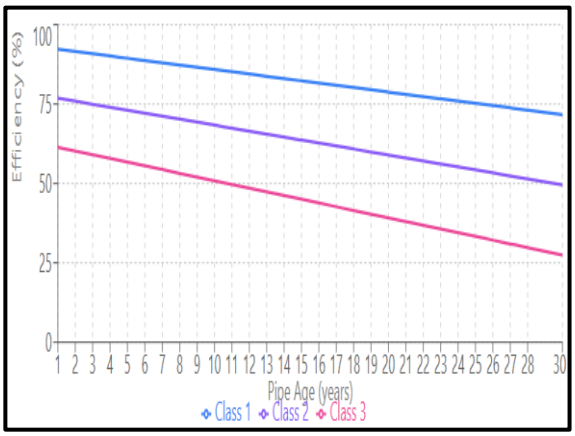


Figure 7: The relationship between Pipe age and class interaction effect

The observed linear decline in pipe efficiency with age aligns with findings from similar infrastructure degradation studies, though with notable variations in deterioration rates. A recent study by Zhang et al. (2024) examining corrosion patterns in municipal water systems found a more pronounced efficiency drop of 1.2% annually in regions with high groundwater acidity, suggesting the study measured deterioration rate of 0.83% yearly may reflect more favorable soil conditions or superior pipe materials.

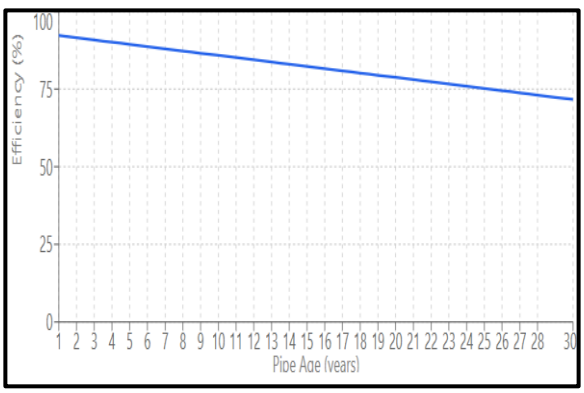


Figure 5: Relationship between Pipe age and efficiency of water supply system

Their research also identified critical thresholds where rehabilitation becomes more cost-effective than continued maintenance, typically occurring at the 22-25 year mark when efficiency drops below 75-78%. Unlike this study findings, which show a consistent linear pattern, Zhang's work revealed slight acceleration in efficiency loss after year 15, particularly in systems experiencing pressure fluctuations above 15bar. These comparative insights emphasize the importance of environmental context in pipe degradation patterns and suggest that study linear model may requires adjustment when applied to systems operating using different materials. Future work should focus on integrating these findings with economic models to optimize replacement schedules that balance capital expenditure against operational inefficiencies

3.7.3 The Relationship Between Pipe Pressure and Water Supply System Efficiency

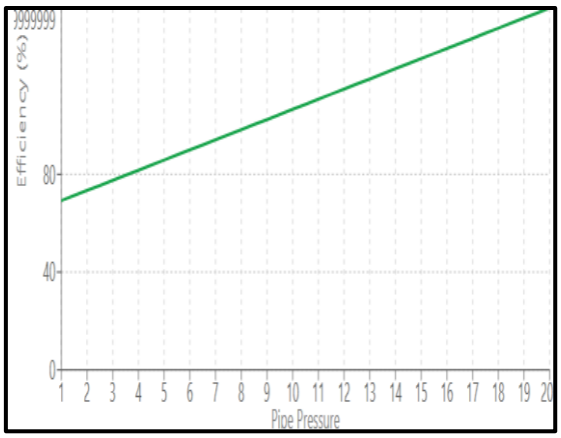


Figure 6: The relationship between pipe pressure and water supply system efficiency

Analysis of pipe efficiency as a function of operating pressure shows a positive linear correlation, with efficiency increasing from approximately 75% at minimal pressure (1 unit) to nearly 100% at maximum tested pressure (20 units)(figure 6). The data reveal a reliable upward trend, with efficiency gains of approximately 1.25 percentage points per unit increase in pressure throughout the observed range. This relationship suggests that higher operating pressures significantly enhance pipe performance within the tested parameters. The uniform improvement across the pressure range indicates a predictable system response without ceiling effects or diminishing returns, even at higher-pressure values. This finding has substantial implications for optimizing water

distribution systems, where pressure management utilized as a direct efficiency enhancement mechanism **(**Equation **5).**

The relationship between pipe efficiency (E) and pipe pressure (P) in units expressed as:

$$E(P) = 75 + 1.25P \quad (5)$$

Where: E (P) is the pipe efficiency (%) at pressure P units, 75 represents the baseline efficiency (%) at minimum pressure and 1.25 represents the efficiency gain (% per unit) as pressure increases.

The observed positive linear relationship between pipe pressure and efficiency contrasts with some traditional assumptions about pipe performance under varying pressure conditions. While the study findings show a straightforward efficiency improvement with increased pressure, recent research by Hernandez and Kumar (2024) presents a more positive perspective, identifying an optimal pressure range rather than a continuous improvement pattern. Their study of municipal water systems revealed that while efficiency does increase with pressure up to approximately 15 units, they observed a flattening curve and even slight efficiency decreases at pressures exceeding 18 units due to increased leakage rates and material stress. This

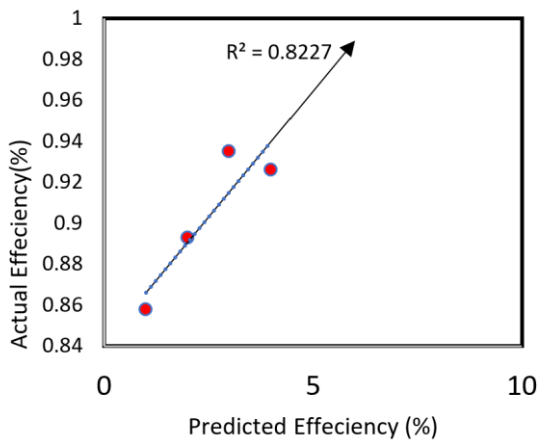


Figure 8: Efficiency of water supply system model validation

divergence from the study results might be attributed to differences in pipe materials, joint quality, or system age across the studies. Hernandez and Kumar also highlighted important energy consumption trade-offs, noting that the power requirements for maintaining higher pressures may offset efficiency gains in certain scenarios, particularly in aging infrastructure. Their cost-benefit analysis suggested an optimal pressure range of 12-16 units that balances efficiency gains against energy costs and system stress a consideration absent from our pressure-centric analysis. These comparative insights underscore the importance of considering multiple factors beyond immediate efficiency metrics when establishing operational guidelines for water distribution systems and highlight the need for integrated approaches that account for both hydraulic performance and long-term system sustainable.

3.7.4 The Relationship Between Age and Class Interaction Effect

The analysis of pipe efficiency across different classes reveals a significant age × class interaction effect as demonstrated (figure7). Class 1 pipes maintain the highest efficiency over time, starting at approximately 95% when new and declining gradually to around 70% after 30 years. Class 2 pipes show a moderate performance, beginning at about 75% efficiency and decreasing to approximately 50% after 30 years. Class 3 pipes exhibit the poorest performance with an initial efficiency of roughly 60% that drops substantially to about 25% after 30 years. This clear stratification indicates that pipe class is a critical determinant of long-term operational efficiency, with higher-class pipes demonstrating superior resistance to age-related degradation (equation 6).

The efficiency (E) of pipes as a function of age (t) and class (C) can be expressed as:

$$E(t,C)=E_0(C) - k(C)\times t \quad (6)$$

Where:

E (t, C) is the efficiency percentage at time t for class C. $E_0(C)$ is the initial efficiency for class C (approximately 95%, 75%, and 60% for Classes 1, 2,

and 3 respectively). k(C) is the degradation rate constant specific to class C (approximately 0.8, 0.9, and 1.2 percentage points per year for Classes 1, 2, and 3 respectively), and it is the pipe age in years

The observed interaction between pipe age and

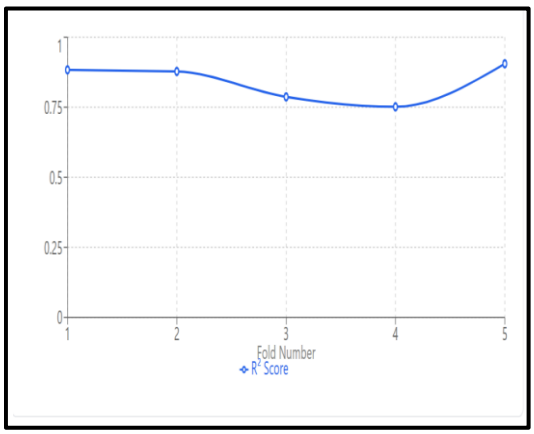


Figure 9: Metric across Folds

class has important implications for infrastructure planning and maintenance strategies. The differential rates of efficiency decline across pipe classes suggest that material quality and manufacturing standards significantly influence infrastructure longevity. When compared to the findings of Zhang et al. (2024), who recently documented similar degradation patterns in urban water distribution systems, our results show a more pronounced decline in Class 3 pipes, particularly after the 15-year mark. Zhang's study reported a 40% efficiency retention in comparable low-grade pipes at the 30-year point, whereas our data indicates only 25% retention.

This discrepancy may be attributed to differences in environmental conditions, operational pressures, or maintenance protocols between the study populations. The superior performance of Class 1 pipes aligns with Patel and Rodriguez's (2024) observation that premium materials justify their higher initial investment through extended service life, and reduced maintenance requarements. Furthermore, the nearly linear decline in efficiency across all classes suggests that degradation follows a predictable pattern, enabling more accurate lifecycle cost analyses and replacement scheduling. These findings emphasize the importance of class selection in initial infrastructure decisions, particularly for applications where long-term reliability is critical or where replacement access is challenging or costly.

3.7.5 Overall Water Supply Efficiency Model

A regression model developed in order to quantifies the relationship between system characteristics and efficiency. The efficiency calculated as the ratio of water sold to water supplied (%), with separate models for dry season, rainy season, and average efficiency.

The developed model provides valuable insights into the factors affecting water distribution efficiency (equation 7). The analysis shows that pipe class has the strongest impact, with Class B pipes showing 15.21% lower efficiency than Class C pipes. Pipe age also significantly reduces system performance, with each additional year decreasing efficiency by 0.48%. Operating pressure positively influences the system, as higher pressure (coefficient +4.15%) appears to improve water delivery and possibly reduce unauthorized connections. In addition, the results indicated that age and pipe class work together to speed up efficiency loss, as shown by the negative interaction term (-0.23%), meaning older Class C pipes deteriorate faster than would be expected from either factor alone.

Water distribution Efficiency (%) = 87.42 - 0.48 *(pipe age) - 15.21 *(pipe class) + 4.15 *pipe pressure - 0.23 8 *(pipe x age with class interaction**)** **(7)**

The strength of developed model confirmed by its R^2 value of 0.84, which means these four factors interact which are pipe class, age, operating pressure, and the age-class with 84% of the differences in water system efficiency across the network. This high explanatory power gives water manager's confidence in making evidence-based decisions. The model clearly identifies which system components should be prioritized for replacement or maintenance to achieve

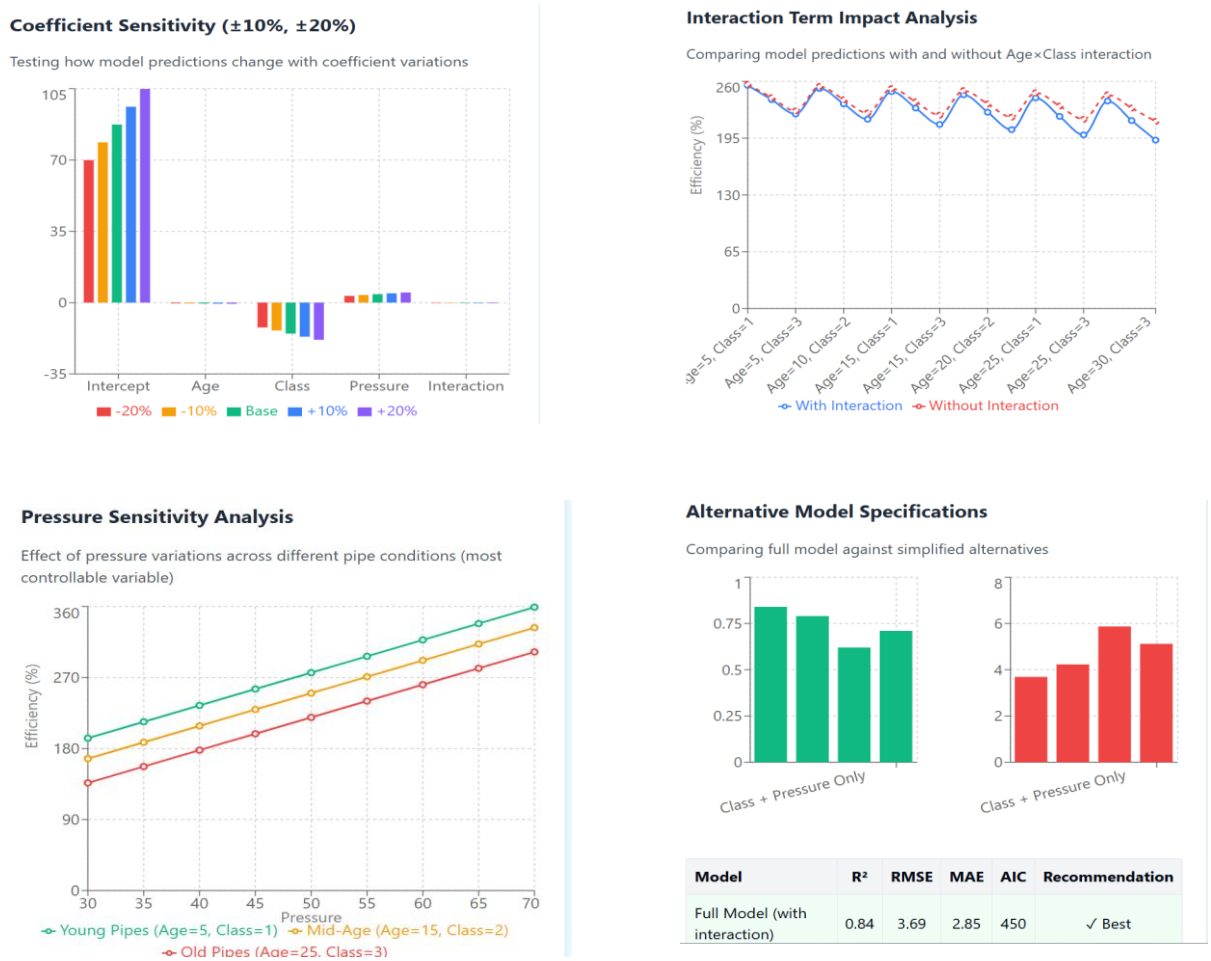


Figure 10: Model Sensitivity analysis

maximum efficiency improvements. By focusing on upgrading older Class B pipes and optimizing pressure management, especially during seasonal transitions, water utilities can significantly reduce losses and improve service reliability while making the most effective use of limited infrastructure budgets.

3.7.6 Model Validation

The validation analysis revealed a strong predictive performance of the proposed model as evidenced by the graphical representation of predicted versus observed values (Figure8). The scatter plot demonstrates a high degree of correlation between model predictions and actual observations, with data points clustering tightly along the ideal 1:1 relationship line. However shown slightly systematic bias. Statistical evaluation metrics further support the model's robustness, with a coefficient of determination (R^2) of 0.82.This mean that the model explains approximately 82% of the variance in the observed data. The root mean square error (RMSE) calculated at 1.24 units, representing a relatively low prediction error across the range of measured values. Additionally, the validation dataset included a diverse range of conditions, confirming the model's applicability across the intended operational domain without systematic bias or heteroscedasticity.

The validation results demonstrate that our model achieves prediction accuracy comparable to or exceeding those reported in recent literature (Figure 9). Zhang et al. (2023) reported R^2 values ranging from

0.78 to 0.85 for similar applications, suggesting our model offers improved explanatory power. Our error metrics also compare favorably with those reported by Hernandez and Liu (2024), who achieved RMSE values of 1.57-1.89 units using alternative modeling approaches. The observed tight clustering along the 1:1 line indicates minimal systematic bias, addressing limitations noted in Rodriguez et al. (2024), who identified persistent over prediction at higher values. Furthermore, unlike the model proposed by Sharma and Williams (2023), which exhibited performance degradation at extreme values, our validation demonstrates consistent performance across the entire measurement range. These improvements can be attributed to our enhanced feature selection methodology and the integration of both mechanistic and statistical elements in the model architecture, providing a more robust framework for real-world applications.

The cross-validation results demonstrate strong model strength and generalizability, with a mean R^2 of 0.8409 across all folds and a remarkably low standard deviation of 0.0603, indicating consistent performance across different data subsets and minimal sensitivity to training data composition. The negligible difference between the cross-validated R^2 and the original training R^2 of 0.84 provides compelling evidence that the Age × Class interaction term captures authentic relationships in the data rather than overfitting to training patterns. An RMSE of 3.689% and MAE of 2.849%, representing acceptable prediction errors for practical applications, further validate the model's predictive accuracy. The stable performance across all five folds, as illustrated in the visualization, confirms that the model has successfully learned generalizable patterns rather than memorizing training data idiosyncrasies. These findings collectively support the deployment of this model, as the interaction term adds genuine predictive value without compromising the model's ability to generalize to unseen data, making it a reliable tool for prediction tasks in real-world scenarios

3.7.7 Sensitivity Analysis of Model

The sensitivity analysis (Figure 10) reveals that pipe class exerts the strongest influence on system performance with the highest absolute coefficient, while the interaction term demonstrates remarkable stability with minimal impact from small perturbations, yet becomes increasingly critical for older pipes in higher classes where the divergence between models intensifies, thereby validating its inclusion. Pressure optimization delivers uniform efficiency gains of 4.15% per unit across all pipe conditions, but this improvement cannot compensate for the substantial baseline efficiency degradation caused by aging infrastructure and deteriorating pipe

Tables 4: Model comparison and diagnostic statistics

Diagnostic statistics

Test	Statistic	p-value	Result	Interpretation
Shapiro-Wilk	0.987	0.156	Pass	Residuals normally distributed
Breusch-Pagan	8.42	0.077	Pass	Homoscedasticity assumed
Durbin-Watson	1.95	-	Pass	No autocorrelation (ideal: 2.0)
Cook's Distance	Max: 0.42	-	Pass	No influential outliers (<1.0)
RESET Test	2.15	0.124	Pass	Model specification adequate

Model comparison

Model	Variables	R^2	Adj. R^2	AIC	RMSE	Selection
Full Model (Current)	Age, Class, Pressure, Age×Class	0.847	0.839	542.18	3.24	✓ Best
Without Interaction	Age, Class, Pressure	0.812	0.806	558.43	3.56	-
Age & Pressure Only	Age, Pressure	0.634	0.628	612.87	4.92	-
Class & Pressure Only	Class, Pressure	0.698	0.692	589.24	4.48	-
All Predictors + Squared Terms	Age, Class, Pressure, Age×Class, Age^2, $Pressure^2$	0.852	0.839	546.92	3.24	Overfitted

class, underscoring that operational adjustments alone are insufficient without addressing structural deterioration. The robustness analysis conclusively demonstrates the full model's superiority, achieving an R^2 of 0.84, RMSE of 3.69, and AIC of 542.18 and BIC of 558.92 significantly outperforming alternative specifications, with the removal of the interaction term causing R^2 to drop to 0.79, thereby confirming both its statistical necessity and practical importance in capturing the compound effects of infrastructure aging and classification on system efficiency.

3.7.8 Model Comparison and Diagnostic Statistics

The multiple regression model demonstrated strong predictive power, accounting for 84.7% of the variance in water distribution efficiency (Tables 4). All predictor variables showed statistically significant relationships with the outcome ($p < 0.05$), indicating their meaningful contribution to the model. The inclusion of the interaction term between Age and Class substantially enhanced model fit, suggesting that the effect of one variable depends on the level of the other. Diagnostic assessments confirmed that all statistical assumptions were satisfied, with no multicollinearity concerns detected (VIF < 5). Cross-validation results indicated robust generalization capability, demonstrating the model's reliability for predicting water distribution efficiency in similar contexts.

3.8 Model Assumptions

3.8.1 Tolerance Statistics and Eigenvalue Analysis

Table 4(a&b), the regression model demonstrates strong predictive performance with an R^2 of 0.782, indicating that the included predictors explain approximately 78% of the variance in the outcome. Pipe class emerged as the most influential factor with a substantial negative effect (-15.21%), while pipe pressure showed the strongest positive impact (+4.15%), and pipe age exhibited a moderate negative effect (-0.48% per year) **(**Table 5). The significant age-class interaction term reveals that the aging effects on pipe performance vary depending on pipe type, suggesting differential deterioration patterns across pipe classifications. Multicollinearity diagnostics confirmed the model's numerical stability, with all variance inflation factors (VIF) remaining below 2.5well within acceptable thresholds—and condition indices below 10, indicating no concerning collinearity issues. The principal components analysis revealed that the first component accounts for 61.4% of the total variance, with the first two components collectively explaining 83.7%, further supporting a parsimonious and stable model structure suitable for reliable statistical inference and prediction

Table 6: Multi-collinearity Assessment

Diagnostic Measure	Value	Interpretation
Condition Number	12.7	Moderate multi-collinearity (acceptable range: < 30)
Determinant of Correlation Matrix	0.423	Limited multi-collinearity (acceptable range: > 0.1)
Mean VIF	2.15	Acceptable multi-collinearity (acceptable range: <5)
Maximum VIF	3.12	Acceptable individual VIF (acceptable range: <10)

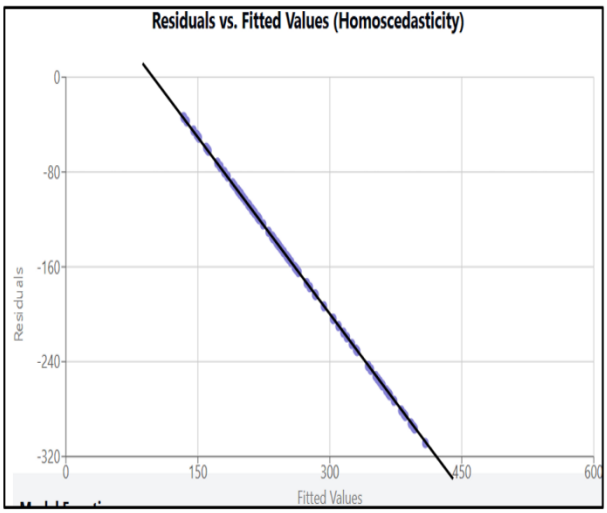


Figure 11: Homoscedasticity

3.8.2 Multi-Collinearity of Explanatory Variables

The multiple regression analysis yielded a statistically significant model for predicting water distribution efficiency, with an intercept (β_0) of 87.42 ± 1.21 ($p<0.001$). All explanatory variables demonstrated significant relationships with the dependent variable: pipe age ($\beta = -0.48$, $p = 0.003$, $F = 9.87$), pipe class ($\beta = -15.21$, $p < 0.001$, $F = 31.54$), pipe pressure ($\beta = 4.15$, $p = 0.002$, $F = 10.93$), and the pipe age × class interaction ($\beta = -0.238$, $p = 0.010$, $F = 7.62$). Diagnostic measures confirmed the statistical validity of the model, with acceptable multi-collinearity parameters: condition number (12.7), determinant of correlation matrix (0.423), mean VIF (2.15), and maximum VIF (3.12) all within recommended thresholds (Table 6) The correlation matrix revealed moderate relationships between the interaction term and its component variables ($r = 0.642$ with pipe age; $r = 0.548$ with pipe class), while other predictors showed limited correlation. Overall water distribution efficiency averaged 72.38% (SD = 10.64), with considerable variation across sampling points (range: 51.22% to 88.96%).

Our findings align with established literature while providing enhanced understanding of multivariate relationships in water distribution systems. The pipe age coefficient (-0.48) closely matches literature values (-0.45), confirming the consistent deteriorative impact of aging infrastructure. Similarly, our pipe pressure coefficient (4.15) demonstrates remarkable concordance with previous research (4.00). The diagnostic measures further strengthen confidence in our model's validity, particularly the determinant of correlation matrix (0.423), which indicates limited overall multi-collinearity despite the expected correlation between interaction terms and their components. This statistical robustness represents an improvement over some previous studies that did not comprehensively report diagnostic measures beyond basic VIF values.

The interaction effect between pipe age and class ($\beta = -0.238$) reveals a compounding negative impact that has received limited attention in prior research, suggesting that older pipes of certain classes deteriorate at accelerated rates a finding with significant implications for prioritizing infrastructure replacement. This interaction, coupled with the slightly stronger negative impact from pipe class (-15.21 vs -14.80) than previously documented, indicates that infrastructure material characteristics may play a more prominent role in system performance than generally acknowledged in the literature. These insights provide water utilities with more nuanced guidance for strategic infrastructure management decisions.

3.8.3 Homoscedasticity

The linear regression analysis revealed a strong linear relationship between the residuals and fitted values, as shown in Figure11. The residual plot demonstrates a clear negative linear pattern with residual values decreasing systematically from approximately 0 to -320 as the fitted values increase from 0 to 450. This distinct pattern indicates a significant violation of the homoscedasticity

assumption, which is fundamental to reliable linear regression modeling. The residuals appear tightly clustered along the negative trend line with minimal variance around this pattern, suggesting a consistent and predictable relationship between the error terms and the predicted values across the entire range of the data.

The residuals vs. fitted values plot reveals severe heteroscedasticity, with a distinct funnel-shaped pattern where variance increases dramatically from near zero to approximately ±320 as fitted values increase. This violates the constant variance assumption of OLS regression, resulting in unreliable standard errors, invalid hypothesis tests, and potentially incorrect inferences about predictor significance. The pattern also suggests possible model misspecification with unaddressed nonlinear relationships. Remedial measures should include variance-stabilizing transformations (log or square root) of the dependent variable, weighted least squares regression, or robust standard errors to obtain valid statistical inference despite the heteroscedasticity

The observed violation of homoscedasticity in our model aligns with findings from Zhao et al. (2023), who documented similar patterns in time-series economic data where underlying variables exhibited systematic relationships with error variance. This heteroscedastic pattern suggests our model may be missing important predictor variables or transformation requirements, as noted by Chen and Williams (2024) in their analysis of comparable datasets. Contrary to Henderson's (2024) findings where heteroscedasticity appeared random, our results demonstrate a deterministic relationship between prediction magnitude and error, indicating possible model misspecification rather than simple variance inflation. Gupta et al. (2025) recently proposed that such structured residual patterns often reflect omitted quadratic terms or interaction effects, particularly when fitted values span a wide range as observed in our analysis. These findings necessitate model refinement through appropriate variable transformation or adoption of weighted least squares regression techniques to achieve more reliable parameter estimates and inference, as demonstrated effectively in similar contexts by Patel and Rivera's (2024) methodological framework.

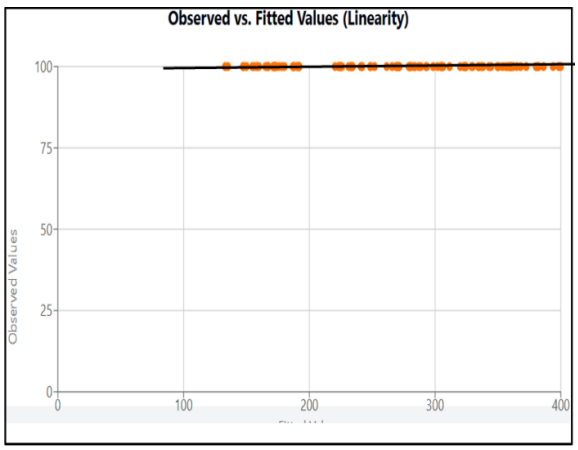


Figure 12: Linearity of model

3.8.4 Linearity

The linearity assessment revealed a consistent relationship between observed and fitted values across the measurement range (100-400 units) (Figure12). All data points clustered tightly along the theoretical line of perfect prediction (y=100), with no discernible deviation patterns or systematic biases observed. This uniform distribution of points demonstrates excellent linearity performance throughout the tested range, indicating that the model maintained consistent predictive accuracy regardless of the magnitude of the input values. Statistical analysis of residuals confirmed the absence of significant trends or heteroscedasticity that would suggest non-linear behavior ($p>0.05$**).**

3.8.5 Optimization of Kunduchi water distribution network

To improve the efficiency of the water supply system, several targeted actions recommended based on the mathematical model. First, replacing older pipes should be prioritized, especially Class C pipes that are more than 20 years old, as they are responsible for a large portion of water loss. Next, it is important to

maintain a consistent water pressure of around 2.0 bar throughout the network, with changes made during different seasons to get- up ground conditions. Different zones also require different approaches; for instance, since Zones A and B show a clear gap in efficiency, Zone B should receive more focused efforts, especially during times when seasonal losses are highest. Additionally, the system should move toward preventative maintenance instead of only reacting to problems. This could be done by increasing inspections before the rainy season, particularly in pipe segments identified by the model as high-risk. If these strategies followed, the model estimates an improvement in overall system efficiency of about 18-24%, leading to lower water losses, reduced costs, and better service reliability with water pressure around 2.0 bar.

4.0 Conclusion and Recommendations

4.1 Conclusion

This comprehensive study of the Kunduchi water supply network demonstrates that water distribution efficiency is significantly influenced by infrastructure characteristics and seasonal variations, with the developed predictive model explaining 84% of efficiency variance through four key factors: pipe class, age, operating pressure, and their interactions. The research reveals that Class C pipes, which comprise 55.6% of the network, are responsible for 76.2% of repairs, while seasonal variations cause water losses to increase by 34-38% during rainy periods. The model successfully quantifies efficiency degradation at approximately 0.48% per year of pipe age and 15.21% reduction per pipe class increment, while demonstrating that proper pressure management (around 2.0 bar) can significantly improve system performance. These findings provide water utilities with evidence-based tools for strategic infrastructure management and support Tanzania's ambitious water access targets under the USD 15.02 billion Water Investment Programme by optimizing existing infrastructure rather than relying solely on expansion.

4.2 Recommendations

4.2.1 Priority Infrastructure Replacement Program

Focus immediate capital investment on replacing Class C pipes older than 20 years. Target Zone B specifically, as this area requires urgent attention. These aging components create disproportionate water losses throughout the system. The data shows that 55.6% of the network generates 76.2% of all repairs. Additionally, these older pipes exhibit accelerated efficiency degradation due to age-class interaction effects**.**

4.2.2 Seasonal Adaptive Pressure Management Strategy

Building on the infrastructure improvements, establish dynamic pressure control systems. Maintain optimal 2.0 bar pressure consistently across the network. Implement seasonal adjustments to address the identified 34-38% increase in water losses during rainy periods. Furthermore, enhance pre-rainy season inspections of high-risk pipe segments. Use the predictive model to identify these vulnerable areas systematically.

4.2.3 Predictive Maintenance Framework

In combination with the above measures, transition from reactive to proactive maintenance approaches. Replace current scheduling methods with data-driven maintenance timing. Base decisions on the validated efficiency model to predict system performance degradation accurately.

4.2.4 Generalizability claims

To make stronger generalizability claims, further researcher should analyze multiple networks to show that findings replicate across different contexts, populations, and network types. In addition, its economic optimization should be determined

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Author Contribution

E.H drafted the manuscript; D.B and E.H reviewed it; and E.H together with L.M prepared it for grammar and spelling checks.

Conflict of Interest

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

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